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Measurement of risk spillover effect based on EV-Copula method

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Based on the extreme value theory, copula function, and conditional value at risk (Abbreviated as CoVaR) model, an extreme value copula CoVaR (EV-Copula CoVaR) model is established. In application, the risk spillover effect of the carbon trading market on the stock market of China is investigated. Firstly, using the index synthesis method, the carbon trading price index is synthesized through the price data of the test area of carbon emission, then the risk spillover effect of the carbon market is measured by the EV-Copula CoVaR, and the dynamic risk spillover ΔCoVaR of the carbon market to each stock market is investigated. Finally, the downside ΔCoVaR under different significance levels is measured, and the relationship between the self-risk and spillover risk of the carbon market is explored, the largest risk spillover effect to the stock market is the electricity market. The smaller the significance level, the greater the carbon market self-risk, and the greater the risk spillover of the carbon market to the stock market, which shows that there is a positive correlation between them.

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Introduction

With the rapid development of the global financial market system, international economic cooperation and business exchanges have become increasingly frequent. Meanwhile, with the rapid development of global financial market integration, the openness of financial systems in various countries is also constantly improving, and the linkage effect between cross-border markets is becoming increasingly evident. However, financial capital with different risk characteristics not only expands the scale of financial business and improves the efficiency of financial market operation, but also has an impact on the stability of the market, with the most significant being the continuous intensification of financial risks. In August 2007, the subprime mortgage crisis in the United States swept across the world, led to the rapid deterioration of the global economy, and seriously disrupted the financial system. The cause of the crisis is the lack of risk prediction, supervision, and management of the financial market.

In recent years, problems in the form of a "carbon foam" are putting some fossil energy companies worth hundreds of billions of dollars into trouble. The so-called "carbon foam" means that the current value of fossil fuels is overestimated, and people will have to significantly reduce greenhouse gas emissions in the long run. low-carbon development and climate issues have become a consensus and social responsibility for human social development. Under the urgent situation of global carbon emissions, emission reduction has expanded from the technical level to the financial market level. As a special asset, carbon emission rights have formed a carbon emission trading market through trading and conversion between physical markets. Carbon emissions trading is a mechanism that limits greenhouse gas emissions and promotes sustainable development goals by establishing a carbon market. This mechanism promotes emission reduction and low-carbon investment by setting a total limit on emission quotas and allowing companies to trade emission quotas among themselves. The goal of carbon emissions trading is to encourage enterprises to reduce greenhouse gas emissions through economic incentive mechanisms. Enterprises can manage their emissions by purchasing or selling emission quotas, providing economic incentives for those who can effectively reduce emissions and have excess emission quotas. At the same time, it also provides opportunities for enterprises with higher emission reduction costs to make up for the emission gap. Countries around the world are gradually establishing carbon emission trading markets to promote their low-carbon development through market-oriented means. As regards theory, Azomahou et al. (2006) reveal that carbon emissions come from energy consumption, which is an important factor related to the production and consumption of the world economy. Oberndorfer (2008) shows that the changes in EU carbon emission rights prices are positively correlated with the stock returns of the most important electricity companies in Europe, and the stock price effect of carbon emission rights prices has periodicity and may vary in different countries. Daskalakis, and Markellos (2009) find a positive relationship between carbon prices and electricity risk premiums under the EU carbon emission trading system, and the impact of a decrease in carbon price returns on electricity price risks is greater than that of an increase in carbon price returns. Kijima et al. (2010) propose a model and pricing formula for the emission trading license market. Pindyck (2008) finds that carbon emissions can lead to carbon risks. Bushenll et al. (2013) consider that the emission trading system will have an impact on cash flow and expected returns. Fowlie, and Reguant (2022) use US energy price variation as a proxy for variation that will be induced by a domestic carbon price and simulate the impacts of a domestic carbon price on US manufacturing with and without these subsidies. With the rapid development of the carbon emissions trading market, there are also certain risks, including market supply and demand, political changes, financial crisis, climate change, and other factors. Therefore, it is necessary to invest more cautiously. A natural question is how to scientifically and reasonably identify and measure market risk, which is conducive to taking effective risk management measures to ensure the implementation of global low-carbon and sustainable development. Undoubtedly, establishing a mathematical model and measuring risk is necessary, which can provide us with some meaningful guidelines in risk measurement.

