Energy Financial Risk Management in China Using Complex Network Analysis

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ABSTRACT

Effective energy financial risk management is crucial to ensure that China’s economic system can remain stable. This article utilizes the quantile vector autoregressive spillover index model, complex networks, and deep learning methods to simultaneously assess both the internal and external energy financial market risks in China. Spillover effects under different market conditions are also examined. The research findings indicate that: (1) Under extreme market conditions, static total spillover values between internal and external markets exceed 70%, while under normal market conditions, they are only around 53% and 13%, respectively; (2) Crude oil and fuel oil as well as energy and stocks are important nodes in both internal and external markets; and (3) The attention-convolutional neural network-long short-term memory model outperforms the second-best performing model, and achieves an improvement of 12.9% and 21.4% in terms of mean absolute error and root mean square error, respectively; inclusion of early warning indicators leads to further improvements of 19.8% and 31.9%, respectively.

KEYWORDS

Complex network, Deep learning, Extreme risks, Risk spillover, Risk warning

INTRODUCTION

To combat global warming and achieve sustainable development, understanding the risk contagion characteristics among energy resources and predicting changes in their risk trend are critical steps. They can help to identify key areas, effectively control risk sources, and anticipate future directions, thus providing more efficient assistance toward achieving stipulated sustainability goals. Scientific research has shown that one of the main causes of climate change is the burning of fossil fuels. According to data provided by the United Nations, coal, oil, and gas account for more than 75% of global greenhouse gas emissions and nearly 90% of all carbon dioxide emissions. Therefore,
reducing the consumption of fossil fuels and steadily promoting the use of renewable energy sources have become feasible ways to mitigate climate-related risks (Elie et al., 2021). The 14th Five-Year Plan for the modern energy system issued by the Chinese National Energy Administration in 2022 emphasized that the acceleration of energy as a commodity naturally undergoes price fluctuations because of changes in market supply and demand. When these fluctuations exceed the warning line, they can cause energy security issues and subsequently affect the development of the national economy (Zhang, 2018). Therefore, clarifying the fluctuating characteristics of energy prices and timely risk monitoring are essential to maintain stable economic growth both in China and globally. These measures also help achieve sustainable development.

Energy prices and energy finance are closely intertwined because fluctuations in energy prices directly affect market participants and decision-makers in the energy finance market. Energy finance involves the integration of energy resources and financial resources into a series of financial activities. These activities generate risks that not only cause oscillations within the energy commodity market (Bunn et al., 2017; Geng et al., 2017) but also spill over to other markets, thus disrupting normal transactions. In practice, this spillover is often not unidirectional, but manifests as mutual overflow between different markets (Zhang & Sun, 2016; Kang et al., 2017) and forms a complex network of interwoven markets. Therefore, effective control of energy financial risks requires the simultaneous management of risk spillover characteristics within and across internal and external markets, a better understanding of the risk transmission mechanisms among multiple markets, and the implementation of precise risk prevention and control measures.

However, the existing literature on energy financial risk contagions applies a limited focus on singular, localized, and international aspects. Little research has been conducted on the risk transmission mechanism between China’s internal and external energy finance markets. Moreover, there is a lack of studies developing risk warning models. Using the aforementioned analysis, we primarily focused this study on the following aspects: First, we selected futures data from multiple internal energy finance markets (crude oil, fuel oil, asphalt, coke, coking coal, and methanol) and data from various external markets that may show risk associations with the energy market (carbon, interest rates, exchange rates, bonds, gold, and stocks). Second, considering the research purpose and data applicability, we adopted the relatively novel quantile vector autoregressive (QVAR) model to capture the spillover characteristics of both internal and external risks to the energy market at three quantile levels (0.05, 0.5, and 0.95); thus, the heterogeneity of risk transmission mechanisms was analyzed under different market conditions. Subsequently, we analyzed internal and external risk spillover characteristics from the perspective of complex networks to gain a better understanding of risk interdependence in the energy finance market. Third, we constructed a Chinese energy financial risk early warning system using an attention-convolutional neural network long short-term memory (Attention-CNN-LSTM) model to enhance risk identification and prediction capabilities. This model provides an effective risk management tool and unlocks decision-making references for relevant institutions and investors.

In this paper we provide a comprehensive review of the existing literature on energy risk regulation and prediction; outline the construction process for the QVAR spillover index model and Attention-CNN-LSTM Model; present an empirical analysis; share our conclusion; and offer recommendations for energy risk regulation.

LITERATURE REVIEW

Most studies indicate that risk spillover in energy finance markets exhibits characteristics such as multi-directionality, time-varying patterns, asymmetry, and nonlinearity. Moreover, spillover effects show significant variations under different market conditions (Sim & Zhou, 2015). Therefore, selecting appropriate methods when measuring risk correlations is a prerequisite for the accurate analysis of the risk transmission mechanism between internal and external energy finance markets. Within the scope of
energy finance risk spillover, scholars have employed diverse methods to capture risk interdependencies across markets, and promising results have been obtained. First, in combination with other models, the GARCH model is commonly used to capture risk transmission and spillover effects between markets; a key benefit is its ability to accurately characterize volatility clustering and fat-tail features in financial markets. For example, Yao and Li (2023) proposed the GARCH-MIDAS-GAS-copula model and used it to analyze risk spillover effects in stock markets. Karimi et al. (2023) examined the spillover effects of cryptocurrencies on gold and crude oil markets using both GJR-GARCH and EVT copula models, showing that cryptocurrencies exhibit relatively low levels of risk spillover to existing gold and crude oil markets. Zhang et al. (2022) used a DCC-GARCH-based method to analyze risk spillover among multiple markets, including stock and carbon emission markets; their findings identified the carbon emission market as the primary risk transmitter, while the green bond market acts as the main risk receiver. Similarly, many studies have applied GARCH-related models to analyze risk spillover within the energy finance domain, achieving favorable outcomes (Zheng et al., 2022; Jiang et al., 2021). In other fields, this type of model has also been widely endorsed and used (Mensi et al., 2014; Shahzad et al., 2018; Dahl et al., 2020; Huriso et al., 2023).

In addition to the GARCH model, other mainstream methods used to analyze market interdependencies are the CoVaR model, vector autoregression (VAR) model, Diebold and Yilmaz spillover index model, Granger causality test, wavelet coherence, and Copula model. For example, Chen et al. (2022) examined the impact of oil and exchange rates on Chinese stock prices using the CoVaR model and found that stock market volatility is sensitive to the oil market. Luu Duc Huynh (2019) analyzed risk spillover effects among cryptocurrencies using VAR-SVAR Granger causality analysis and found that Bitcoin often acts as a recipient of spillover effects. Zhang et al. (2021) used the time-varying vector autoregressive Diebold and Yilmaz spillover index model to analyze the changing correlation between energy and stock markets during the pre- and post-pandemic periods. Their findings showed that the energy market acted as a risk receiver and experienced an increased level of risk absorption after the pandemic. Yadav et al. (2023) examined the volatility spillover characteristics of energy commodities using various methods, such as the Granger causality test and the Diebold and Yilmaz spillover index model. They found that volatility exhibits stronger persistence in the long run. Kirikkaleli and Güngör (2021) studied the relationship between commodity price indexes using wavelet coherence analysis and found that commodity price indexes affect energy price indexes significantly. Zhou et al. (2022) studied volatility spillover among multiple energy markets using the Vine Copula model and found that renewable energy markets exhibit stronger volatility spillover characteristics that are particularly pronounced during market booms. Because of the high scalability of these methods, they have been widely employed and improved in other fields (Wang & McPhail, 2014; Makkonen & Mitze, 2019; Mtar & Belazreg, 2021; Hung, 2021; Zeng et al., 2023).

Analyzing the correlation between markets can help to identify transmission mechanisms and intensities of risks, but it cannot predict potential risks in the future. To better manage risks in the energy finance domain and prevent the occurrence of systematic risks, forecasting spillover risks is crucial. Recently, deep learning methods have achieved good performance in capturing, processing, and decomposing data features, among other aspects. Compared with traditional forecasting methods and machine learning approaches, deep learning can better learn, train on, and predict time series data. As a result, deep learning has been widely used by scholars across various fields (Li et al., 2021; Du & Shu, 2022; Liang et al., 2022). The application of deep learning to forecast the overall risk spillover value in energy finance is a novel analytical approach developed in this study.

