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Research on China's Energy Financial Risk Early Warning and Internal Risk Control Spillover Characteristics

Abstract: - It is of great significance to scientifically and effectively assess the spillover effects of internal and external risks in China's energy finance and build an accurate risk early warning system to steadily promote the realization of the " carbon peaking and carbon neutrality " goal. Multiple internal and external market data are selected, and the spillover index model based on quantile vector autoregression is used to capture the internal and external risk spillover characteristics under different market conditions and visualize them through complex networks. In addition, the early warning index of nonlinear Granger causal test is incorporated into the Attention-CNN-LSTM model to construct a risk early warning system. The empirical results show that: (1) There are significant risk spillover effects both inside and outside China's energy financial market under different market conditions, and the risk spillover index under extreme market conditions is greater than that based on conditional mean and conditional median. (2) The internal crude oil and fuel oil markets and the external energy and stock markets occupy an important position in the overall risk spillover system. (3) Comparing and analyzing the prediction effects of six different models, the MAE and RMSE of the Attention-CNN-LSTM model were 0.7686 and 0.9077, respectively, which were optimized by 12.9% and 21.4% respectively compared with the second-best performing CNN-LSTM model; Moreover, after adding the early warning indicators, the prediction effect of the Attention-CNN-LSTM model is improved by 19.8% and 31.9% respectively in MAE and RMSE compared with the original model, so it is more suitable for constructing China's energy financial risk early warning system.

Keywords: Energy Finance, Extreme Risk, Overflow Index, Risk Warning, Complex Networks.

I. NTRODUCTION

In order to address global warming, China has proposed the "double carbon" target based on its responsibility to promote the building of a community of human destiny and the inherent requirement to achieve sustainable development, which has injected a strong impetus for the international community to fully and effectively implement the Paris Agreement and demonstrated China's ambition and great power's role in addressing climate change. However, one of the main causes of climate change is the burning of fossil fuels, and according to the UN data, coal, oil and natural gas account for more than 75% of global greenhouse gas emissions and nearly 90% of all carbon dioxide emissions. Therefore, reducing fossil energy consumption and steadily promoting renewable energy use has become a feasible approach to mitigate climate-related risks [1]. 2022, the "14th Five-Year Plan for Modern Energy System" issued by the National Energy Administration again mentions accelerating the transformation of energy to low-carbon, and energy As a commodity, changes in its structure will naturally affect its price fluctuations through market supply and demand, and once such fluctuations exceed the warning line, they will cause energy security problems, which in turn will affect the development of the national economy [2]. Therefore, it is important to understand the volatility characteristics of energy prices and to prevent risks in a timely manner in order to maintain a solid national real economy and to accomplish the "double carbon" target on time.

Energy finance is a series of financial activities formed by integrating energy resources and financial resources, and the risks it generates not only trigger oscillations within the energy commodity market [3-5], but also spillover externally thus affecting normal transactions in other markets, however, this spillover is not unidirectional, but is manifested as characteristics of mutual spillovers between different markets [6-8]. For example, Liu et al. investigate extreme risk spillovers among global energy markets, noting that risks are mainly transmitted to each other within energy markets, and this phenomenon is more pronounced especially during periods of extreme upward volatility[9]. Ji et al. explore the correlation between energy and agricultural products and find that energy and agricultural products tend to fluctuate together, exhibiting mutual spillovers, and that the volatility between energy and agricultural markets is greater when the market experiences extreme downward movements than when it moves upward[10]. Similarly, Mensi et al. analyze the spillover relationship between global green bonds (GBs), WTI oil, and G7 equity markets and find that each market both exports and receives risk externally and is largely transmitted from G7 equity markets to WTI oil and green bonds[11]. It is true that China is currently in an

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important period of low-carbon transition, and exploring the risk transmission mechanism of internal and external markets of energy finance can help us find the source of risks more quickly and precisely when they occur, so as to effectively prevent the collapse of the whole system and even the stagnation of the real economy caused by further risk transmission.

In recent years, the literature on energy financial risk contagion has been characterized by single point, localization and internationalization, and few scholars have conducted internal and external risk spillover analysis on China's energy financial market alone. Based on this, this paper focuses on the following aspects: firstly, we collect relevant market data from previous literature, mainly including futures data of various energy sources and external market data with possible spillover effects on energy; secondly, we capture the internal and external spillover characteristics of the energy market using the quantile vector autoregressive model-based spillover index method (QVAR-DY); then, we use complex networks to visualize the characteristics of the above risk spillover structure. Finally, the Attention-CNN-LSTM model is used to construct an early warning system for China's energy finance risk and to propose targeted risk prevention suggestions.

II. Literature Review

A. *Choice of Metrics for Risk Spillover and Complex Networks*

Most studies have shown that risk spillovers in energy financial markets are multi-directional, time-varying, asymmetric and non-linear, and such spillover effects show significant differences across different market states [12]; therefore, choosing a more relevant method to measure risk correlation is a prerequisite for accurately analyzing the internal and external risk transmission mechanisms in energy financial markets. There are not many early methods to study financial risk spillover effects, but they mainly have limitations such as unidirectional, linear, static and difficult to quantify, e.g. Ji et al. used ΔCoVaR to explore the risk correlation between a single market and the whole system, which focuses on one-way propagation from one subject to another and is not able to quantify the multi-directional risk linkage between markets effects between markets in multiple directions can be quantified[13]. The GARCH model is often used for its simplicity and its ability to characterize volatility aggregation and spikes and thick tails [14-16], but it can only reflect the existence of intermarket spillovers and cannot further explain the magnitude and direction of spillovers, so it is often improved and then applied to related studies in later studies ([17-19]. In addition, there are also models that are often used in combination with other methods to measure and analyze risk linkages, thus compensating for the deficiencies in one aspect [20, 21]. As scholars' research in the field of risk spillover continues to intensify, the models innovated in recent years have become more receptive and compatible, and the DY spillover index model is a good example. Specifically, Diebold and Yilmaz combined the VAR model and the generalized forecast error variance decomposition model to construct the DY spillover index model [22], which can effectively measure the time-varying trend of the magnitude of spillover effects among different markets by reasonably solving the shortcomings of the traditional variance decomposition results that depend on the order of variables, and is therefore widely used by scholars in several studies [23-28]. However, the drawback is that this approach relies on conditional mean estimates, which can only reflect the average risk in the whole market, and it is difficult to make a reasonable risk measure for those "black swan" and "gray rhino" events, so it is not suitable for those with relatively high sensitivity. Therefore, it is not suitable for the study of energy financial risk spillover effects, which are relatively sensitive.

Complex networks can visualize the correlation between various markets by means of network topology diagrams and can calculate the density of the whole network, which can more intuitively reflect the importance of each element in the system, the role it plays and the strength of the relationship between two markets.

Therefore, this paper first analyzes the internal and external risk spillover characteristics of energy finance using the quantile vector autoregressive model-based spillover index method (QVAR-DY) proposed by Ando [29], which can effectively capture the size of risk spillover under extreme event shocks and can measure the time-varying effect of risk spillover at different quantile points separately. The obtained risk network association matrix is then used as the adjacency matrix to evaluate and visualize the overall network structure using complex networks.

B. *Risk Warning Method Selection*

If the study of risk spillover effects is compared to the search for an army that can win battles, then the study of risk early warning is the search for an excellent commander. In the process of preventing and resolving financial risks, risk early warning is the first challenge ahead, and accurate risk prediction is a prerequisite for controlling and resolving risks more quickly, more effectively, and with lower losses. The traditional risk early warning models, such as the KLP signal method proposed by Kaminsky and the FR probability model proposed by Frankel and Rose [30, 31], are mainly based on various information indicators to estimate the probability of a crisis occurring in a long period of time, which does not provide a good explanation for the occurrence of a crisis from a temporal point of view, and the range of future forecasts is too long. The range of future forecasts is too long and therefore does not accurately reflect the likelihood of financial risks in the short term. Logistic regression models have also been used for risk early warning studies, e.g., Kumar used a logit model to study the possibility of currency collapse in emerging markets, but this approach is prone to underfitting and is generally not very accurate[32]. With the advent of the era of big data and artificial intelligence, scholars began to try to put machine learning into the study of financial risk early warning, using more attributed to artificial neural network models [33] and support vector machines [34], but the traditional machine learning methods are often weaker than deep LSTM models, as classical deep learning models, are able to learn, train and predict stock volatility well and are often used by scholars for time-series prediction analysis [35]. After that, in order to be able to further improve the prediction accuracy of LSTM models, it is a classical research idea in the field of risk warning to combine them with other models to construct new models and compare the prediction effects of fittin[36, 37], for example, Ji Xingquan et al. used Attention-CNN -LSTM model to predict short-term electricity prices and found that the prediction results were better than those of LSTM and CNN-LSTM models alone in all aspects[38].

Based on this, this paper takes the total time-varying spillover results of risk spillover as the research object of risk early warning, and adopts the Attention-CNN-LSTM model to forecast energy financial risks after selecting several early warning indicators and influencing factors at the same time to construct an energy financial risk early warning system in China.