Risk measurement is mainly obtained by calculating value at risk (VaR). With the globalization of the economy and the liberalization of the financial environment, the connections between different financial institutions are becoming closer and more complex. The mutual influence and risk exposure of financial institutions have gradually increased. Adrian, Brunnermeier (2016) propose the CoVaR, which reveals the risk spillover of one financial institution to another financial institution or to the financial system, thus filling the gap that VaR does not consider risk spillover in risk measurement. It is known that CoVaR may be calculated by quantile regression and DCC-GARCH methods. Among them, the quantile regression method is somewhat rough because it can only measure linear risk spillover effects. Therefore, Girardi and Ergun (2019) propose to use the DCC-GARCH method to calculate CoVaR. Financial markets should generally have complex characteristics such as volatility aggregation and time-varying variance. The linear risk spillover measured by quantile regression is not convincing. Although the DCC-GARCH method improves this shortcoming, tail risk spillovers and non-linear correlation structures in financial markets cannot be fully measured. Mainik and Schaanning (2014) propose to calculate CoVaR by the copula method. For the research and application of the copula model, Wu et al. (2012) use copula-based GARCH models to investigate the economic value of co-movement between oil price and exchange rate (US dollar index). Aloui et al. (2013) apply the copula-GARCH approach to consider the conditional dependence structure between crude oil prices and US dollar exchange rates. Sebai and Naoui (2015) establish the connection between oil prices and the US dollar exchange rate using a copula approach and the DCC-MGARCH model. Hung (2019) investigates the conditional dependence structure between crude oil prices and three US dollar exchange rates (China, India, and South Korea) from a new perspective using a copula-GARCH approach. Hung (2020) studies both the constant and time-varying conditional dependency for crude oil, stock markets, green bonds, and assets by using the conditional copula model. At present, the international environment is complex and changeable, which is bound to have a negative impact on the financial market, especially it may lead to systematic risk in the financial market if some extreme events occur. Therefore, we must consider extreme events such as war and major natural disasters in the study of market risk. Further, we should consider the risk contribution, that is dynamic systematic ΔCoVaR, which can describe the dynamic variation of systematic risk. Our work attempts to fill this gap, which is the reason why we consider using extreme value theory in the present study. Extreme value theory is a modeling and statistical analysis method for extreme variability that rarely occurs, but once it occurs, it has a significant impact. It provides us with a good robust asymptotic model, which can be used to model the tail of the distribution and assess risk. Research shows that linear models cannot capture the impact of extreme events such as war and major natural disasters on the market. On the contrary, nonlinear models have advantages in this respect. Copula function can effectively describe non-linear relationships and can separate the marginal distribution and the structural relationship between random variables, hence it has many advantages in practical applications. Obviously, the combination of extreme value theory and the copula method can better measure the tail relationship between variables.

There are several reasons why this research selects China as a case study. First, China attaches great importance to climate change and sustainable issues and has made unremitting efforts and positive contributions to addressing climate change from the perspective of global long-term fundamental interests. After the signing of the Paris Agreement, China has proposed phased emission reduction targets for 2020 and 2030. Currently, the annual trading volume of the carbon market is about 50 million tons, and China has become an important carbon emission trading market in the world. Second, the stock market of China has become the second largest stock market in the world, and the future development prospects of the stock market are optimistic. With the advancement of government policies and the adjustment of market structure, the stock market will gradually develop towards a more open, standardized, and transparent direction. Against the backdrop of investors gradually upgrading, the stock market will bring more investment opportunities and space to global investors. Finally, the carbon market can effectively leverage its resource allocation function, and guide social capital to flow to environmental protection enterprises, further promoting industrial structure optimization, therefore, There is a close connection between the carbon market and the stock market.