In summary, there are currently various models to characterize risk spillover indexes. However, the aforementioned models are not suitable for the research in this paper because they may overlook the nonlinear characteristics between markets, measure only binary relationships, capture only average shocks, and fail to quantitatively evaluate the intensity and direction of risk spillover effects. Therefore, in this study, we adopted the quantile VAR model proposed by Ando (2022) to assess the internal and external risk interconnections in energy finance under different market conditions. Compared
with the aforementioned models, this model possesses the following advantages that align with the requirements of this study:

- The quantile VAR model can reflect differences in quantiles; therefore, it is able to characterize asymmetric risk spillover effects better than other models.
- It provides dynamic correlation results of spillovers at different quantiles, thus enabling comprehensive analyses of market relationships under different risk levels.
- It can simultaneously consider multiple risk transmission mechanisms among markets, thus enabling the comprehensive evaluation of both internal and external risk spillover effects.
- It can provide more accurate information on risk transmission and measurements of risk spillover effects, thus aiding the monitoring and management of financial risks.

Furthermore, we transformed the risk correlation matrix into a complex network for further analysis. Complex network analysis can help to uncover hidden associations and patterns in the energy finance market. Studying the topological characteristics of nodes can disclose potential correlations and interaction modes within the market, thus uncovering driving factors of market behavior and underlying patterns. Ultimately, this approach facilitates fine-grained monitoring and regulation of the energy finance market (Mutambik et al., 2021). In addition, in this paper, we innovatively applied the Attention-CNN-LSTM deep learning model to predict the total spillover index value within the energy finance risk interconnection system. We used this prediction to construct a risk early warning system, thereby enhancing the intensity of risk prevention and control.

MODEL CONSTRUCTION

Spillover Index Model Based on Quantile Vector Autoregression

In this paper, we used a spillover index model based on quantile vector autoregression to capture the characteristics of risk transmission inside and outside of the Chinese energy finance market and to explore whether heterogeneity exists in risk spillover under different quantiles. In general, an n-dimensional p-order quantile vector autoregressive process $QVAR(P)$ is defined as shown in equation (1):

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau)y_{t-i} + e_t(\tau), \quad t = 1, 2, \cdots, T,$$

(1)

In this equation, $y_t$ is an n-dimensional column vector, $c(\tau)$ represents the intercept vector at quantile $\tau$, $B_i(\tau)$ represents the n-dimensional lag coefficient matrix at quantile $\tau$, and $e_t(\tau)$ is an n-dimensional error column vector. Before estimating the lag coefficient matrix $B_i(\tau)$ and the intercept vector $c(\tau)$, we need to make certain amendments to the error term $e_t(\tau)$ to satisfy the preconditions for the interpretability of the equation: Assuming that the error term satisfies the conventional quantile regression constraint $Q(e_t(\tau)|y_{t-1}, \cdots, y_{t-p}) = 0$, we know the estimate of $y$ at quantile $\tau$ under this assumption is: $Q(y_t|y_{t-1}, \cdots, y_{t-p}) = c(\tau) + \sum_{i=1}^{p} B_i(\tau)y_{t-i}$.

The framework of the DY spillover index is then built into the QVAR model, which is embedded to calculate the spillover index separately for multiple quartiles. Thus, a model is constructed that can measure the spillover index at different quartiles, and thus, can better respond to the volatility
spillover effect under extreme conditions. Specifically, equation (1) is first rewritten as an infinite-order vector moving average process, as shown in equation (2):

\[ y_t = \mu(\tau) + \sum_{s=1}^{\infty} A_s(\tau)e_{t-s}(\tau), \quad t = 1,2,\ldots T. \]  

(2)

It is important to note the calculations shown in equations (3) and (4).

\[ \mu(\tau) = (I_n - B_1(\tau) - \cdots - B_p(\tau))^{-1}c(\tau), \]

(3)

\[ A_s(\tau) = \begin{cases} I_n, & s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \cdots + B_p(\tau)A_{s-p}(\tau), & s > 0 \end{cases}. \]

(4)

In these equations, \( y_t \) is obtained by summing the error terms \( e_t(\tau) \) to infinite order, which can also be expressed as the sum of the mutually orthogonal error terms \( e_t(\tau) \) to infinite order, as shown in equations (5)–(7):

\[ y_t = \mu(\tau) + \sum_{s=1}^{\infty} \phi_s(\tau)e_{t-s}(\tau), \quad t = 1,2,\ldots T, \]

(5)

\[ \phi_s(\tau) = A_s(\tau) \cdot \Gamma(\tau), \]

(6)

\[ e_t(\tau) = \Gamma^{-1}(\tau) \cdot e_t(\tau). \]

(7)

Here, \( \Gamma(\tau) \) is a lower triangular Cholesky decomposition matrix; a one-step forward prediction of \( y_t \) in equation (5) yields the following values shown in equation (8):

\[ y_{t+1} = \mu(\tau) + \sum_{s=1}^{\infty} \phi_s(\tau)e_{t+1-s}(\tau). \]

(8)

Thus, the one-step prediction error is shown in equation (9):

\[ y_{t+1} - Q_1(y_{t+1}) = \varphi_0(\tau)e_{t+1}(\tau). \]

(9)

And therefore, the forward h-step prediction error is obtained as shown in equation (10):

\[ y_{t+h} - Q_h(y_{t+h}) = \sum_{s=1}^{h} \phi_s(\tau)e_{t+1+h-s}(\tau). \]

(10)

For a single variable in series \( \{y_t\} \), the forward h-step prediction error can be expressed as shown in equation (11):

\[ y_{t,1+h} - Q_h(y_{t,1+h}) = \sum_{s=1}^{h} (\varphi_{s1}(\tau)e_{t,1+h-s}(\tau) + \cdots + \varphi_{sn}(\tau)e_{t,n-1+h-s}(\tau)). \]

(11)
The prediction error variance $D_i^h(\tau)$ of $y_{i,t+h}$ is thus: 
$$
\sum_{s=1}^{h} (\varphi_{in}^s(\tau))^2 + \cdots + (\varphi_{in}^s(\tau))^2 
$$
so that the ratio caused by the sequence $\{\varepsilon_{i,j}(\tau)\}$ is

$$
\omega^h(\tau) = \frac{\varphi_{ij}^h(\tau)^2 + \cdots + \varphi_{ij}^h(\tau)^2}{D_i^h(\tau)}
$$
in the prediction error variance of the forward $h$ steps. The variance decomposition of the prediction error enables the understanding of the ratio from internal to external shocks at different quantile levels, which in turn allows to construct the gross spillover index $TSI(\tau)$, the net spillover index $NSI_{ij}(\tau)$, and the directional spillover indexes $DSI_{ij}(\tau)$ and $DSI_{ji}(\tau)$ at different quantile levels. These are respectively defined in equations (12)–(15):

$$
TSI(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \omega^h(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \omega^h(\tau)} \times 100,
$$

(12)

$$
DSI_{ij}(\tau) = \frac{\sum_{j=1}^{N} \omega^h(\tau)}{\sum_{j=1}^{N} \omega^h(\tau)} \times 100,
$$

(13)

$$
DSI_{ji}(\tau) = \frac{\sum_{i=1}^{N} \omega^h(\tau)}{\sum_{i=1}^{N} \omega^h(\tau)} \times 100,
$$

(14)

$$
NSI_{ij}(\tau) = DSI_{ij}(\tau) - DSI_{ji}(\tau),
$$

(15)

The total spillover index represents the sum of the spillover risks of the whole system at the $\tau$-quantile; the directional spillover index represents the one-way spillover effect of a market to another market; the net spillover index represents the difference between the outward spillover and inward-received risk values of a single market; if the net spillover index of a certain market is greater than 0, it indicates that the market is a net emitter of risk; conversely, if the value is less than 0, it signifies that the market is a net receiver of risk.