The rest of the paper is organized as follows: Chapter 3 briefly describes the construction process of QVAR-DY risk spillover model and Attention-CNN-LSTM model; Chapter 4 applies the model to Chinese energy finance internal and external market data, captures the static and dynamic characteristics of internal and external risk spillover under different market states and visualizes them through complex network diagrams, then constructs a risk early warning system and presents the empirical results; the last chapter gives the conclusion of the paper and puts forward policy recommendations.

III. MODEL CONSTRUCTION

A. *Spillover Index Model based on Quantile Vector Autoregression*

This paper will capture the internal and external risk transmission characteristics of China's energy finance market using a quantile vector autoregressive based spillover index model to explore whether there is heterogeneity in risk spillover at different quantile points. In general, define an n-dimensional p-order quantile vector autoregressive process $QVAR(P)$:

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

Which y_t is an n-dimensional column vector, $c(\tau)$ represent the intercept vector at quantile τ, $B_i(\tau)$ represent n-dimensional lag coefficient matrix at quantile τ, $e_t(\tau)$ is an n-dimensional error column vector. Before estimating the lag coefficient matrix $B_i(\tau)$ and the intercept vector $c(\tau)$, requires certain assumptions to be given to the error term $e_t(\tau)$ in order to satisfy the preconditions for the interpretability of the equation. That is, assuming that the error term satisfies the conventional quantile regression constraint $Q_\tau(e_t(\tau)|y_{t-1}, \cdots y_{t-p}) = 0$, the estimate of y at quantile τ under this assumption is: $Q_\tau(y_t|y_{t-1}, \cdots y_{t-p}) = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i}$.

Then, the framework of the DY spillover index is built and the QVAR model is embedded in it to calculate the spillover index at multiple quartiles separately, thus constructing a model that can measure the spillover index at different quartiles, which can better respond to the volatility spillover effect under extreme conditions (Ando et al., 2022). Specifically, equation (1) is first rewritten as an infinite-order vector moving average process:

$$y_t = \mu(\tau) + \sum_{s=1}^{\infty} A_s(\tau) e_{t-s}(\tau), t = 1, 2, \cdots T \tag{2}$$

It is important to note that,

$$\mu(\tau) = (I_n - B_1(\tau) - \cdots - B_p(\tau))^{-1} c(\tau) \tag{3}$$

$$A_s(\tau) = \begin{cases} 0, s < 0 \\ I_n, s = 0 \\ B_1(\tau) A_{s-1}(\tau) + \cdots + B_p(\tau) A_{s-p}(\tau), s > 0 \end{cases} \tag{4}$$

Here, 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:

$$y_t = \mu(\tau) + \sum_{s=1}^{\infty} \varphi_s(\tau) \varepsilon_{t-s}(\tau), t = 1, 2, \cdots T \tag{5}$$

$$\phi_s(\tau) = A_s(\tau) \cdot \Gamma(\tau) \tag{6}$$

$$\varepsilon_t(\tau) = \Gamma^{-1}(\tau) \cdot e_t(\tau) \tag{7}$$

Here $\Gamma(\tau)$ is a lower triangular Cholesky decomposition matrix, and a one-step forward prediction of y_t in equation (5) yields.

$$y_{t+1} = \mu(\tau) + \sum_{s=1}^{\infty} \varphi_s(\tau) \varepsilon_{t-s+1}(\tau) \tag{8}$$

Thus the one-step prediction error is:

$$y_{t+1} - Q_\tau(y_{t+1}) = \varphi_0(\tau) \varepsilon_{t+1}(\tau) \tag{9}$$

And so on, the forward h-step prediction error is obtained as:

$$y_{t+h} - Q_\tau(y_{t+h}) = \sum_{s=1}^{h} \varphi_s(\tau) \varepsilon_{t-s+h} \tag{10}$$

For a single variable in series $\{y_{it}\}$, the forward h-step prediction error can be expressed as:

$$y_{i,t+h} - Q_\tau(y_{i,t+h}) = \sum_{s=1}^{h} (\varphi_{i1}^s(\tau) \varepsilon_{1,t-s+h}(\tau) + \cdots + \varphi_{in}^s(\tau) \varepsilon_{n,t-s+h}(\tau)) \tag{11}$$

The prediction error variance $D_i^h(\tau)$ of $y_{i,t+h}$ is thus: $\sum_{s=1}^{h} (\varphi_{i1}^s(\tau)^2 + \cdots + \varphi_{in}^s(\tau)^2)$, so that the ratio caused by the sequence $\{\varepsilon_{jt}(\tau)\}$ is $\omega_{ij}^h(\tau) = \frac{\varphi_{ij}^1(\tau)^2 + \cdots + \varphi_{ij}^h(\tau)^2}{D_i^h(\tau)}$ in the prediction error variance of the forward h steps. The variance decomposition of the prediction error allows to understand the ratio from the own to the external shocks at different quantile levels, which in turn allows to construct the gross spillover index $TSI(\tau)$, the net spillover index $NSI_{\cdot j}(\tau)$, and the directional spillover indices $DSI_{i\cdot}(\tau)$ and $DSI_{\cdot i}(\tau)$ at different quantile levels, defined respectively as follows:

$$TSI(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \omega_{ij}^h(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \omega_{ij}^h(\tau)} \times 100 \tag{12}$$

$$DSI_{i\cdot}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \omega_{ij}^h(\tau)}{\sum_{j=1}^{N} \omega_{ij}^h(\tau)} \times 100 \tag{13}$$

$$DSI_{\cdot i}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \omega_{ji}^h(\tau)}{\sum_{j=1}^{N} \omega_{ji}^h(\tau)} \times 100 \tag{14}$$

$$NSI_{\cdot i}(\tau) = DSI_{\cdot i}(\tau) - DSI_{i\cdot}(\tau) \tag{15}$$

The total spillover index represents the sum of the spillover risks in the whole system at the τ -quantile, the directional spillover index represents the one-way spillover effect of a market to another market, and the net spillover index represents the difference between the outward spillover and inward-received risk values of a single market, which can reflect whether a market is a risk transmitter or a risk receiver.

B. Elaboration of CNN-LSTM Model based on Attention Mechanism

Energy financial risk is not only related to the carbon, stock, exchange rate, interest rate, bond and gold markets, but also to its own previous moment's value. The advantage of long and short-term recurrent neural networks (LSTM) is that they can discover the intrinsic patterns of long series and have high prediction accuracy, but they often produce overfitting due to the size of the feature volume, so it is necessary to extract features from the data before feeding them into the LSTM framework. The CNN-LSTM model based on the attention mechanism can not only make up for the shortcomings of CNN in long series dependence, but also further improve the overall prediction accuracy at anomalies or jump points, so it is more suitable for the early warning analysis of energy financial risks, and the operation of the whole system is shown in Figure 1.

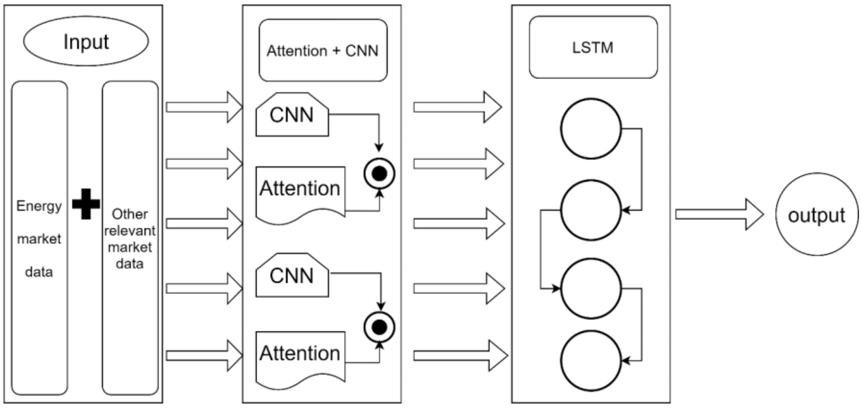

Fig. 1 Schematic diagram of Attention-CNN-LSTM model

The attention mechanism is similar to weighted summation, where the importance of the input features is first considered, then the Softmax activation function is applied to make the sum of all weights 1, and finally the input features are multiplied by the corresponding weights and summed.

$$e_t^k = \upsilon_e^T \sigma(W_e[h_{t-1}, c_{t-1}] + U_e h_t + b_e) \tag{16}$$

$$a_t^k = \frac{\exp(e_t^k)}{\sum_{i=1}^{n} \exp(e_t^i)} \tag{17}$$

$$\overline{z}_t = \sum_t^T a_t^T h_t \tag{18}$$

where υ_e^T , b_e , W_e , U_e and are parameters to be learned; a_t^k is the k-th attention weight at time t; e_t^k denotes the importance of h_t ; and $\overline{z}_t$ denotes the attention output.

CNN is mainly used for downscaling and feature extraction of energy financial risks, and the results are used as input for LSTM, which is calculated as follows:

$$h_l = ELU(W_l \square\ X + b_l) \tag{19}$$

where h_l is the output of the data after CNN, ELU is the activation function, W_l represents the weight matrix, $\square$ represents the convolution operation, and b_l represents the bias vector.