The main contributions of the work are as follows. First, we use the US Department of Commerce index synthesis method to synthesize the carbon trading price index, it provides guidance for carbon index synthesis. Then we establish EV-Copula CoVaR model and measure the risk spillover effect of the carbon trading market to the stock market, which provides a new idea for the research of risk spillover of the carbon trading market. Finally, we explore the relationship between significance level and risk spillover intensity, it is found that the smaller the significant level, the greater the risk of the carbon market, and the larger ΔCoVaR, which indicates that there is a positive correlation between the risk of the carbon market and spillover risk.

The remainder of the paper is organized as follows. Section "Literature review" provides the literature review. Section "Methodology" gives the methodology of this article. Section "Empirical results" presents the numerical results. Finally, Section "Conclusion and suggestions" concludes the research and gives suggestions.

Literature review

In the risk measurement of financial markets, the study of tail dependence risk has attracted increasing attention, and copula functions are used to characterize tail dependence. The copula method compensates for the drawbacks of linear correlation in characterizing the correlation between variables. Therefore, the copula correlation function and the correlation measures are widely used in financial data analysis. Sklar (1959) first proposed the copula theory, which has excellent performance in measuring non-linear and dependent relationships. Embrechts and McNeil (1999) use the copula approach in the financial field. With the widespread application of copula theory in the financial field, many works have been conducted on copula theory and copula linkage method. Embrechts et al. (2003) use the copula function to calculate VaR, and show that the VaR has a better fitting effect with the actual value. Patton (2006) applies the time-varying copula function to the exchange rate problem and studies the linkage of different exchange rate markets. Garcia, Tsafack (2011) propose a copula model that includes symmetric and asymmetric states to study the linkage between the bond market and the stock market, the results show that in the asymmetric state copula model, there is weak linkage between the bond market and the stock market. Stber and Czado (2014) propose a Bayesian method to estimate the parameters of the R-Vine copula model and use this method to study the linkage between the exchange rate of US dollar and nine currencies. Oh and Patton (2017) make the dynamic parameters of the copula function obey the generalized auto-regression model, and use the newly constructed copula function to study the systematic risk level of 100 American companies, the results show that the systematic risk level during the 2008 financial crisis is higher than the systematic risk level before the financial crisis. Bensaida (2018) applies vine copula model with Markov regime-switching to study the linkage and contagion of the US debt market and the Eurozone debt market. Gomez-Gonzalez, Rojas-Espinosa (2019) use the DCC-GARCH model and copula function to study the linkage of exchange rate markets in 12 countries of the Asia-Pacific Region, the research results show that the level of exchange rate fluctuations between countries has a strong linkage during periods of extreme market appreciation and depreciation.

As for the measurement of indicators of risk spillover effect, three typical approaches are DCC-GARCH, quantile regression, and copula function methods. Jiang et al. (2022) measure the risk spillover effect between carbon pilot sites in China based on the time domain and frequency domain, the research shows that the risk spillover between carbon pilot sites has significant time-varying performance in the time domain perspective. Han et al. (2022) use the Paasche index method to compile the unified price index of carbon market of China, and establish TVP-VaR model to study the time-varying spillover effects of carbon market, EUA futures market, and non-ferrous metal futures market, The results show that the direction and intensity of spillover effects between the non-ferrous metal, EUA futures market and the carbon market are asymmetric and time-varying. Wang et al. (2022) use the error variance decomposition method to construct the spillover index and explore the direction and intensity of risk spillover between China's carbon market and traditional energy, finance, new energy, materials, electricity, industry, real estate and other stock markets based on dynamic and static perspectives. Keilbar, Wang (2021) investigate the risk spillover effect of banks considering the marginal effect of the quantile regression method, and measure it using the network risk index, they find that this method provides a new perspective for market risk measurement. Yin et al. (2021) propose symmetric and asymmetric ΔCoVaR methods on the basis of quantile regression to investigate possible risks in the oil market and find that international risk spillovers are significantly affected by oil price shocks. Geenens, Dunn (2022) propose a new non-parametric framework to estimate CoVaR, and find the non-parametric method is particularly applicable and its performance is superior to industry counterparts by Monte Carlo simulation. Zhou et al. (2022) apply the quantile network framework and GARCHSK model to study the multidimensional risk spillover effects among carbon, energy, and non-ferrous metal markets, and test the diversification of investment portfolios. However, in the above literature, there is a lack of work on extreme value theory and copula method to study risk spillovers, especially the dynamic risk spillover effects, which is the motivation to carry out this study.