**Elaboration of the CNN-LSTM Model Based on the Attention Mechanism**

The advantage of LSTM is that it can uncover the intrinsic patterns of long sequences and has high prediction accuracy, but it often results in overfitting because of the size of features; therefore, extracting features from the data before inputting them into the LSTM framework is necessary. The Attention-CNN-LSTM model can not only compensate for the shortcomings of CNN in long series dependence but also further improve the overall prediction accuracy at anomalies or jump points. Therefore, it is more suitable for the prediction of energy-food risk series, and the operation process of the whole system is shown in Figure 1. The Attention-CNN-LSTM model consists of data preprocessing, an attention-based CNN unit, an LSTM unit, and an output unit. A detailed description is provided as follows:

- Data preprocessing: To handle abnormal data, the nearby mean is used for replacement. Additionally, to address variations in variable scales, data are normalized. The dataset is then partitioned into training, testing, and validation sets.
Attention-based CNN unit: Multiple overlapping continuous subsequences are extracted from the original dataset and used as input for the attention-based CNN unit. This unit employs an attention mechanism that enables it to focus on significant features during CNN operations.

LSTM unit: The output of the previous unit serves as input for this unit. A time series prediction model is constructed using the LSTM architecture, which captures temporal dependencies in the data.

Output unit: The final hidden layer of the LSTM network generates the output of the model. This output can be a prediction or a classification, depending on the specific task.

The steps for the operations of the Attention-CNN-LSTM model are as follows:

Feature extraction is performed using CNN, as shown in equation (16):

\[
 h_l = ELU(W_l \odot X + b_l),
\]

In this equation, \( h_l \) is the output of the data after CNN, \( ELU \) is the activation function, \( W_l \) represents the weight matrix, \( \odot \) represents the convolution operation, and \( b_l \) represents the bias vector.

The attention mechanism is applied to weight and fuse the features. The calculations for this step are shown in equations (17)–(19):

\[
 e^k_t = v^T \sigma(W_v [h_{t-1}, c_{t-1}] + U_v h_t + b_v),
\]

\[
 a^k_t = \frac{\exp(e^k_t)}{\sum_{i=1}^n \exp(e^i_t)},
\]

Figure 1. Schematic diagram of the attention-convolutional neural network long short-term memory (Attention-CNN-LSTM model)
\[\sum_{i} a_i^T h_i, \] (19)

In these equations, \( u^T, b, W, \) and \( U \) are parameters to be learned; \( a^T \) is the k-th attention weight at time t; \( e^T \) denotes the importance of \( h_i \), and \( \pi \) denotes the attention output.

Modeling and prediction are conducted using LSTM, as shown in equations (20)–(25):

\[
f_t = \sigma(W_f \cdot [h_{t-1}, \pi] + b_f),
\]
(20)

\[
i_t = \sigma(W_i \cdot [h_{t-1}, \pi] + b_i),
\]
(21)

\[
\tilde{C}_t = ELU(W_C \cdot [h_{t-1}, \pi] + b_c),
\]
(22)

\[
C_t = f_t \ast C_{t-1} + i_t \ast \tilde{C}_t,
\]
(23)

\[
o_t = \sigma(W_o \cdot [h_{t-1}, \pi] + b_o),
\]
(24)

\[
h_t = o_t \ast ELU(C_t),
\]
(25)

In these equations, \( f \) denotes the forgetting gate, \( W \) denotes the weight matrix of the corresponding gate, \( h_{t-1} \) denotes the hidden state at period t-1, \( \pi \) denotes the input of the layer at time t, \( b \) denotes the bias of the corresponding gate, \( i_t \) denotes the input gate, and \( o_t \) denotes the output gate.

**EMPIRICAL ANALYSIS**

**Model Parameter Setting**

Before the empirical analysis, setting the required parameters is necessary. In both the QVAR model and the time-varying parameter vector autoregression (TVP-VAR) spillover index model, the optimal lag order \( p \) was determined to be 1 based on the combination of multiple criteria, including BIC, SC, and HQ. Additionally, a rolling window size of 200 was set for the QVAR model, and the prediction horizon \( h \) was fixed to 100 periods.

**Variable Selection and Descriptive Statistical Analysis**

To comprehensively analyze the spillover effects of energy financial risks both inside and outside the market, as well as to further examine the structural characteristics of risk transmission among different submarkets within the energy finance market, we referred to previous literature and selected multiple submarkets with potential correlation effects and external related markets for analysis. Given the availability of data, the internal markets selected were the existing closing price data of crude oil, coking coal, coke, methanol, asphalt, and fuel oil in the Chinese futures market from January 2, 2019, to December 30, 2022. These data were preprocessed using the logarithmic yield method. We selected the external markets primarily from variables such as the carbon market (represented by the Hubei carbon trading market), stock market (represented by the Shanghai Composite Index), foreign exchange market (represented by the U.S. dollar against the Renminbi), interest rate market (represented by the overnight Shanghai Interbank Offered Rate), bond market (represented by the Shanghai Government Bond Index), and the gold market. We extracted data for these markets from January 5, 2015, to December 30, 2022. In addition, we selected the Shanghai Energy Industry Comprehensive Index as a proxy variable for the energy finance market and added it to the analysis of external market spillover effects. The frequency of data for each market was daily, and to eliminate the influence of scale differences, standardization processing was uniformly carried out. Table 1 shows the descriptive statistical analysis of each variable, and the Jarque-Bera
test results reject the null hypothesis of normal distribution for all variables at the 1% level. The unit root test also shows that the variables are significantly stationary; therefore, the analysis of risk spillover effects can be conducted.

**Static Characteristics of Risk Spillovers in Energy Finance Markets**

*Analysis of Internal Directional Spillover Characteristics Under Different Market States*

In terms of model order, according to the Akaike information criterion, the optimal lag order of the QVAR-DY spillover index model selected in this paper is order 1, and the number of periods for the forecast error variance decomposition is 10. The conditional mean-based spillover index approach is introduced first to analyze the factor market within energy, and this approach is used for a comparison with risk spillover under the conditional median (0.5 quantile). The total spillover index under the conditional mean in Table 2 is 53.2%, which is almost identical to the value of 53.01% under the conditional median shown in Table 3. This similarity indicates a significant total risk spillover effect within the energy market. Further analysis of the values across multiple markets shows a high degree of similarity in volatility spillovers for both. At the directional spillover level, the size of the spillover and spillover into different markets fluctuate within the range of 37.7% (methanol) to 67.1% (fuel oil) and 45.8% (coking coal) to 61.3% (fuel oil), respectively. A noteworthy point is that fuel oil accounts for a large share of both risk spillovers and spillovers, and fuel oil is an important source of systemic risk in China's energy internal market. The main reason for this result may be that fuel oil is widely used in a number of industries, including power, steel, building materials, and petrochemicals, and holds an important position in the overall energy system. In terms of the strength of inter-market relationships, strong levels of volatility spillovers exist between crude oil and fuel oil, crude oil and bitumen, fuel oil and bitumen, and coking coal and coke; however, the relationships between crude oil and coking coal, as well as between coke and methanol, are relatively weak. From a net spillover perspective, crude oil, fuel oil, and bitumen have higher spillover effects on several other markets, thus making their net spillover values positive. Consequently, these are net risk exporters in the overall risk network, whereas coking coal, coke, and methanol are net risk receivers.
However, the spillover effects based on conditional mean and conditional median can reflect the risk spillover characteristics only under normal market conditions. When the market is subject to extreme upward and downward pressures, the risks of the entire financial system often show a sudden jump within a short period of time. At this time, the spillover effects generated under normal conditions may not accurately reflect the true volatility spillover features between markets. Therefore, further calculation of risk spillover at the 0.05 and 0.95 quantiles is necessary to describe the most likely transmission mechanism when major events occur. The data presented in Tables 4 and 5 show that the total spillover index on the left and right tails reaches as much as 78.05% and 77.59%, respectively. These results are significantly higher than those based on the conditional mean or conditional median spillovers and exhibit high symmetry. This pattern may be due to the deepening level of energy finance with economic development, resulting in a closer connection between various markets; moreover, different submarkets are in a sensitive warning state, thus exhibiting a stronger reaction to extreme events. From the perspective of directional spillover, each element within the energy market shows relatively high levels of both inflow and outflow spillover at the 0.05 and 0.95 quantiles. These high levels indicate that the risks caused by extreme shocks will not exhibit significant heterogeneity because of different positive and negative directions. Minor changes often exist in only the relative sizes of risks among different submarkets. For example, when faced with positive shocks, fuel oil exhibits the highest inflow and outflow values, whereas when faced with negative shocks, the maximum inflow value shifts to crude oil and asphalt. In addition, from the perspective of net spillover, at the 0.05 quantile, fuel oil and crude oil are almost equally the largest.