LSTM is derived from recurrent neural networks, and by introducing a gate function, it can better capture the time-varying patterns of long sequences. It mainly consists of a unit state and an oblivion gate, a selection memory gate and an output gate, where the oblivion gate is used to decide how much of the previous state needs to be forgotten, the selection memory gate is used to decide which new information to retain, and the output gate is used to determine how much to pass for output. The three gates operate in combination to reasonably solve the difficult problem of gradient disappearance and gradient explosion, and have relatively high prediction accuracy.

$$f_t = \sigma(W_f \cdot [h_{t-1}, \overline{x}_t] + b_f) \tag{20}$$

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

$$\tilde{C}_t = ELU(W_C \cdot [h_{t-1}, \overline{x}_t] + b_C \tag{22}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{23}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, \overline{x}_t] + b_o \tag{24}$$

$$h_t = o_t * ELU(C_t) \tag{25}$$

where f_t denotes the forgetting gate, W denotes the weight matrix of the corresponding gate, respectively, h_{t-1} denotes the hidden state at period t-1, $\overline{x}_t$ denotes the input of the layer at time t, b denotes the bias of the corresponding gate, respectively, i_t denotes the input gate, and o_t denotes the output gate.

IV. Empirical analysis

A. *Variable Selection and Descriptive Statistical Analysis*

In order to conduct a comprehensive analysis of the internal and external risk spillover effects in the energy finance market and to explore in more detail the structural characteristics of risk contagion among different markets and among submarkets within the energy finance market, this paper refers to previous literature and selects multiple submarkets with possible correlation effects with the external correlation markets for analysis. Given the availability of data, the internal markets are selected from the closing price data existing in the Chinese futures markets of crude oil, coking coal, coke, methanol, asphalt, and fuel oil from January 2, 2019 to December 30, 2022, and preprocessed according to the logarithmic rate of return; the external markets are mainly selected from the carbon market (Hubei carbon trading market as The external markets are mainly selected from the carbon market (represented by Hubei carbon trading market), stock market (represented by SSE Composite Index), exchange rate market (represented by USD to RMB), interest rate market (represented by Shanghai Interbank Offered Rate), bond market (represented by SSE Treasury Bond Index) and gold market from January 5, 2015 to December 30, 2022. In addition, the SSE Energy Industry Composite Index is selected as a proxy variable for the energy financial market to be added to the analysis of external market spillover effects. The data frequencies of each market are daily and are standardized in order to exclude the effect of differences in magnitudes. The descriptive statistical analysis of each variable is shown in Table 1, and the Jarque-Bera test results show that all variables reject the original hypothesis of normal distribution at the 1% level, and the unit root test also shows that the variables are significantly smooth and can be used for the next risk spillover analysis.

Table 1 Descriptive statistical analysis of internal and external indicators of the energy market

	n	max	min	mean	std	Kurtosis	Skewness	Jarque-Bera	ADF
Crude Oil	972	0.101	-0.142	0.0004	0.024	2.902	-0.254	346.54^{***}	-10.25^{***}
Fuel Oil	972	0.145	-0.144	0.0001	0.025	3.179	-0.287	416.96^{***}	-9.82^{***}
Asphalt	972	0.095	-0.102	0.0004	0.021	2.792	-0.230	319.65^{***}	-9.46^{***}
Coke	972	0.070	-0.110	0.0004	0.023	2.287	-0.519	252.19^{***}	-9.81^{***}
Coking Coal	972	0.110	-0.104	0.0005	0.024	3.146	-0.155	399.12^{***}	-9.68^{***}
Methanol	972	0.073	-0.100	0.0001	0.018	2.331	-0.224	224.80^{***}	-9.94^{***}
Energy	1947	0.067	-0.105	-0.0001	0.018	4.038	-0.668	1458.40^{***}	-11.86^{***}
Carbon	1947	0.176	-0.164	0.0004	0.030	4.648	-0.031	1742.00^{***}	-13.60^{***}
Interest Rate	1947	1.490	-0.628	-0.0003	0.111	29.228	2.461	70895.00^{***}	-15.92^{***}
Exchange Rate	1947	0.018	-0.014	0.0000	0.002	5.441	0.288	2413.20^{***}	-11.10^{***}
Bond	1947	0.398	-0.229	0.0159	0.039	9.769	0.515	7784.00^{***}	-9.61^{***}
Gold	1947	0.050	-0.062	0.0003	0.008	5.555	-0.074	2489.6^{***}	-11.79^{***}
Stock	1947	0.056	-0.089	0.0000	0.014	7.459	-1.157	4920.10^{***}	-11.80^{***}

Note: Jarque-Bera stands for normality test, ADF stands for unit root test, and *** stands for 1% level of significance.

B. Static Characteristics of Risk Spillovers in Energy Finance Markets

1) Analysis of internal aggregate spillover characteristics under different market states: In terms of model order, the optimal lag order of the QVAR-DY spillover index model selected in this paper is order 1 according to the AIC criterion, and the number of periods for the forecast error variance decomposition is 10. The conditional mean-based spillover index approach is first introduced to analyze the factor market within energy and used to compare with the risk spillover under the conditional median (0.5 quantile). The total spillover index under the conditional mean in Table 2 is 53.2%, a figure that is almost identical to the 53.01% under the conditional median in Table 3, indicating a significant total risk spillover effect within the energy market. A further look at the values across multiple markets reveals a high degree of similarity in volatility spillovers for both. At the directional spillover level, the size of the spillover and spillover into the 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. It is worth noting that fuel oil accounts for a large share of both risk spillovers and spillovers, and is an important source of systemic risk in China's energy internal market. The main reason for this 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, there are strong levels of volatility spillovers between crude oil and fuel oil, crude oil and bitumen, fuel oil and bitumen, and coking coal and coke, while the relationships between crude oil and coking coal, 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 and thus are net risk exporters in the overall risk network; in contrast, coking coal, coke and methanol are net risk receivers.

Table 2 Total spillover index at conditional mean(%)

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

Table 3 Total spillover index under the median condition(%)

	Crude Oil	Fuel Oil	Asphalt	Coke	Coking Coal	Methanol	From
Crude Oil	39	28.41	21.48	1.92	1.58	7.62	61
Fuel Oil	28.07	38.5	20.49	2.71	2.11	8.12	61.5
Asphalt	22.83	22.05	40.96	2.86	2.66	8.65	59.04
Coke	2.44	3.04	3.82	54.33	29.89	6.48	45.67
Coking Coal	2.09	2.52	3.56	30.34	55.04	6.44	44.96
Methanol	10.44	11.36	11.17	6.47	6.47	54.09	45.91
To	65.87	67.38	60.52	44.31	42.71	37.31	TCI
Net	4.87	5.88	1.48	-1.37	-2.25	-8.61	53.01

However, the spillover effects based on the conditional mean and conditional median can only reflect the risk spillover characteristics under normal market conditions, and in the face of extreme market upside and downside pressures, the risk of the entire financial system often shows short jumps in a short period of time, when the spillover effects generated under normal conditions may not accurately reflect the true volatility spillover characteristics among markets, so further calculations at the 0.05 and The risk spillover at the 0.05 and 0.95 quartile is further calculated to portray the more likely transmission mechanism in the event of a major event. By looking at Tables 4 and 5, we can see that the total spillover indices in the left and right tails are as high as 78.05%

and 77.59%, respectively, and the data are significantly higher than the spillover values based on the conditional mean or conditional median and have a high degree of symmetry, probably because with the deepening energy financialization of the economy, the markets are more closely connected and the submarkets are in a state of sensitive warning, thus The submarkets are in a sensitive state of alert and thus more responsive to shocks from extreme events. At the directional spillover level, the elements within the energy market show high levels of spillover and spillover at both the 0.05 and 0.95 quartiles, indicating that the risk caused by extreme shocks does not have a large heterogeneity due to the difference in positive and negative directions, and some small changes tend to exist only in the relationship between the magnitude of risk among the submarkets, for example, in the face of positive shocks, fuel oil shows the highest premiums and spillovers in the face of negative shocks, while the maximum value of spillovers shifts to crude oil and bitumen in the face of negative shocks. In addition, from a net premium perspective, fuel oil and crude oil are almost tied as the largest net risk transmitters at the 0.05 quantile, while coking coal is the most risk-receiving market at this time; while at the 0.95 quantile, fuel oil's net premium is well ahead of crude oil in first place, while coke becomes the center of risk reception. Overall, the role played by each market remains consistent across market states, and the overall risk transmission system is relatively stable.