Methodology

Exploring the risk spillovers between the carbon market and the stock market is important for the scientific prevention of carbon trading market risks. Based on the EV-Copula CoVaR model, we study the spillover effect between the carbon trading market and the stock market.

Carbon trading price index synthesis. Index measurement methods include principal component analysis, synthesis, diffusion index, and other methods. The article uses the US Department of Commerce index synthesis method (Gao et al., 2015) to synthesize the carbon trading price index, and the steps are as follows:

Step 1. Calculate the symmetrical varying rate of each group

Let $Y_{ij}(t)$ be the i-th index variable of the j-th group at time t, j(=1, 2, 3) denotes the group of five carbon-emitting provinces in China (Group 1: Beijing; Group 2: Shenzhen; Group 3: Shanghai, Guangdong and Hubei), i(=1, 2,⋯, k_j) is the number of indicators in each group, and k_j is the number of test areas in group j. The symmetry varying rate is defined as

$$C_{ij}(t) = 200\times\left[Y_{ij}(t) - Y_{ij}(t-1)\right]\left[Y_{ij}(t) + Y_{ij}(t-1)\right]^{-1}, t = 2, 3, \cdots, n \tag{1}$$

Define the standardization factor as follows:

$$A_{ij} = \frac{1}{n-1}\sum_{t=2}^{n}\left|C_{ij}(t)\right| \tag{2}$$

Then, we normalize the symmetry varying rate as

$$S_{ij}(t) = A_{ij}^{-1}C_{ij}(t), t = 2, 3, \cdots, n \tag{3}$$

Step 2. Calculate the standardized average varying rate of each group

Write the average varying rate as

$$R_j(t) = \left(\sum_{i=1}^{k_j} W_{ij}\right)^{-1}\sum_{i=1}^{k_j}\left[W_{ij}S_{ij}(t)\right], j = 1, 2, 3; t = 2, 3, \cdots, n \tag{4}$$

where W_{ij} is weight of the i-th test area of the j-th group. Due to the limited availability of carbon industry indicators, if the weight selection is based on the data itself, it will result in the weight of certain indicators with small absolute values but large growth fluctuations occupying an important position. Therefore, the weights in this article are set to 1. The standardization factor is given by

$$F_j = \left[\sum_{t=2}^{n}\left|R_1(t)\right|\right]^{-1}\sum_{t=2}^{n}\left|R_j(t)\right|, j = 1, 2, 3 \tag{5}$$

where $R_1(t)$ denotes the average varying rate of carbon market, $F_1 = 1$. Then the standardized average varying rate is defined as

$$V_j(t) = F_j^{-1}R_j(t), t = 2, 3, \cdots, n \tag{6}$$

Step 3. Synthesize price index

Let $I_j(1) = 100$, $\bar{I}_j$ is the average returns on the benchmark date, and the initial composite index is written as

$$I_j(t) = I_j(t-1)\left(200 - V_j(t)\right)^{-1}\left(200 + V_j(t)\right), j = 1, 2, 3; t = 2, 3, \cdots, n \tag{7}$$

Thus, the final composite index is defined as $CI_j(t) = \left(I_j(t)/\bar{I}_j\right)\times 100$, which is the chain price index.