Table 2. Mean-based directional volatility spillover effects and connectedness (%)

<table>
<thead>
<tr>
<th></th>
<th>Crude oil</th>
<th>Fuel oil</th>
<th>Asphalt</th>
<th>Coke</th>
<th>Coking coal</th>
<th>Methanol</th>
<th>From</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude oil</td>
<td>39.3</td>
<td>28.8</td>
<td>21.2</td>
<td>1.8</td>
<td>1.6</td>
<td>7.4</td>
<td>60.7</td>
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<tr>
<td>Fuel oil</td>
<td>28.5</td>
<td>38.7</td>
<td>20.4</td>
<td>2.3</td>
<td>1.9</td>
<td>8.1</td>
<td>61.3</td>
</tr>
<tr>
<td>Asphalt</td>
<td>22.4</td>
<td>21.8</td>
<td>41.1</td>
<td>3.1</td>
<td>2.8</td>
<td>8.9</td>
<td>58.9</td>
</tr>
<tr>
<td>Coke</td>
<td>2.1</td>
<td>2.9</td>
<td>3.7</td>
<td>53.7</td>
<td>30.9</td>
<td>6.7</td>
<td>46.3</td>
</tr>
<tr>
<td>Coking coal</td>
<td>1.9</td>
<td>2.5</td>
<td>3.3</td>
<td>31.4</td>
<td>54.2</td>
<td>6.6</td>
<td>45.8</td>
</tr>
<tr>
<td>Methanol</td>
<td>10</td>
<td>11.2</td>
<td>11.5</td>
<td>7</td>
<td>6.6</td>
<td>53.7</td>
<td>46.3</td>
</tr>
<tr>
<td>To</td>
<td>64.9</td>
<td>67.1</td>
<td>60.2</td>
<td>45.6</td>
<td>43.8</td>
<td>37.7</td>
<td>TCI</td>
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<tr>
<td>Net</td>
<td>4.2</td>
<td>5.8</td>
<td>1.3</td>
<td>-0.8</td>
<td>-1.9</td>
<td>-8.6</td>
<td>53.2</td>
</tr>
</tbody>
</table>

Table 3. Median-based directional volatility spillover effects and connectedness (%)

<table>
<thead>
<tr>
<th></th>
<th>Crude oil</th>
<th>Fuel oil</th>
<th>Asphalt</th>
<th>Coke</th>
<th>Coking coal</th>
<th>Methanol</th>
<th>From</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude oil</td>
<td>39</td>
<td>28.41</td>
<td>21.48</td>
<td>1.92</td>
<td>1.58</td>
<td>7.62</td>
<td>61</td>
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<td>Fuel oil</td>
<td>28.07</td>
<td>38.5</td>
<td>20.49</td>
<td>2.71</td>
<td>2.11</td>
<td>8.12</td>
<td>61.5</td>
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<td>Asphalt</td>
<td>22.83</td>
<td>22.05</td>
<td>40.96</td>
<td>2.86</td>
<td>2.66</td>
<td>8.65</td>
<td>59.04</td>
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<td>Coke</td>
<td>2.44</td>
<td>3.04</td>
<td>3.82</td>
<td>54.33</td>
<td>29.89</td>
<td>6.48</td>
<td>45.67</td>
</tr>
<tr>
<td>Coking coal</td>
<td>2.09</td>
<td>2.52</td>
<td>3.56</td>
<td>30.34</td>
<td>55.04</td>
<td>6.44</td>
<td>44.96</td>
</tr>
<tr>
<td>Methanol</td>
<td>10.44</td>
<td>11.36</td>
<td>11.17</td>
<td>6.47</td>
<td>6.47</td>
<td>54.09</td>
<td>45.91</td>
</tr>
<tr>
<td>To</td>
<td>65.87</td>
<td>67.38</td>
<td>60.52</td>
<td>44.31</td>
<td>42.71</td>
<td>37.31</td>
<td>TCI</td>
</tr>
<tr>
<td>Net</td>
<td>4.87</td>
<td>5.88</td>
<td>1.48</td>
<td>-1.37</td>
<td>-2.25</td>
<td>-8.61</td>
<td>53.01</td>
</tr>
</tbody>
</table>
net risk transmitters, whereas coking coal receives the most risk. However, at the 0.95 quantile, the net spillover value of fuel oil far surpasses that of crude oil and ranks first, whereas coke becomes the center of risk reception. Overall, the roles played by various markets remain consistent under different market conditions, and the entire risk transmission system remains relatively stable.

Analysis of External Directional Spillover Characteristics Under Different Market States

Similar to the internal market order determination method, based on the Akaike information criterion, we chose a lag order of 1 for the QVAR-DY spillover index model, and the number of periods for which the prediction error variance decomposition is performed is 10. Here, we conducted the analysis from four aspects: First, the data presented in Tables 6 and 7 show that the spillover indexes based on conditional mean and conditional median have similar net spillover values, directional spillovers, and total spillover indexes. Second, from the perspective of internal market correlations, the correlation between the energy market and the stock market is much stronger than that among other markets. This correlation may be due to the increasing level of energy finance, more energy commodity trades being reflected by stocks or related indexes (resulting in their closer relationship with the stock market), and a strong spillover effect between the two markets. Third, from the perspective of directional spillover, the levels of external risk spillover in stock and energy markets are relatively high, reaching 43.9% and 41.3%, respectively. Moreover, their inflow spillover values also exceed those of other markets, accounting for 39% and 38.5%, respectively. This result indicates that the energy market and the stock market occupy important positions in the entire financial system and play a pivotal role as the primary

<table>
<thead>
<tr>
<th>Table 4. Directional volatility spillover at 0.05 quantile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Crude oil</td>
</tr>
<tr>
<td>Fuel oil</td>
</tr>
<tr>
<td>Asphalt</td>
</tr>
<tr>
<td>Coke</td>
</tr>
<tr>
<td>Coking coal</td>
</tr>
<tr>
<td>Methanol</td>
</tr>
<tr>
<td>To</td>
</tr>
<tr>
<td>Net</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 5. Directional volatility spillover at 0.95 quantile (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>Crude oil</td>
</tr>
<tr>
<td>Coke</td>
</tr>
<tr>
<td>Coking coal</td>
</tr>
<tr>
<td>Methanol</td>
</tr>
<tr>
<td>To</td>
</tr>
<tr>
<td>Net</td>
</tr>
</tbody>
</table>
source of systemic risk transmission. Finally, from a net spillover perspective, the stock market, energy market, interest rate market, and carbon market are primarily risk transmitters, whereas the foreign exchange market, bond market, and gold market are primarily risk receivers.

Compared with the spillover indexes based on conditional mean and conditional median, the total spillover indexes on the left and right tails increase to 77.18% and 77.6%, respectively, when faced with major positive and negative shocks. These results are more than three times higher and exhibit a more significant correlation effect. Observing directional spillover shows that regardless of whether the 0.05 or 0.95 quantiles are observed, the directional spillovers of all markets exceed 70%, and specific spillovers even exceed 80%. This result indicates that the impact of extreme events further aggraves the fragility of the market, and the entire system exhibits a “weak” sensitive state. From the perspective of net spillover indexes, the spillover roles employed by certain markets change under different market conditions. For instance, the carbon market and interest rate market are risk transmitters in normal market conditions, but they become risk receivers at the 0.05 quantile, whereas the bond market and gold market switch from risk receivers to risk transmitters when faced with negative shocks. In contrast, the energy, foreign exchange, and stock markets always maintain a stable output status.