Table 4 Total spillover index at 0.05 quantile (%)

	Crude Oil	Fuel Oil	Asphalt	Coke	Coking Coal	Methanol	From
Crude Oil	21.13	19.32	18.3	13.14	13	15.12	78.87
Fuel Oil	19.47	21.06	17.94	13.2	13	15.33	78.94
Asphalt	18.26	17.81	21.37	13.5	13.59	15.48	78.63
Coke	14.16	14.42	13.96	22.91	19.23	15.33	77.09
Coking Coal	14.01	14.24	14.07	19.39	23.04	15.25	76.96
Methanol	16.01	16.22	15.98	14.99	14.59	22.21	77.79
To	81.91	82	80.24	74.22	73.42	76.5	TCI
Net	3.04	3.05	1.6	-2.87	-3.54	-1.29	78.05

Table 5 Total spillover index at 0.05 quantile (%)

	Crude Oil	Fuel Oil	Asphalt	Coke	Coking Coal	Methanol	From
Crude Oil	21.53	19.5	18.08	13.02	13.01	14.87	78.47
Fuel Oil	19.46	21.64	18.08	12.99	12.99	14.85	78.36
Asphalt	18.14	18.19	21.53	13.48	13.75	14.92	78.47
Coke	13.45	13.84	13.93	23.27	19.96	15.56	76.73
Coking Coal	13.55	13.76	14.33	19.69	23.5	15.17	76.5
Methanol	15.39	15.55	15.64	15.23	15.19	23.01	76.99
To	79.98	80.83	80.05	74.4	74.9	75.36	TCI
Net	1.51	2.46	1.58	-2.33	-1.6	-1.63	77.59

2) Analysis of external aggregate spillover characteristics under different market states: As with the internal market fixed-order approach, the lag order of the QVAR-DY spillover index model is chosen to be order 1 and the number of periods for the forecast error variance decomposition is 10. Here, four main aspects are analyzed. Firstly, it can be seen from Tables 6 and 7 that the conditional mean and conditional median based spillover indices are more similar in terms of net spillover value, directional spillover and total spillover index. Secondly, in terms of intra-market correlation, the energy market and the stock market are much more strongly correlated than other markets, probably due to the increased financialization of energy, with more energy commodity transactions reacting through stocks or related indices, making it more closely related to the stock market showing a stronger spillover effect between the two markets. Then from the perspective of directional spillover, the level of external risk spillover is higher in equity and energy markets, reaching 43.9% and 41.3% respectively, not only that, their risk spillover values are also larger than other markets, 39% and 38.5% respectively, indicating that energy and equity markets occupy an important position in the overall financial system and play a pivotal role as the primary source of systemic risk contagion. Finally, from a net spillover perspective, the equity, energy, interest rate and carbon markets are mainly risk exporters, while the exchange rate, bond and gold markets are mainly risk receivers.

Table 6 Total spillover index at conditional mean(%)

	Energy	Carbon	Interest Rate	Exchange Rates	Bonds	Gold	Stock	From
Energy	61.5	0.9	0.5	0.8	0.6	1.1	34.6	38.5
Carbon	1.1	94.7	0.6	1	0.7	0.8	1	5.3
Interest Rate	0.6	0.6	95.8	0.8	0.7	0.9	0.6	4.2
Exchange Rates	2.3	1.2	0.8	86.8	0.8	3.6	4.5	13.2
Bonds	1.5	0.8	1.3	0.7	92.7	1.6	1.4	7.3
Gold	1.5	1	1	3	1.3	90.5	1.7	9.5
Stock	34.3	0.9	0.6	1.1	1	1.1	61	39
To	41.3	5.4	4.8	7.5	5.1	9	43.9	TCI
Net	2.8	0.1	0.6	-5.8	-2.2	-0.5	4.9	16.7

Table 7 Total spillover index at 0.5 quantile(%)

	Energy	Carbon	Interest Rate	Exchange Rates	Bonds	Gold	Stock	From
Energy	62.53	0.86	0.68	0.88	0.9	1.41	32.74	37.47
Carbon	1.03	95.31	0.55	0.97	0.53	0.65	0.97	4.69
Interest Rate	0.41	1.02	96.19	0.56	0.49	0.76	0.56	3.81
Exchange Rates	1.96	1.56	1.16	86.88	0.77	3.93	3.73	13.12
Bonds	1.4	0.68	1.55	0.59	92.83	1.39	1.55	7.17
Gold	1.94	1.22	1.05	3.62	1.26	88.76	2.15	11.24
Stock	32.47	1.22	0.76	1.47	1.25	1.37	61.48	38.52
To	39.21	6.56	5.75	8.08	5.2	9.52	41.7	TCI
Net	1.74	1.87	1.94	-5.03	-1.97	-1.72	3.17	16.57

Compared to the conditional mean and conditional median based spillover indices, the total spillover indices in the left and right tails rise to 77.18% and 77.6%, respectively, in the face of positive and negative major event shocks, which is more than three times higher and the correlation effect is more significant. Looking at the directional spillover, we find that the directional spillover is above 70% for all markets at both the 0.05 quantile and 0.95 quantile, and even above 80% for a few markets, indicating that extreme event shocks further deepen the vulnerability of the market and the whole system shows a "weak" sensitivity. This indicates that extreme events have further increased the vulnerability of the market, and the whole system is in a "weak" and sensitive state. From the perspective of the net spillover index, the spillover roles played by some markets in different market states have changed, such as the carbon and interest rate markets are risk exporters in normal market states and become risk receivers at the 0.05 percentile, while the bond and gold markets switch from risk receivers to risk transmitters in the face of negative shocks. In contrast, the energy market, exchange rate market and stock market always remain stable exporters.

Table 8 Total spillover index at 0.05 quantile(%)

	Energy	Carbon	Interest Rate	Exchange Rates	Bonds	Gold	Stock	From
Energy	21.78	12.12	11.68	11.79	11.8	12.26	18.56	78.22
Carbon	13.23	22.35	12.48	13.15	12.99	12.68	13.12	77.65
Interest Rate	12.98	12.67	23.9	12.77	12.41	12.26	13.02	76.1
Exchange Rates	13.3	13.03	12.35	22.91	12.78	12.3	13.32	77.09
Bonds	13.03	12.55	12.1	12.7	23.39	13.02	13.21	76.61
Gold	13.31	12.75	12.03	11.79	13.23	23.57	13.31	76.43
Stock	18.43	11.97	11.97	11.89	11.95	11.94	21.86	78.14
To	84.27	75.08	72.61	74.09	75.17	74.47	84.55	TCI
Net	6.05	-2.56	-3.49	-3	-1.44	-1.96	6.41	77.18

Table 9 Total spillover index at 0.95 quantile(%)

		Energy	Carbon	Interest Rate	Exchange Rates	Bonds	Gold	Stock
Energy	22.06	12.27	11.5	11.48	12.4	12.11	18.17	77.94
Carbon	12.96	21.85	11.86	13.46	13.57	13.7	12.61	78.15

Interest Rate	12.9	13.33	22.53	12.8	13.23	13.01	12.19	77.47
Exchange Rates	12.56	13.39	12.34	23.12	13.47	12.8	12.32	76.88
Bonds	13.01	13.27	12.35	12.92	22.21	13.58	12.66	77.79
Gold	12.99	13.55	12.16	11.96	13.58	23.03	12.72	76.97
Stock	18.04	12.16	11.5	11.29	12.61	12.39	22	78
To	82.47	77.98	71.7	73.9	78.87	77.59	80.67	TCI
Net	4.54	-0.17	-5.76	-2.98	1.07	0.62	2.68	77.6

Both in the internal and external markets, we can see that when faced with extreme event shocks, the risk of the entire system rises significantly compared to the normal market state, warning us that when faced with major event shocks, we should not use the risk spillover characteristics of the normal market state as the reference standard for risk prevention, but should re-evaluate the risk correlation of the entire market so as to formulate reasonable and effective countermeasures.

C. Dynamic Characteristics of Risk Spillover in Energy Finance Market

The results of the static analysis alone cannot observe the time-varying characteristics of the spillover effect, so a rolling time window (of length 200) is further added to the model to analyze the dynamic evolution pattern of the risk spillover.

1) time-varying characteristics of internal aggregate spillover in different market states: Figure 2 shows the time-varying characteristics of the two extreme market states, the normal market state, and the total spillover index based on the conditional mean, and the overall trend shows that the trend of risk spillover fluctuations based on the conditional mean and on the 0.5 quantile is almost the same, mainly showing: rising (before 2020) - falling (from 2020 to the second half of 2020) - rebounding (from the second half of 2020 to the sample period The main reasons may be as follows: on the one hand, on October 8, 2018, the IPCC released the Special Report on Global Warming of 1.5°C, which pointed out the path to achieve the temperature control target, and energy, as a key element that has an impact on climate, has been widely concerned in terms of commodity pricing and market transactions, etc. The market tolerance rate has decreased, vulnerability has increased and thus the risk premium index has been climbing, and this It took more than a year for this situation to slow down. On the other hand, the full-scale outbreak of the epidemic in 2020 exposes several markets to the risk of collapse and dilutes the links between external markets, leaving the risks generated by energy markets to be absorbed and transferred internally, resulting in a rapid increase in total spillover risk. This may be due to the fact that investors react more quickly to good news as the epidemic gradually improves, and thus the risk premium in the 0.05 quantile rises earlier.