The models. The EV-Copula model is constructed to calculate CoVaR, when using the copula model, the following two aspects are considered: The first one is the marginal distribution, considering the statistical characteristics of the financial series with sharp peaks and thick tails, we use the generalized Pareto distribution (GPD) to perform calculations (Wang and Yang, 2019). The second one is the middle part of sequence, which is calculated by empirical distribution. After getting the marginal distribution, we choose the copula function with the best fitting effect to describe the correlation among the marginal sequences.

Model of extreme marginal distribution. The extreme value theory only models the distribution of the tail data, and does not involve the overall situation of the distribution. Peaks over threshold (POT) model and block maxima method (BMM) model are two common extreme value theoretical models. The POT model needs to set a threshold in advance, and takes the data set that exceeds the threshold as the research object. BMM model usually studies the magnitude data set, and prefers the extreme value problem with obvious seasonal data. Due to the limitation of obtaining tail data, the application of this model is limited. Assuming that the distribution function of random variable X is F, the conditional probability distribution of X exceeding a certain threshold μ is defined as

$$\begin{aligned}F_\mu(x) &= P\left(X-\mu\le x\middle|X>\mu\right)\\ &= \left[1-F(\mu)\right]^{-1}\left[F(x+\mu)-F(\mu)\right], x>0\end{aligned} \tag{8}$$

where $F_\mu(x)$ is the over-threshold distribution.

This study uses the GPD distribution to describe the upper and lower tail returns of the sample sequences, and uses the empirical distribution to describe the intermediate data. The marginal distribution of the yield sequence x is given by

$$F(x) = \begin{cases}\frac{N_{u_L}}{N}\left(1-\xi\frac{x-\mu}{\beta(\mu)}\right)^{-\frac{1}{\xi}}, x<\mu_L\\ Ecdf(x), \mu_L\le x\le\mu_R\\ 1-\frac{N_{\mu_R}}{N}\left(1+\xi\frac{x-\mu}{\beta(\mu)}\right)^{-\frac{1}{\xi}}, x>\mu_R\end{cases} \tag{9}$$

where $\xi \in R$ is the distribution shape parameter, $Ecdf(x)$ is empirical distribution function of the yield series on the interval $\mu_L \le x \le \mu_R$, μ is the threshold, μ_L is the lower tail threshold, μ_R is the upper tail threshold, $\beta(\mu)$ is the positive function scale parameter related to μ, and N_μ is the number of observations smaller than the threshold μ. The determination of threshold μ is a sufficient condition for ξ and $\beta(\mu)$ accurate estimation. It will lead to biased estimation if the threshold μ is small. However, it will turns out that the variance of parameter estimation becomes big if the threshold μ is too big. In practical applications, most of them adopt the screening principle (Dumouchel, Waternaux (1983)), that is one needs select the quantiles that exceed the threshold and account for 10% of the total samples to determine the threshold. This paper uses this method to determine the yield series upper and lower tail threshold.

Functions of copula dependent structure. With the rapid development of modern financial market, the original risk analysis method based on linear correlation cannot fully meet the needs of risk management with the complexity and variability of market risk. It is well known that copula function can effectively deal with the asymmetric and nonlinear relationship among variables, which has attracted more and more attention. Copula function has been rapidly applied to time series analysis, financial risk management, insurance pricing and mechanical design, and it can easily construct the joint distribution, also save the computing time. The most commonly used copula functions in the study include elliptic copula function family, mixed copula function family and Archimedean copula function family. We select Archimedean copula function family to calculate risk spillover, among which Archimedean copula function family includes Joe copula, Clayton copula, Gumbel copula, Frank copula, BB1

Table 1 Sample markets and data sources.