When both internal and external markets face extreme events, the risks of the entire system are significantly higher compared with normal market conditions. This result represents a warning that

### Table 6. Mean-based directional volatility spillover effects and connectedness (%)

<table>
<thead>
<tr>
<th></th>
<th>Energy</th>
<th>Carbon</th>
<th>Interest rate</th>
<th>Exchange rate</th>
<th>Bonds</th>
<th>Gold</th>
<th>Stock</th>
<th>From</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carbon</td>
<td>61.5</td>
<td>0.9</td>
<td>0.5</td>
<td>0.8</td>
<td>0.6</td>
<td>1.1</td>
<td>34.6</td>
<td>38.5</td>
</tr>
<tr>
<td>Interest rate</td>
<td>1.1</td>
<td>94.7</td>
<td>0.6</td>
<td>1</td>
<td>0.7</td>
<td>0.8</td>
<td>1</td>
<td>5.3</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.6</td>
<td>0.6</td>
<td>95.8</td>
<td>0.8</td>
<td>0.7</td>
<td>0.9</td>
<td>0.6</td>
<td>4.2</td>
</tr>
<tr>
<td>Bonds</td>
<td>2.3</td>
<td>1.2</td>
<td>0.8</td>
<td>86.8</td>
<td>0.8</td>
<td>3.6</td>
<td>4.5</td>
<td>13.2</td>
</tr>
<tr>
<td>Gold</td>
<td>1.5</td>
<td>0.8</td>
<td>1.3</td>
<td>0.7</td>
<td>92.7</td>
<td>1.6</td>
<td>1.4</td>
<td>7.3</td>
</tr>
<tr>
<td>Stock</td>
<td>34.3</td>
<td>0.9</td>
<td>1</td>
<td>3</td>
<td>1.3</td>
<td>90.5</td>
<td>1.7</td>
<td>9.5</td>
</tr>
<tr>
<td>To</td>
<td>41.3</td>
<td>5.4</td>
<td>4.8</td>
<td>7.5</td>
<td>5.1</td>
<td>9</td>
<td>43.9</td>
<td>TCI</td>
</tr>
<tr>
<td>Net</td>
<td>2.8</td>
<td>0.1</td>
<td>0.6</td>
<td>-5.8</td>
<td>-2.2</td>
<td>-0.5</td>
<td>4.9</td>
<td>16.7</td>
</tr>
</tbody>
</table>

### Table 7. Median-based directional volatility spillover effects and connectedness (%)

<table>
<thead>
<tr>
<th></th>
<th>Energy</th>
<th>Carbon</th>
<th>Interest rate</th>
<th>Exchange rate</th>
<th>Bonds</th>
<th>Gold</th>
<th>Stock</th>
<th>From</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carbon</td>
<td>62.53</td>
<td>0.86</td>
<td>0.68</td>
<td>0.88</td>
<td>0.9</td>
<td>1.41</td>
<td>32.74</td>
<td>37.47</td>
</tr>
<tr>
<td>Interest rate</td>
<td>1.03</td>
<td>95.31</td>
<td>0.55</td>
<td>0.97</td>
<td>0.53</td>
<td>0.65</td>
<td>0.97</td>
<td>4.69</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>0.41</td>
<td>1.02</td>
<td>96.19</td>
<td>0.56</td>
<td>0.49</td>
<td>0.76</td>
<td>0.56</td>
<td>3.81</td>
</tr>
<tr>
<td>Bonds</td>
<td>1.96</td>
<td>1.56</td>
<td>1.16</td>
<td>86.88</td>
<td>0.77</td>
<td>3.93</td>
<td>3.73</td>
<td>13.12</td>
</tr>
<tr>
<td>Gold</td>
<td>1.4</td>
<td>0.68</td>
<td>1.55</td>
<td>0.59</td>
<td>92.83</td>
<td>1.39</td>
<td>1.55</td>
<td>7.17</td>
</tr>
<tr>
<td>Stock</td>
<td>1.94</td>
<td>1.22</td>
<td>1.05</td>
<td>3.62</td>
<td>1.26</td>
<td>88.76</td>
<td>2.15</td>
<td>11.24</td>
</tr>
<tr>
<td>To</td>
<td>32.47</td>
<td>1.22</td>
<td>0.76</td>
<td>1.47</td>
<td>1.25</td>
<td>1.37</td>
<td>61.48</td>
<td>38.52</td>
</tr>
<tr>
<td>Net</td>
<td>39.21</td>
<td>6.56</td>
<td>5.75</td>
<td>8.08</td>
<td>5.2</td>
<td>9.52</td>
<td>41.7</td>
<td>TCI</td>
</tr>
<tr>
<td>TCI</td>
<td>1.74</td>
<td>1.87</td>
<td>1.94</td>
<td>-5.03</td>
<td>-1.97</td>
<td>-1.72</td>
<td>3.17</td>
<td>16.57</td>
</tr>
</tbody>
</table>
in the face of major event shocks, the risk spillover characteristics under normal market conditions cannot be taken as a reference standard for risk prevention. Instead, the overall market should be reevaluated from a risk correlation perspective to develop reasonable and effective response measures.

Dynamic Characteristics of Risk Spillover in the Energy Finance Market

Time-Varying Characteristics of Internal Aggregate Spillover in Different Market States

Figure 2 illustrates the temporal characteristics of total spillover indexes based on the conditional mean for extreme market conditions, normal market conditions, and overall trends. The fluctuation patterns of risk spillover based on conditional mean and 0.5 quantile are nearly identical and exhibit a distinctive pattern of ascent (prior to 2020), descent (from 2020 to the second half of 2020), and recovery (from the second half of 2020 until the end of the sample period). At the 0.05 and 0.95 quantiles, the volatility trends align closely until approximately 2021, when they diverge and display certain asymmetrical characteristics. This asymmetry could be related to specific factors within the internal market. First, the crude oil market is highly influenced by global economic activities and geopolitical tensions. The global economic recession caused by the COVID-19 outbreak in 2020 led to a significant decline in crude oil demand and resulted in volatile price fluctuations. As vaccine development progressed and economic recovery gained momentum, the crude oil market gradually
rebounced from the second half of 2020 until the end of the sample period, contributing to an overall increase in the spillover index in the internal market. Second, the coke and coking coal markets are closely tied to the steel industry. In the first half of 2020, the steel industry experienced reduced demand because of the impact of the pandemic, leading to price declines in the coke and coking coal markets. However, with the global economic recovery in the second half of 2020 and beyond the sample period, increased steel demand fueled the recovery of both the coke and coking coal markets; this recovery is reflected by an upward trend of spillover indexes. Furthermore, the asphalt and methanol markets are also influenced by macroeconomic changes and supply-demand dynamics in the industry. The global economic uncertainty of 2020 generated downside risks in the asphalt and methanol markets. However, since 2021, with the gradual recovery of the global economy, these markets have gradually overcome their downturn, exhibiting certain asymmetrical characteristics reflected in spillover trends.

**Analysis of Internal Dynamic Spillover Characteristics Under Different Market States**

Figures 3 through 5 present dynamic spillover effects, dynamic inflow effects, and dynamic net spillover effects within the internal Chinese energy finance market for the 0.5 quantile, the 0.05 quantile, and the 0.95 quantile, respectively. The risk spillover and inflow in each submarket exhibit considerable volatility. Significant jumps in these dynamics occurred around the outbreak of the COVID-19 pandemic, indicating noteworthy turning points. Notably, each submarket displays different long-term spillover trends following the impact of the pandemic, and remarkable heterogeneity was observed across different market conditions. Specifically, at the 0.5 quantile, crude oil and fuel oil exhibit stable fluctuations. Coke, coking coal, and methanol demonstrate a persistent upward trend. Asphalt displays unique oscillations between high and low values. At the 0.05 and 0.95 quantiles, after the COVID-19 pandemic, the volatility trends across all six markets appear less pronounced. The differences in volatility trends across these quantiles can be analyzed from multiple perspectives. First, in terms of supply-demand dynamics, the relatively stable fluctuations in crude oil and fuel oil markets can be attributed to a balanced supply-demand relationship. During the global pandemic, although demand declined, a corresponding reduction in supply was also observed, and thus, a certain equilibrium was maintained. However, the sustained upward trends in coke, coking coal, and methanol markets could be linked to increased demand from related industries as the global economy gradually

![Figure 2. Internal aggregate spillover characteristics of energy finance markets under different market states](image)
recovered, leading to a shortage of supply. The volatility in the asphalt market could be influenced by its supply-demand relationship, which is highly sensitive to macroeconomic fluctuations, particularly during external shocks, such as the pandemic.