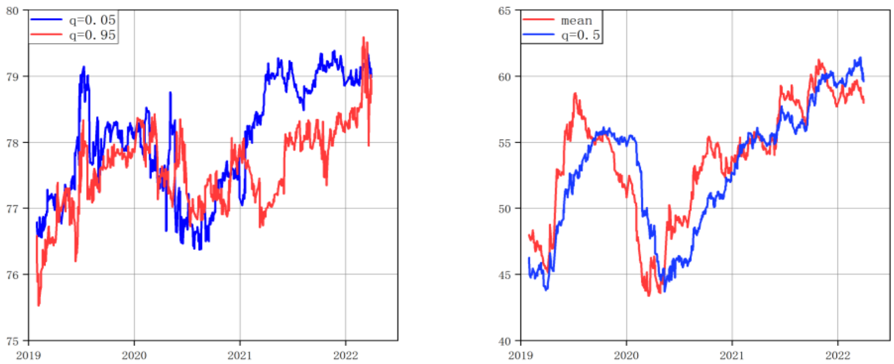

Fig. 2 Characteristics of aggregate spillovers within energy finance markets in different market states

2) Analysis of internal dynamic directional spillover characteristics under different market states: Figures 3 to 5 show the dynamic spillover, dynamic spillover, and dynamic net spillover effects of the Chinese energy finance internal market at the 0.5 quantile, 0.05 quantile, and 0.95 quantile, respectively, with the risk spillover and risk spillover in each submarket showing strong volatility, and the major jump points in the sample period almost all occurring around 2020 when the epidemic is in full swing, and it is worth noting that each submarket exhibits different long-term spillover trends after It is worth noting that the submarkets exhibit different long-term spillover trends after being hit by the epidemic, and that such trends are significantly heterogeneous across market states. Specifically, at the 0.5 quantile, crude oil and fuel oil exhibit smooth fluctuations; coke, coking coal, and methanol exhibit a sustained upward trend; while asphalt exhibits a peculiar up-and-down fluctuation. In the 0.05 and 0.95 quartiles, the trend of volatility in all six markets after the outbreak is less pronounced, probably because the risk premium level remains high in extreme market conditions, so that the risk level does not switch significantly in the face of the outbreak, but only slightly fluctuates. In terms of the net premium index, crude oil and fuel oil have always played the role of risk transmitters over time in the three market states, while the other four markets have seen a shift in risk premium status. In addition to this, there are also role shifts at the same point in time across market states, e.g., until 2020, the asphalt market is as a net exporter at the 0.5 quantile but a net receiver at the 0.05 quantile; around 2021, the coke market acts as a risk transmitter at the 0.5 quantile but switches to a risk receiver at the 0.05 and 0.95 quantile.

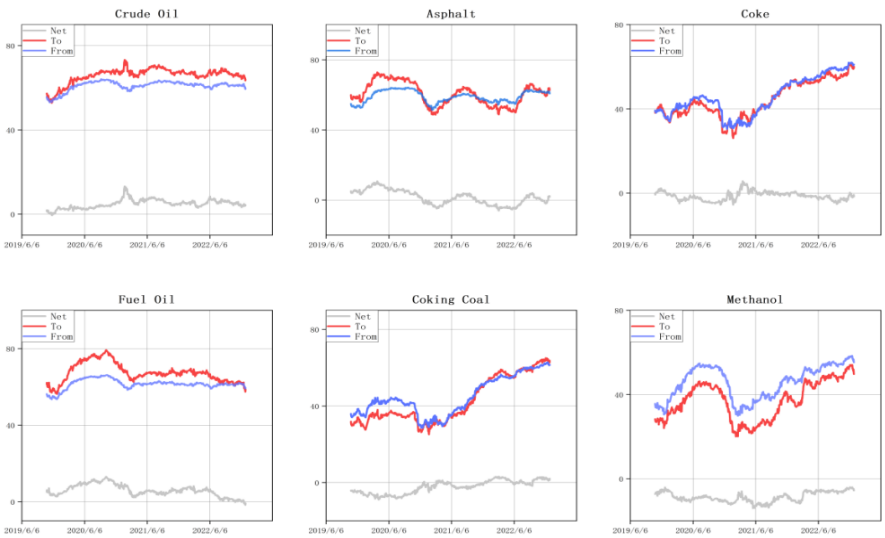

Fig. 3 Internal dynamic directional spillover index on the 0.5 quantile

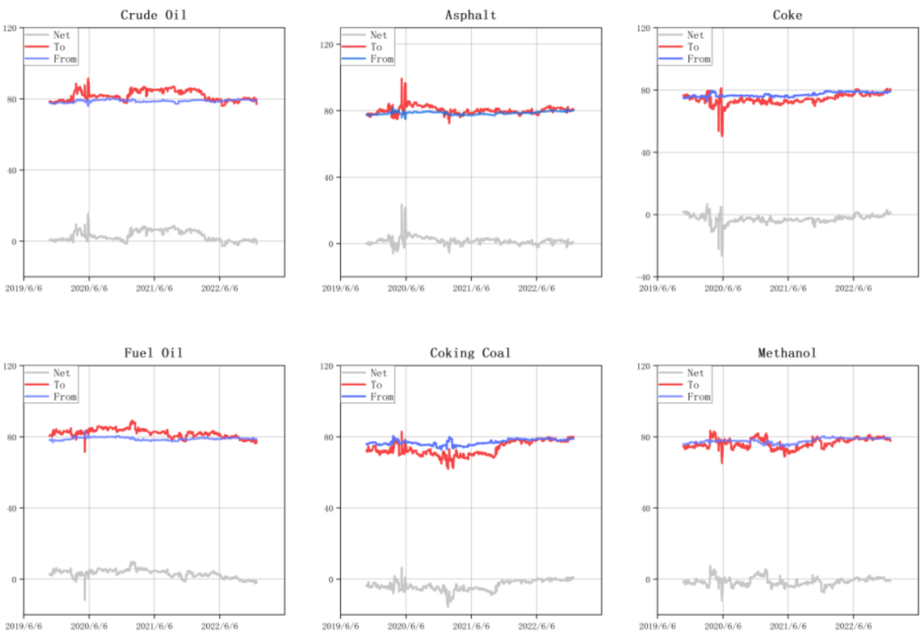

Fig. 4 Internal dynamic directional spillover index on the 0.05 quantile

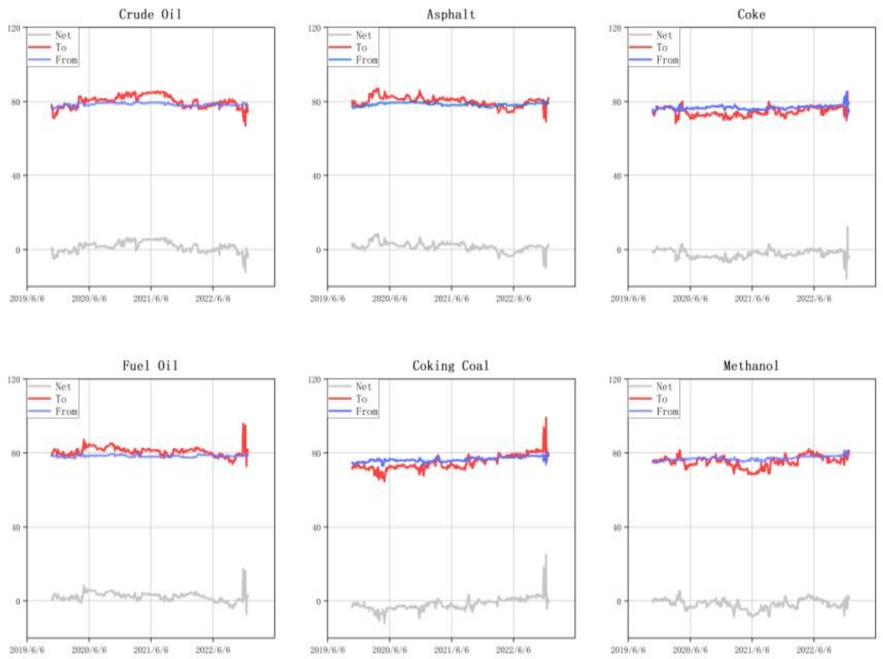

Fig. 5 Internal dynamic directional spillover index on the 0.95 quantile

3) Time-varying characteristics of external aggregate spillover under different market states: In terms of the overall volatility trend, unlike the volatility characteristics of the energy intra-market, the aggregate spillover characteristics based on the conditional mean and conditional median show a gradual risk retreat in the face of an epidemic shock, and this downward trend is only buffered in 2022. The reason for this is that after the outbreak, economic development is at a standstill, the whole system nearly stops functioning, and the correlation between different markets quickly fades, so that risks generated within the market cannot be transmitted to other markets, and the overall level of risk spillovers between markets rapidly decreases. In 2020, the total spillover risk rises due to unconventional monetary policy measures and global interest rate cuts, as well as the initial containment of the epidemic, but this situation does not last long before falling back into a "liquidity trap". At the 0.05 and 0.95 quartiles, total spillover levels oscillate back and forth between 70% and 85%, with stronger aggregation and a faster transition from low to high spillover levels, suggesting that risk spillover effects are more sensitive in extreme conditions. In addition to this, the overall risk level decreases after the outbreak, with the volatility decreasing to between 70% and 80%, suggesting that the outbreak weakens the inter-market connectivity.

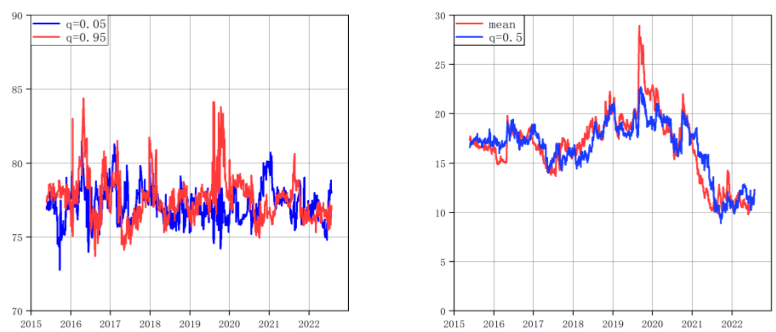

Fig. 6 External aggregate spillover characteristics of energy finance markets in different market states

4) Analysis of external dynamic directional spillover characteristics under different market states: Figures 6 to 8 show the spillover, spill-in and net spillover effects among multiple external markets in different market states. It can be seen that the directional spillover indices of each market are subject to a certain degree of uncertainty and volatility, and the external spillover and internal reception of risk in each market move in the same direction when subjected to external shocks. The next section focuses on three specific aspects to analyze the risk spillover characteristics and the possible underlying reasons for their changes.

First, the spillover and spill-in characteristics of each market are analyzed in terms of time-varying characteristics. The energy finance market goes through four main phases at the 0.5 quantile: a decline from late 2015 to late 2017, a rebound from 2018 to 2019, a fall from late 2019 to late 2021, and a further rise from late 2021 to the end of the sample period, with the possible intrinsic cause being the adoption of the Paris Agreement at the end of 2015, which increased restrictions on traditional fossil energy combustion and weakened the The rapid fall from 2019 to the end of 2021 is attributed to the full spread of the domestic epidemic, economic stagnation and a significant weakening of the correlation across the system. These characteristics of the energy markets are also validated in the equity markets, as the economy gradually recovers, markets gradually regain connectivity, and spillover risks begin to rise. Market spillover sizes for carbon, exchange rates, interest rates, bonds and gold fluctuate mainly between 0% and 30%, with significant points of change occurring between late 2019 and early 2020, with the full-scale outbreak of the epidemic also being a key prying board for their changes. At the 0.05 and 0.95 quartiles, the overall level of risk premia is well above the normal market state and remains at high levels with small fluctuations across markets, probably because the entire market is uniformly in a state of high vigilance and even in the face of extreme upside and downside risks is considered within the range of normal shocks as it does not cause large disruptions.

Secondly, looking at the cross-sectional spillover levels in different markets, the energy and equity markets have been the two markets with higher risk spillovers, dominating the overall market, with several other markets having more similar levels of risk spillovers. In addition to this, each market has higher levels of spillovers in extreme market conditions than in normal market situations.

Finally, from a net spillover perspective, each market has a state shift in the risk premium system. At the 0.5 quantile, the energy, equity and carbon markets play the role of risk transmitters most of the time, the exchange rate, bond and gold markets mainly play the role of risk receivers, while the interest rate market switches back and forth between the two roles and is less stable. In extreme upside and extreme downside states, energy and equity markets still play risk exporters most of the time, but carbon, exchange rate, gold and bond markets turn out to be unstable, and notably interest rate markets start to play risk receivers at this point.

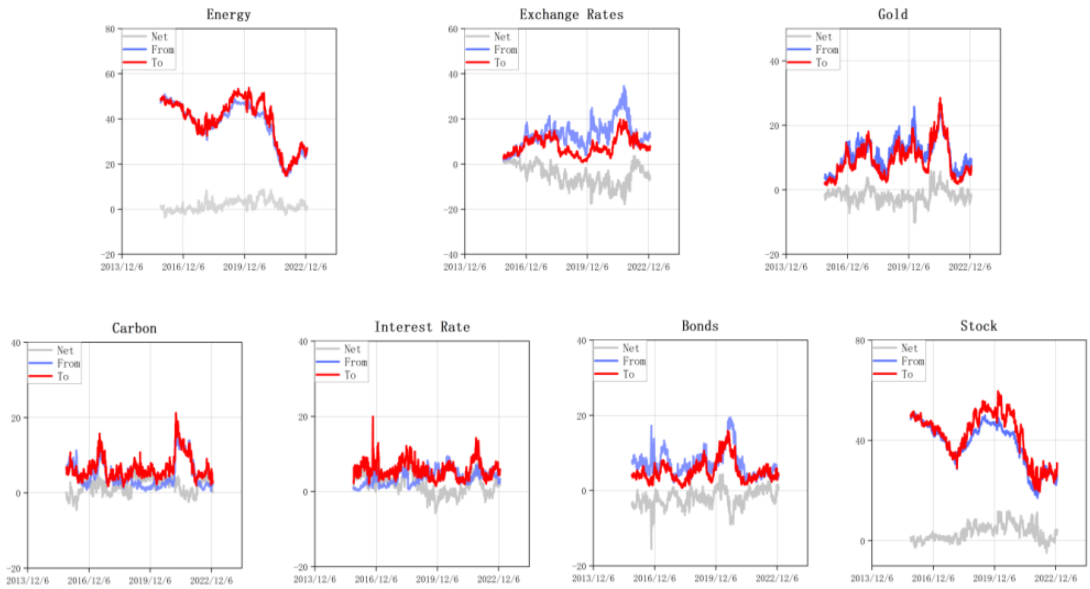

Fig. 7 External dynamic directional spillover index at the 0.5 quantile

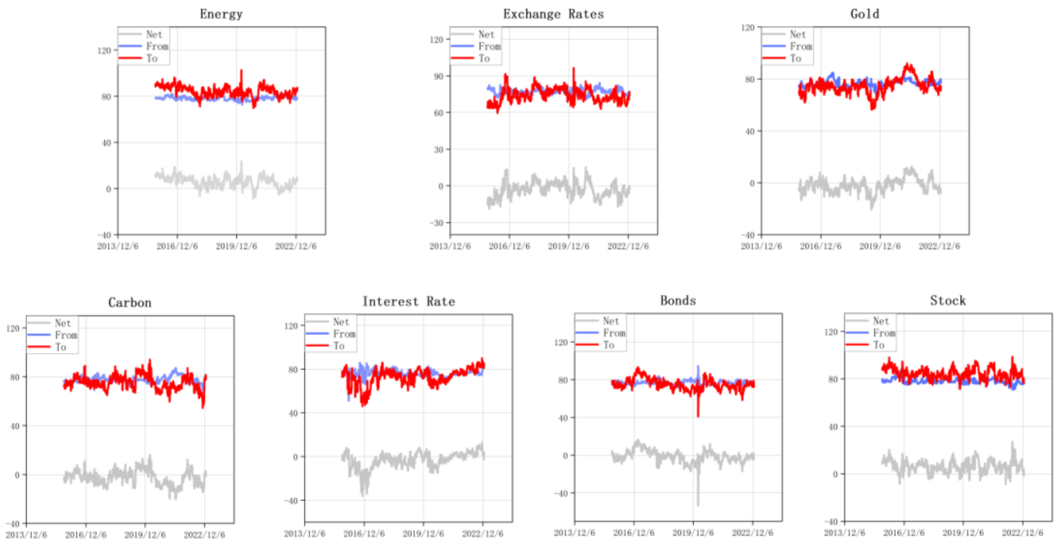

Fig. 8 External dynamic directional spillover index at the 0.05 quantile

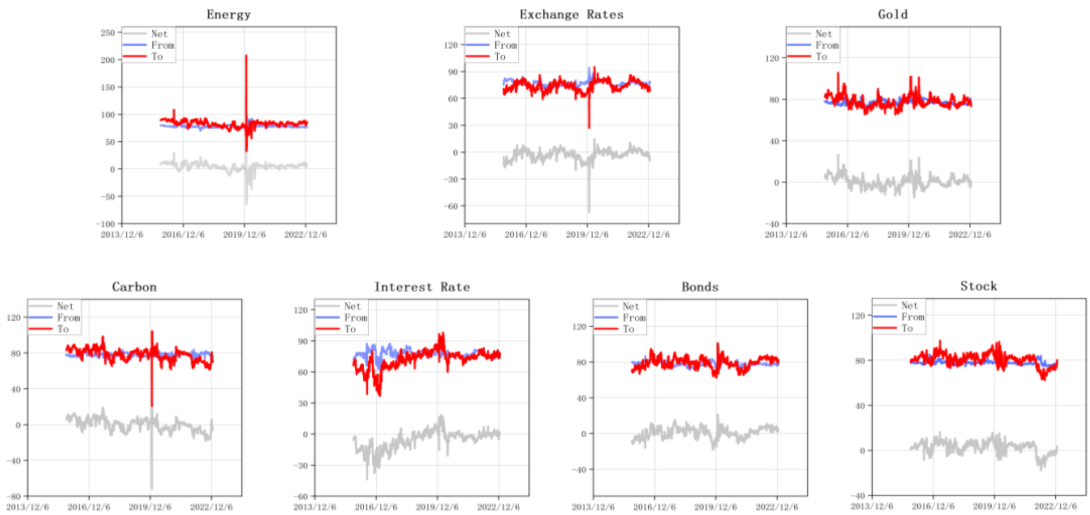

Fig. 9 External dynamic directional spillover index at the 0.95 quantile

D. Complex Network Analysis of Energy Financial Risks in China

In order to further clarify the dynamic interaction process of volatility spillover between each market, the following will visualize the inter-market correlation by drawing network correlation diagrams (Figure 9 and Figure 10) for different market states, and calculating the density of each sub-network to illustrate the tightness of the network.