Second, geopolitical tensions exert varying degrees of influence on different energy markets. For instance, the crude oil market is strongly influenced by geopolitical dynamics in the Middle East, resulting in relatively stable price fluctuations. As essential raw materials in the steel industry, coke and coking coal prices are greatly influenced by global trade situations and geopolitical factors, resulting in higher volatility. Moreover, the long-term spillover trends observed in individual submarkets are also influenced by macroeconomic conditions. For example, during the economic recovery period after 2020, increasing demand for infrastructure construction and industrial production in the global economy contributed to rising prices in markets associated with these sectors, such as coke, coking coal, and methanol. However, affected by economic recession and low investment activities, asphalt and methanol markets exhibited relatively unstable fluctuations.

Finally, considering the global energy transition context, variations in performance may arise among different energy markets. Markets aligned with environmental sustainability goals, such as methanol, could experience influences from driving forces and investment hotspots, exhibiting relatively stable spillover effects. In contrast, their susceptibility to environmental pressures and changing market demands adds complexity to traditional fossil fuel markets such as crude oil and fuel oil, resulting in higher levels of volatility.

**Time-Varying Characteristics of External Aggregate Spillover Under Different Market States**

From an overall perspective of volatility trends, differing from the volatility characteristics of the internal market, the total spillover effects based on conditional mean and 0.5 quantile exhibit a
Figure 4. Internal dynamic spillover indexes at the 0.05 quantile

Figure 5. Internal dynamic spillover indexes at the 0.95 quantile
gradual decline in risk following the impact of the pandemic; this downward trend was mitigated in 2022. One reason for this mitigation may be attributed to pandemic control and economic recovery efforts. Over time, various measures have been implemented worldwide to control the pandemic and stimulate economic growth. These measures include strengthening medical protection and promoting both vaccination campaigns and plans. These measures gradually stabilized market sentiments, improved investor confidence, and thereby reduced the extent of risk spillover. Another factor can be analyzed from the perspective of interventions and market regulation. Many countries have proactively employed monetary and fiscal measures to mitigate the impact of the pandemic on the economy. Central banks lowered interest rates and provided liquidity support, while relevant authorities introduced fiscal stimulus plans; all these actions helped to stabilize external markets. In addition, enhanced market supervision by regulatory institutions has effectively enabled the monitoring and management of market risks, thus curbing the spread of risk spillover. At the 0.05 and 0.95 quantiles, the total spillover levels oscillated between 70% and 85% and exhibited great clustering, with a faster transition from low- to high-spillover levels. Furthermore, after the pandemic, the overall risk level decreased and the amplitude of fluctuations ranged from 70% to 80%. The changing trend during extreme market conditions can be explained from the perspectives of economic recovery, market intervention, and changes in investor sentiment. Investor sentiment experienced a shift following the impact of the pandemic. Initially, investors panicked and experienced uncertainty, resulting in significant fluctuations in risk levels. However, as signs of pandemic control and economic recovery became more pronounced over time, investor sentiment gradually improved, reducing their aversion to high-risk assets, further lowering risk levels, and minimizing the amplitude of fluctuations.

**Analysis of External Dynamic Spillover Characteristics Under Different Market States**

Figures 7 through 9 show the spillover, inflow, and net spillover effects among multiple external markets under different market conditions. The directional spillover indexes of each market exhibit a certain degree of uncertainty and volatility. When impacted by an external shock, the risk spillover and the reception of internal risk in each market move in the same direction. Now we present an analysis of the possible underlying reasons for the characteristics and changes in risk spillover from three perspectives.

First, we analyzed the spillover and inflow characteristics of each market from the perspective of time-varying characteristics. China’s energy finance market experienced four main phases at the 0.5 quantile; these were a decline from the end of 2015 to the end of 2017, a rebound from 2018 to 2019,
a fall from the end of 2019 to the end of 2021, and a rise from the end of 2021 to the end of the sample period. The possible reasons for these changes are as follows: (1.) the Paris Agreement (signed at the end of 2015) increased restrictions on traditional fossil fuel combustion, thus weakening the average risk spillover in the energy market; (2.) the U.S.-China trade war of 2018 elevated energy resources to one of the key factors supporting China’s status as a major power, resulting in a rapid rise in risk spillover in the energy market. The significant drop from 2019 to the end of 2021 was attributed to the nationwide spread of the COVID-19 pandemic, resulting economic stagnation, and a significant decrease in overall system connectivity. Beginning at the end of 2021 with the effective control of the pandemic and gradual economic recovery, the markets gradually resumed their connectivity, and the spillover risk began to rise. Matching changing characteristics of the energy market were also observed in the stock market. The spillover sizes of markets such as carbon, exchange rates, interest rates, bonds, and gold fluctuated mostly between 0% and 30%, and significant changes occurred at the end of 2019 and the beginning of 2020; these market fluctuations were also key triggers for these changes along with the outbreak of the pandemic. At the 0.05 and 0.95 quantiles, the overall risk spillover level was far higher than that of the normal market state, remained high, and showed slight volatility. Fluctuations of different markets were weak, which may be due to the whole market being in a state of high alertness. Even extreme upward and downward risks are still considered within the normal range of impact and do not cause significant interference.

Second, from the cross-sectional spillover level of different markets, China’s energy and stock markets have always been the two markets with higher risk spillover that dominate the entire market. The risk spillover levels of other markets are relatively similar. In addition, the spillover levels of each market under extreme market conditions are higher than under normal market conditions.

Third, from the perspective of net spillover, each market undergoes a change of status in the risk spillover system. At the 0.5 quantile, the energy market, stock market, and carbon market mostly act as risk transmitters, whereas the exchange rate market, bond market, and gold market mainly act as risk acceptors. The interest rate market fluctuates between these two roles and is less stable. In extreme upward and downward states, the energy and stock markets still carry out risk output in most cases, but the carbon, exchange rate, gold, and bond markets become unstable. Note that at this time, the interest rate market begins to act as a risk acceptor.

**Complex Network Analysis of Energy Financial Risks in China**

In the previous analysis, we examined the static and dynamic characteristics of risk spillover in China’s energy finance market, both internally and externally. To further elucidate the dynamic interactions of volatility spillover among different markets, we present network structure diagrams (Figures 10 and 11) to provide a visual representation of the market interconnections. Additionally, we calculated the density of each subnetwork to highlight the closeness of the network.

The results shown in Table 10 indicate that for both internal and external markets, the network density under extreme market conditions is higher than under general market conditions. A comparison of numerical values shows that the highest network density is observed at the 0.95 quantile. This result can be attributed to a combination of factors, including risk contagion, volatility diffusion, changes in investor behavior, information dissemination, market collective effects, interventions by central banks, and regulatory measures. These factors enhance the interconnectedness among markets and contribute to an increase in network density. Under extreme market conditions, risk contagion and volatility diffusion tend to be more pronounced and widespread. This factor implies a strong interrelation between markets, resulting in more connections and relationships within the network. Risks propagate rapidly across markets, quickly affecting other markets and thereby increasing network density. Moreover, the behaviors and decisions of investors often undergo significant changes and may exhibit collective actions, such as large-scale buying or selling, in pursuit of risk mitigation or high returns. These behaviors foster increased interaction and connectivity among market participants, further augmenting network density. Additionally, speed and market collective effects of information
dissemination are typically amplified. During extreme events or shocks, investors share information rapidly, leading to the emergence of a dominant community effect. This effect intensifies the interconnectedness among market participants, leading to higher network density.