In general, the network correlations in extreme market states are larger than the normal market state cases for both internal and external markets, and show an overall complex and multithreaded character, which is verified by the results of network density in Table 10.

The structural characteristics of the spillover network within the energy finance market can be summarized into the following four features: firstly, from the node color, the red nodes in the figure represent the net risk exporters and the green nodes represent the net risk receivers, and the spillover identities of the six submarkets are more stable; secondly, from the size of the nodes, the nodes of crude oil, fuel oil and bitumen are larger compared to the other submarkets and occupy an important They are also the primary targets of risk prevention and control. Then, in terms of the coarseness of the edges, the correlation between the two markets is more consistent across the three different market states, with the spillover between crude oil and fuel oil, crude oil and bitumen, fuel oil and bitumen, and coke and coking coal being more pronounced, and it is worth noting that in the face of a positive shock (at the 0.05 quantile) the spillover effect between the three markets of crude oil, fuel oil and bitumen and methanol is significantly higher compared to the other two market state is significantly higher. Finally, in terms of degree centrality and side weights, the magnitude of spillovers between submarkets in the extreme market state is less volatile than in the normal market state, reflecting the greater connectivity and similarity across markets in the face of extreme event shocks.

The structural characteristics of the external network of energy finance markets are also analyzed from four perspectives. First, in terms of node color, unlike the robustness of the submarkets in the internal market, some markets shift state under different market states, e.g., the carbon market and the interest rate market, which act as risk receivers in extreme market states, start to act as risk transmitters when the market returns to normal conditions. The gold and bond markets act as risk receivers at the 0.05 and 0.5 quantile and turn into risk spillovers at the 0.95 quantile. Secondly, in terms of the size of the nodes, energy and equity markets show larger nodes in different market states and always occupy a significant position. Besides, in the extreme volatility upside state, gold, bond and carbon markets gradually become the central nodes of the network as their correlations with other submarkets increase relative to both the normal market state and the extreme volatility downside state. Then from the coarseness of the edges, the energy market and the stock market are more significantly correlated in all three market states, and the spillover effect of both is higher. The intrinsic reason may be the gradual financialization of energy in recent years, the stock market is a representative of the financial market, and the whole financial system is interconnected and interacts with each other, thus making the correlation between the two substantially higher relative to other markets. Finally, from the perspective of degree centrality and side weights, the minimum values of network correlation of nodes in extreme market states are much larger than the maximum values in normal market states, indicating that the contagion effect among markets is more severe in extreme market states, the overall network is more closely connected, and the collapse of a single market is more likely to trigger systemic risks and thus cause serious impacts on the real economy.

Table 10 Internal and external market network density values

Internal Market Status	Network Density	External Market Status	Network Density
0.05	0.8	0.05	0.786
0.5	0.6	0.5	0.675
0.95	0.933	0.95	0.905

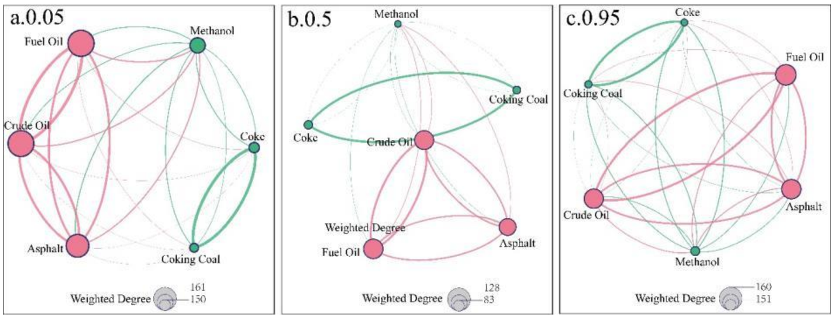

Fig. 10 Energy Finance Internal Market

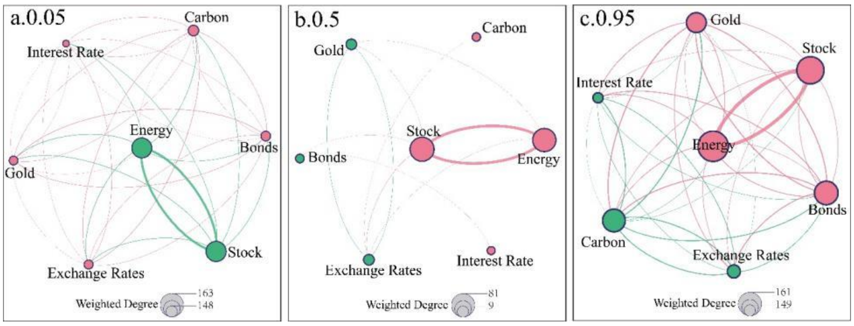

Fig. 11 Energy Finance External Markets

E. Robustness Tests for Different Quantile Selection

In order to exclude the possible instability of the randomness of quantile selection on the risk spillover results, this paper takes the total internal and external market spillover index as the experimental object and further selects all quantile points on 0~1 for robustness analysis. In Figure 11, (a) and (b) denote the time-varying values of risk spillovers at different quartiles for the internal and external markets of Chinese energy finance, respectively. Warmer shades represent higher network correlations, and it can be seen that for extreme downward markets below 20% and extreme upward markets above 80% the connectivity of both internal and external markets is stronger. Specifically, the overall average connectivity for the internal market is around 50% and increases year by year, and the overall average connectivity for the external market is around 20%. These trends are consistent with the analysis done above, indicating that the extreme quantile points selected are robust.

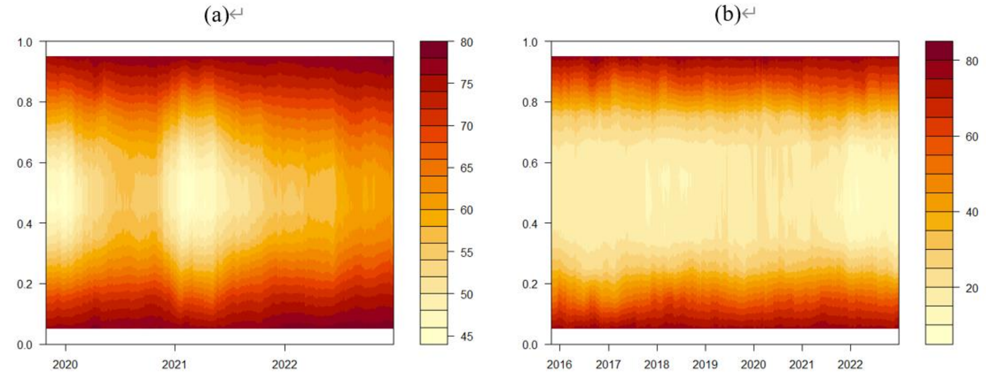

Fig. 12 Time-varying values of risk spillover at different quartiles

F. Energy Finance Risk Early Warning Study

1) Early warning indicator selection: After analyzing the internal and external risk spillover characteristics of the energy financial market, we observe that there are certain correlation effects among different markets and sub-markets within the energy market, and that these connectivity effects show significant heterogeneity, so that solutions can be developed based on the characteristics of new information when risks occur. Therefore, this paper further analyzes the early warning of energy financial risks in China and constructs an effective risk warning system to predict and stop the outbreak of risks in advance. In terms of data selection, considering that the spillover effect in the face of positive or negative shocks is much larger than the risk value under normal market conditions, and the impact of systemic risk would be the collapse of the entire economic system, the time-varying value of the total risk spillover under extreme market conditions is selected as the proxy variable for risk warning.

In terms of the selection of early warning indicators, considering the uniqueness of China's economic operating system and related market environment as well as the connectivity of energy financial risks among multiple external markets, data related to the carbon market, stock market, interest rate market, gold market, exchange rate market, and bond market are initially selected, which is more in line with Tobias and Brunnermeier's (2016) study. consistent with Tobias and Brunnermeier. The specific proxy variables are shown in Table 11 [39].

Table 11 China Energy Financial Risk Warning Indicators

Indicators	Proxy variables
Carbon	Hubei Carbon Trading Market Log Yield
Interest Rate	SSE Composite Index Log Yield
Exchange Rates	Overnight shibor log yield
Bonds	Gold Price Log Yield
Gold	RMB to USD Log Yield
Stock	SSE Treasury Index Log Yield

In terms of early warning model design, the parameters of the Attention-CNN-LSTM early warning model are set as follows: the number of convolutional layers is 1, the learning rate is 0.0001, the number of training rounds is 200, the batch training size is 24, and the optimizer is Adam. the mean absolute error MAE and the root mean square error RMSE are selected as a measure of prediction accuracy, and the formulae are calculated as follows, respectively.

$$MAE=\frac{\sum_{i=1}^{n}\left|y_i-y_i'\right|}{n} \tag{26}$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}(y_i'-y_i)^2}{n}} \tag{27}$$

where n denotes the number of forecast periods, y_i' denotes the risk forecast, and y_i denotes the true value of risk.

2) Risk warning system construction: After the initial selection of risk warning indicators, the correlation and causality between the indicators need to be further considered in order to ensure that the selected indicators have certain rationality and validity. Granger causality test has the ability to test the causal relationship between variables, but the traditional Granger method is only able to test the linear relationship between variables and is not suitable for the deep learning nonlinear early warning model used in this paper, so the nonparametric nonlinear Granger causality test is considered to examine whether there is a correlation between the selected early warning indicators and China's energy financial risk, and to point out whether it can be used to improve risk forecasting ability. It is a key step to determine whether there is a nonlinear dynamic change relationship between variables before conducting nonlinear causality tests on the variables. Therefore, a VAR model is used to filter the linear relationship between variables, and energy financial risk is added to the regression equation as the explanatory variable, and the BSD and RESET methods are applied to test the model residual series, and the original hypothesis of the test is that there is no nonlinear The original hypothesis is that there is no nonlinear relationship between the variables, and the empirical results show that both are significant at the 1% level, which rejects the original hypothesis that there is a nonlinear relationship. The results are shown in Table 12, which shows that all markets pass the test and the stock market is significant at the 1% level, indicating that the selected indicator can be used as an early warning indicator for energy financial risk in China.

Table 12 Non-linearity test for early warning indicators

H0	P-value	H0	P-value
Carbon Market is not the reason for the energy market	0.083^{*}	Gold Market is not the reason for the energy market	0.069^{*}
Stock Market is not the reason for the energy market	0.000^{***}	Exchange Rates Market is not the reason for the energy market	0.087^{*}
Interest Rate Market is not the reason for the energy market	0.090^{*}	Bonds Market is not the reason for the energy market	0.092^{*}

Note: * represents the 10% level of significance, *** represents at the 1% level of significance.

In order to fully reflect that the fitting effect of the Attention-CNN-LSTM model is better than other models, six models, including LSTM, CNN-LSTM, BP neural network, support vector machine (SVM) and random forest (RF), are also selected for comparative analysis of the prediction effect, in addition to this paper, we will also study the risk warning indicators before and after the addition of In addition, this paper will also study the change characteristics of the prediction effect of the Attention-CNN-LSTM model before and after the addition of risk warning indicators, and determine whether the addition of risk warning indicators can improve the fitting prediction effect of the model. Figure 12 shows the prediction comparison results of the six models and the changes of the prediction results of the Attention-CNN-LSTM model before and after adding the warning indicators, from which it can be directly seen that the risk prediction effect of the Attention-CNN-LSTM is better than the other five models and is closer to the real risk value, while the SVM and BP significantly deviate from the real value of The CNN-LSTM, LSTM and RF models have similar prediction effects, all of which are slightly weaker than the Attention-CNN-LSTM model. Figure 13 gives a comparison of the prediction effect of the

Attention-CNN-LSTM model before and after the addition of the warning indicators, and it can be seen that the prediction effect of the model is further improved with the addition of the warning indicators. The prediction effects of different models can only be roughly guessed from the graphs, while for those models that perform more similarly on the graphs, further precise comparisons of model evaluation metrics are required. From the level of model evaluation metrics in Table 13, the Attention-CNN-LSTM model performs the best, possessing lower MAE and RMSE values than the other five models, optimizing 12.9% and 21.4% in MAE and RMSE, respectively, than the CNN-LSTM model, which also has better prediction results. Besides, it can be found that the support vector machine and BP neural network are not applicable to the study in this paper and have large prediction errors. Table 14 gives the MAE and RMSE of the model improved by 19.8% and 31.9%, respectively, after the inclusion of the early warning indicators, which again verifies that the inclusion of the early warning indicators is effective. In summary, the Attention-CNN-LSTM model with the inclusion of early warning indicators has better risk prediction effects and can be used for risk warning in the Chinese energy finance market.

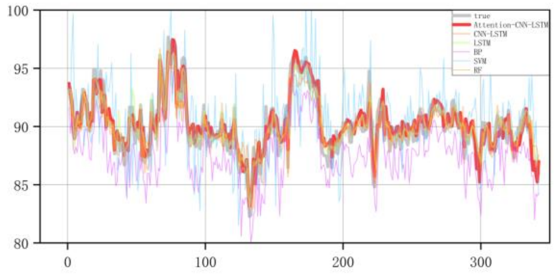

Fig. 13 The prediction effect of several different models

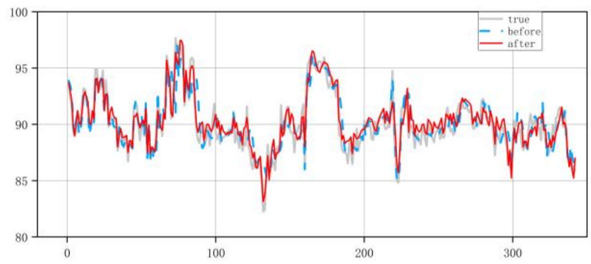

Fig. 14 Comparison of model prediction effects before and after adding early warning indicators

Table 13 Comparison of evaluation indicators of different forecasting models

Evaluation Indicators	Attention-CNN-LSTM	CNN-LSTM	LSTM	BP	SVM	RF
MAE	0.7686	0.8828	0.8930	2.5178	2.2847	1.0619
RMSE	0.9077	1.1553	1.2206	2.9687	2.9426	1.3794

Table 14 Comparison of evaluation indicators before and after adding early warning indicators

Evaluation Indicators	Attention-CNN-LSTM(+)	Attention-CNN-LSTM(-)
MAE	0.7686	0.9587
RMSE	0.9077	1.3326

V. Conclusions and Recommendations

A. Conclusion

The main subject of this paper is the internal and external risk spillover characteristics of China's energy financial market and the construction of an accurate risk early warning system. The research process includes capturing risk spillover effects using a quantile vector autoregressive based spillover index model, visualizing the risk transmission mechanism among markets using complex network graphs, conducting robustness tests for quantile randomness selection, and constructing a risk early warning system based on Attention-CNN-LSTM model-based risk warning system is constructed. The following conclusions are drawn: first, in terms of static spillover characteristics, the total spillover characteristics based on conditional mean and conditional median in the internal market are similar, 53.2% and 53.01%, respectively, exhibiting a high spillover index, and the value is elevated to 78.05% (extreme downside) and 77.59% (extreme upside) in extreme market states. Among the unilateral submarkets, crude oil and fuel oil both show higher spillover and spill-in effects relative to other markets in different market states and occupy a significant position in the market. The total spillover effects in the extreme downside (77.18%) and extreme upside (77.6%) market states in the external markets are more than four times higher than those based on the conditional mean (16.7%) and conditional median (16.57%), where the energy finance and equity markets show more significant risk contagion characteristics in all market states relative to other markets and are the main targets of concern for systemic risk. Second, in terms of dynamic spillover characteristics, both internal and external markets exhibit strong time-varying characteristics of aggregate spillover in different market states. In terms of net spillover perspective, crude oil and fuel oil in the internal market always maintain the risk transmitter status in different market states, while all other four markets have risk role shifts; all markets in the external market have risk status shifts and the whole system is more volatile. Third, from the complex network diagram, the network correlation in the extreme market state is significantly greater than the normal market state situation. Fourth, from the risk early warning model, the Attention-CNN-LSTM model has more accurate prediction performance and lower MAE and RMSE values compared with the other five models, and the prediction effect of the model is further improved after adding early warning indicators, which is suitable for constructing an energy financial risk early warning system in China.

B. Recommendations

Based on the above findings, this paper will put forward the following policy recommendations: First, government departments should not only consider the risk spillover from external markets to the energy industry when formulating energy finance risk prevention and control measures, but also further consider the risk spillover between submarkets within the energy finance market, because the risk generated by internal submarkets is significantly different from each other, and only by doing a full range of spillover Only by capturing a full range of spillover characteristics can we intercept the source of risk more precisely and effectively prevent further contagion of risk. Secondly, more attention should be paid to the significant risks arising from extreme market conditions, because in extreme market conditions, the risk spillover index between internal and external markets rises significantly and the network density increases significantly, which makes the market contagion more efficient and thus can cause more serious losses in a shorter period of time. Finally, it is necessary to consider various factors affecting the risk of China's energy finance market in a comprehensive and multi-faceted manner, taking into account the uniqueness of the Chinese market, to build a more accurate risk warning system, to most effectively reduce the harm caused by systemic risks, and to improve the efficiency of energy finance risk prevention.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

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