Overall, both in internal and external markets, network connectivity under extreme market conditions is greater than under normal market conditions. The complex, multi-threaded characteristics of network connectivity are primarily the result of the higher level of risk contagion and market volatility diffusion during extreme conditions (e.g., when an extreme event or occurs in a market) in related markets caused by chain reactions and cross-impacts. Consequently, the network connectivity increases, resulting in a complex and multi-threaded system. Moreover, during economic crises or major geopolitical events, various asset classes, industries, and markets are often universally affected. These common shocks
enhance interdependence among markets, thereby increasing network connectivity. Additionally, investor behavior and strategies tend to change. Investors may be more inclined toward concentrating risks or adopting risk-aversion actions, thus increasing interdependence among markets. This trend may be because investors are seeking either higher returns or protection of their assets from risks. Furthermore, the speed of information transmission and market collective behavior is often more important. Investors respond to uncertainty and volatility in the market by quickly transmitting information and taking similar actions; these activities increase interconnectedness among markets.

The specific characteristics of the internal spillover network structure in the energy finance market can be summarized as follows: First, regarding the node colors, red nodes represent net risk-outputting sectors, and green nodes represent net risk-receiving sectors. This reflects both the roles each submarket plays in the overall spillover network and the flow of spillover risks. The spillover identities of the six submarkets remain relatively stable, and this stability may be attributed to longstanding business connections and relatively stable supply-demand relationships among these markets. Certain markets tend to generate risks and transmit them to other markets (red nodes), whereas others receive risks from other markets (green nodes).

Second, in terms of node size, nodes representing crude oil, fuel oil, and asphalt are relatively larger compared with other submarkets, indicating their significant positions and prioritization in risk management. This result is likely because of the importance of these energy products in the energy supply chain and their wide range of applications. Crude oil, as one of the most important global energy sources, exerts a significant influence on the energy finance market. Fuel oil and asphalt,
both of which are both closely related to energy supply and demand, also have large trading volumes and significant market shares.

Third, according to the thickness of edges, interconnectivity between pairs of markets remains consistent across the three different market conditions. Notably, strong spillover connections exist between crude oil and fuel oil, crude oil and asphalt, fuel oil and asphalt, as well as between coke and coking coal. This pattern may be due to tighter supply-demand relationships and trading connections among them. For example, the spillover connection between crude oil and fuel oil can be explained because fluctuations in crude oil prices affect fuel oil prices because the fuel oil market depends heavily on crude oil as its primary input.

Fourth, focusing on degree centrality and edge weights, we found that the spillover between submarkets during extreme market conditions is generally larger than during normal market conditions, indicating stronger interconnectivity and similarity in the performance of markets when faced with extreme events or shocks. When such extreme events occur, investor behavior tends to exhibit large-scale selling or buying behavior. This behavior leads to increased spillover effects among markets, and the structure of the energy finance market demonstrates stronger connectivity and similarity.

The external network of the energy finance market can also be analyzed from four aspects. In contrast to the stability observed in the internal market, certain markets undergo state transitions under different market conditions. For example, under extreme market conditions, the carbon and
interest rate markets act as risk receivers, but they transition to risk-transmitting sectors when the market returns to normal. The gold and bond markets act as risk-receiving sectors at the 0.05 and 0.5 quantiles, but become risk-spillover sectors at the 0.95 quantile. These transitions can be explained from four aspects: First, external factors play an influencing role in the energy finance market. Under extreme market conditions, global economic shocks and financial turmoil may lead to the assumption of different roles by certain markets. For example, the carbon and interest rate markets (as risk-receiving sectors) may be influenced by a global economic slowdown or financial market instability, but they transition to risk-transmitting sectors when the market returns to normal.

Second, market supply-demand dynamics and investor behavior can also influence transitions. For instance, the gold market, as a safe-haven asset, is typically a risk-receiving sector when market sentiment worsens. However, with the gradual return of market stability, investors may reduce their demand for gold, causing its transition into a risk-spillover sector. Similarly, the bond market, as a fixed-income instrument, is usually a risk-receiving sector under increasing market uncertainty. However, during improved market sentiment, the bond market may transition to a risk-spillover sector as investors seek higher returns.

Third, financial and market regulations can impact the direction of risk transmission via interventions by central banks and regulatory authorities. For example, the interest rate market serves as a vital channel for monetary transmissions and may become a risk-transmitting sector when central banks lower interest rates; however, when central banks raise interest rates, the interest rate market may transition to a risk-receiving sector. Similarly, the carbon market may be affected by changes in environmental policies and carbon pricing mechanisms, resulting in its different roles under different market conditions.

Fourth, the complexity of the global economic and financial systems also has an effect. The intricate nature of the global financial system implies that the relationships and roles that define exchange between markets may change under different market conditions. Node color transitions of external markets can result from the interplay of multiple factors, including international financial linkages, currency fluctuations, and the decision-making behavior of market participants. Furthermore, judging from node sizes, we found that the energy and stock markets exhibit larger consistency in their holding of significant positions. Additionally, under extreme upward volatility conditions, gold, bond, and carbon markets show increased connectivity with other submarkets compared with normal market conditions and extreme downward volatility conditions; under such extreme upward volatility conditions, these markets gradually become central nodes within the network. Then, by examining the thickness of edges, the energy market and stock market show significant correlations under all three market conditions, indicating high spillover effects between both markets. The underlying reason may be the increasing financialization of the energy sector over recent years, with the stock market being a representative of the financial market. The increasing interconnectedness of the entire financial system leads to a substantial increase in the correlation between these two markets compared with others.

Finally, looking at degree centrality and edge weights, we found that the minimum values of network connectivity among nodes in extreme market conditions are significantly higher than the maximum values under normal market conditions. This finding indicates that during extreme market conditions, contagion effects between markets become more pronounced, and network connections become tighter overall. The collapse of a single market can more easily trigger systemic risks, resulting in severe impacts on the real economy.

**Robustness Tests for Different Quantile Selection**

To eliminate the potential instability of spillover results caused by the randomness of percentile selection, we used the overall spillover indexes of the internal and external markets as experimental subjects, and all percentiles from 0 to 1 were subjected to robustness analysis. Figures 12 (a) and (b) represent the time-varying values of risk spillover in China’s internal and external energy finance markets under different percentiles, where warmer tones indicate higher network connectivity. Connectivity between internal and external markets is strong for extreme downward market conditions.
below 20% and extreme upward market conditions above 80%. Specifically, the overall average connectivity of the internal market is around 50%, and it increases year by year, whereas that of the external market is around 20%. These trends are consistent with the results of the previous analysis, demonstrating that the selected extreme percentiles are robust.

**Energy Finance Risk Early Warning Study**

**Early Warning Indicator Selection**

After analyzing the spillover characteristics of China’s energy finance market both internally and externally, we observed certain connection effects between different markets as well as heterogeneity in these effects within the energy market submarkets. Therefore, based on the features of this new information, corresponding solutions can be developed in response to risks as they occur. However, attempting to mitigate systemic risks solely based on spillover effects is a form of after-the-fact cushioning that merely minimizes resulting damage rather than addressing the root cause. Therefore, in this paper, we present further risk warning analysis of China’s energy finance risks and construct an effective risk warning system to predict and prevent the occurrence of risks in advance. Regarding data selection, because spillover effects generated by positive or negative shocks are far greater than the risk values under normal market conditions, and the impacts of systemic risks can even lead to the collapse of the entire economic system, in the subsequent analysis, we chose the time-varying total risk spillover values under extreme market conditions as proxy variables for risk warnings.

Regarding the selection of warning indicators, considering the uniqueness of China’s economic operating system and related market environment, as well as the connectivity of energy finance risks among multiple external markets, we initially selected relevant data from the carbon, stock, interest rate, gold, foreign exchange, and bond markets. This approach is consistent with the research of Adrian & Brunnermeier (2016). Specific proxy variables are shown in Table 11.

Regarding the design of the warning model, we set the Attention-CNN-LSTM warning model with one convolutional layer, a learning rate of 0.0001, 200 training epochs, a batch size of 24, and an Adam optimizer. We selected the mean absolute error (MAE) and root mean square error (RMSE) as indicators to measure the prediction accuracy, using the calculation formulas shown in equations (26) and (27):

\[
MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}, \quad (26)
\]
\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i' - y_i)^2}{n}}, \tag{27} \]

In these equations, \( n \) denotes the number of forecast periods, \( y_i' \) denotes the risk forecast, and \( y_i \) denotes the true risk value.

**Risk Warning System Construction**

After the initial selection of risk warning indicators, to ensure their validity and effectiveness, we needed to further consider correlation and causality between them. The Granger causality test can test the causal relationship between variables. However, traditional Granger methods can test only linear relationships between variables and are not suitable for the deep learning nonlinear warning model used in this paper. Therefore, we used the nonparametric Granger causality test based on nonlinearity to examine the relationship between selected warning indicators and energy finance risks in China while also identifying if indicators can improve risk prediction capabilities. Before performing nonlinear causality tests on variables, we needed to complete the crucial step of determining if a nonlinear dynamic relationship exists between variables. Therefore, we used a VAR model to filter out the linear relationship between variables, added energy finance risks as a dependent variable into the regression equation, and used the BSD and RESET methods to examine the model residual sequence. The null hypothesis of the test is that there is no nonlinear relationship between variables. The empirical results show significant rejection of the null hypothesis at the 1% level, thus supporting the existence of a nonlinear relationship. We also conducted nonlinear Granger causality tests, the results of which are shown in Table 12. All markets have passed the test, and the stock market is significant at the 1% level, indicating that the selected indicators can serve as risk warning indicators for energy finance risks in China.

**Table 11. China energy financial risk warning indicators**

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Proxy Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon</td>
<td>Hubei Carbon Trading Market Log Yield</td>
</tr>
<tr>
<td>Interest rate</td>
<td>SSE Composite Index Log Yield</td>
</tr>
<tr>
<td>Exchange rate</td>
<td>Overnight Shibor Log Yield</td>
</tr>
<tr>
<td>Bonds</td>
<td>Gold Price Log Yield</td>
</tr>
<tr>
<td>Gold</td>
<td>RMB to USD Log Yield</td>
</tr>
<tr>
<td>Stock</td>
<td>SSE Treasury Index Log Yield</td>
</tr>
</tbody>
</table>

**Table 12. Non-linearity test for early warning indicators**

<table>
<thead>
<tr>
<th>H0</th>
<th>P-value</th>
<th>H0</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon market is not the reason for the energy market</td>
<td>0.083*</td>
<td>Gold market is not the reason for the energy market</td>
<td>0.069*</td>
</tr>
<tr>
<td>Stock market is not the reason for the energy market</td>
<td>0.000***</td>
<td>Exchange rate market is not the reason for the energy market</td>
<td>0.087*</td>
</tr>
<tr>
<td>Interest rate market is not the reason for the energy market</td>
<td>0.090*</td>
<td>Bonds market is not the reason for the energy market</td>
<td>0.092*</td>
</tr>
</tbody>
</table>

Note: * represents the 10% level of significance, and *** represents the 1% level of significance.
To demonstrate that the fitting effect of the Attention-CNN-LSTM model is superior to that of other models, we selected six models for comparison analysis, including LSTM, CNN-LSTM, BP neural network, support vector machine (SVM), and random forest (RF). Additionally, we examined the changes in the prediction effect of the Attention-CNN-LSTM model before and after incorporating risk warning indicators to determine whether the addition of risk warning indicators can improve the fitting and prediction effects of the model. Figure 13 shows the comparative results of the predictions of the six models and the changes in the predictions of the Attention-CNN-LSTM model before and after the addition of warning indicators. The results clearly show that the risk prediction effect of the Attention-CNN-LSTM model is superior to that of the five other models, and it is closer to the actual risk value. Moreover, SVM and BP significantly deviate from the actual risk value, whereas CNN-LSTM, LSTM, and RF achieve similar and slightly weaker predictive performances than the Attention-CNN-LSTM model. Figure 14 presents the comparative results of the Attention-CNN-LSTM model’s prediction effects before and after the addition of warning indicators. With the addition of warning indicators, the prediction effect of the model is further improved. Because the graphs allow for only a rough guess of the prediction effects of different models, precise comparisons of evaluation metrics are required for models with similar predictive performance. From the perspective of the model evaluation metrics presented in Table 13, the Attention-CNN-LSTM model performs the best with lower MAE and RMSE values compared with the other five models. Furthermore, the Attention-CNN-LSTM model optimizes the MAE and RMSE of the CNN-LSTM model (which already has good predictive performance) by 12.9%. Moreover, SVM and BP neural networks are not suitable for the research presented in this paper because they exhibit significant prediction bias. Table 14 shows that after incorporating risk warning indicators, the MAE and RMSE of the Attention-CNN-LSTM model increased by 19.8% and 31.9%, respectively, demonstrating that the addition of warning indicators is effective. In conclusion, the Attention-CNN-LSTM model with risk warning indicators achieves a good risk prediction effect and can be employed for energy finance risk warnings in China. The tail of the predictive results shows that currently, the overall risk values are relatively low compared with the entire sample period. However, an emerging trend indicates a potential upward movement in the future. Therefore, taking preemptive risk prevention measures is imperative.
CONCLUSION AND RECOMMENDATIONS

Conclusion

In this study, we selected data from multiple internal and external markets and used the quantile vector autoregressive model to capture the characteristics of internal and external risk spillovers under different market conditions. We employed complex network visualization to illustrate the results. In addition, by incorporating an early warning index based on a nonlinear Granger causality test into the Attention-CNN-LSTM model, we could construct a risk warning system based on big data analysis and information management. The following conclusions can be drawn: First, in terms of static spillover characteristics, the total spillover characteristics based on the conditional mean and median in the internal market are similar, with values of 53.2% and 53.01%, respectively, indicating that the spillover index is high. This value reaches 78.05% (extreme downturns) and 77.59% (extreme upward trends) under extreme market conditions. In unilateral submarkets, crude oil and fuel oil exhibit higher spillover and influx effects than other markets under different market conditions, thus occupying an important position in the market. In external markets, the total spillover effect under extreme downturn (77.18%) and extreme upturn (77.6%) market conditions is more than four times higher than that based on the conditional mean (16.7%) and conditional median (16.57%). Under all...
market conditions, energy finance and stock markets exhibit more significant risk contagion features, compared with other markets, and they are the main concerns of systemic risk.

Second, judging from dynamic spillover characteristics, we found that internal and external markets exhibit strong time-varying total spillover effects under different market conditions. In terms of net spillover, in the internal market, crude oil and fuel oil consistently maintain their roles as risk transmitters under different market conditions, whereas the other four markets undergo risk role transfer. All markets in the external market experience a risk status change, and the overall system is more turbulent.

Third, from the perspective of complex network graphs, under extreme market conditions, network connectivity is significantly higher than under normal market conditions, and fourth, judging from the effectiveness of the constructed risk warning system, we found that the Attention-CNN-LSTM model outperformed the second-best CNN-LSTM model in terms of MAE and RMSE, achieving improvements of 12.9% and 21.4%, respectively. After incorporating the warning indicators, the Attention-CNN-LSTM model based on big data analysis and information management shows a 19.8% increase in MAE and a 31.9% increase in RMSE, compared with the original model. These increases indicate that the risk warning system performs better at risk prediction and is therefore applicable for constructing an early warning system for energy finance risks in China.

Recommendations

Based on the aforementioned research findings, we propose the following policy recommendations. First, when formulating measures to prevent and control energy financial risks, relevant governing bodies should consider not only the spillover risks from external markets on the energy industry but also the risk spillover among different submarkets within the energy financial market. This step is important because the risks generated among internal submarkets exhibit significant differences. The source of these risks can be accurately blocked, and their further contagion can be effectively prevented only by capturing the comprehensive spillover characteristics.

Second, more attention should be directed to the significant risks induced by extreme market conditions. Under extreme market conditions, the index of risk spillover between internal and external markets increases significantly, and the network density increases notably, thereby enhancing market contagion efficiency and causing more severe losses within a shorter period of time. In addition, investors should engage in diversified investments and continuously monitor market fluctuations and trends in the energy industry to implement timely adjustments to their investment strategies.

Third, considering various factors that influence risks in the Chinese energy financial market comprehensively and from multiple perspectives, while also considering the uniqueness of the Chinese market, is essential. Constructing a more accurate risk warning system can effectively reduce the harm caused by systemic risks and enhance the efficiency of major risk prevention.

DATA AVAILABILITY

The data used to support the findings of this study are included within the article.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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REFERENCES


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