Sample Market	Indicator Name	Index Code	Source of Indicators
Carbon Market	China carbon trading price index (THC)	—	Synthesis index of five carbon market indexes
Electricity Market	Huaneng international stock daily closing price (HNGJ)	600011	The largest electricity company in China,
Financial Market	Financial index daily closing price (FI)	399240	Index constructed by Shenzhen Stock Exchange
Real Estate Market	Real estate index daily closing price (RE)	000006	Index constructed by Shanghai Stock Exchange
Industrial Market	Industrial index daily closing price (IN)	000004	Index constructed by Shanghai Stock Exchange
Energy Market	SSE energy daily closing price (TE)	000032	Index constructed by Shanghai Stock Exchange

Data source: iFinD financial data terminal (www.51ifind.com).

copula, BB2 copula, BB3 copula, BB6 copula, BB7 copula etc. (Cherubini et al., (2004)). The following will select the optimal copula function based on the fitting effect of the actual income sequences.

According to Cruz (2004), the m dimensional copula is a function $C(\cdot)$ defined on$I^m = [0,1]^m$, and it satisfies the following conditions:

(1) For each variable defined on $C(\cdot)$, the function monotonically increases.
(2) For any variables $0 \le \mu_k \le 1$, $C(1,\cdots,1,u_k,1,\cdots,1) = u_k$.
(3) For m dimensional vector $u = (u_1,\cdots,u_m)$, if $u_{\rm i} = 0$, $i = 1,\cdots,m$, then we have $C(u) = 0$.

According to the above definition, the m dimensional copula function $C(\cdot)$ is a m dimensional probability distribution function, and its marginal distribution is a uniform distribution defined on $[0,1]^m$. Let F_1 $(x_1),\cdots$, $F_m(x_m)$ be the distribution functions of random variable $X_1,\cdots X_m$, then C $(F_1(x_1),\cdots, F_m(x_{\rm m}))$ denotes the joint distribution function of the $(X_1,\cdots, X_m)$. According to Sklar theorem (1959), if F_1 $(x_1),\cdots$, $F_m(x_m)$ is the marginal distribution function of random vector $(X_1,\cdots, X_m)$, then there is only one m dimensional copula function C, such that for any real number x_i, $i = 1,\cdots,m$, we have

$$F(x_1,\cdots,x_m) = P(X_1 \le x_1,\cdots,X_m \le x_m) = C(F_1(x_1),\cdots,F_m(x_m)) \tag{10}$$

According to Eq. (10), we can easily obtain the following density function:

$$f(x_1,\cdots,x_m) = c(F_1(x_1),\cdots,F_m(x_m))\prod_{i=1}^{m} f_i(x_i) \tag{11}$$

where $f_i(\cdot)$ is the marginal density function, and $c(u_1,\cdots,u_m) = \partial C(u_1,\cdots,u_m)/\partial u_1\cdots\partial u_m$ is the copula function density function. According to Sklar theorem, the different copula functions and marginal distribution functions can be constructed, so the joint distribution functions are not limited to the common normal distribution.

Model of EV-Copula CoVaR. Let X^i and X^j be the yield sequences, the joint density function and the marginal density function defined as $f(x^i, x^j)$, $f_i(x^i)$, $f_i(x^j)$. The conditional density function of sequence X^i under X^j is defined as:

$$f_{i|j}(x^i|x^j) = f(x^i,x^j)/f_j(x^j) \tag{12}$$

Formula (12) can be derived from the copula dependent structure function (13).

$$f_{i|j}(x^i|x^j) = c\Big(F_i(x^i),F_j(x^j)\Big)f_i(x^i) \tag{13}$$

Therefore, the conditional distribution function of the return rate sequence can be obtained by Eq. (14).

$$F_{i|j}(x^i|x^j) = \int_{-\infty}^{x^i} c\Big(F_i(x^i),F_j(x^j)\Big)f_i(x^i)dx^i \tag{14}$$

In Eq. (14), F_i and F_j are the copula marginal distribution functions. Combining with the extreme value theory, the derivative of F_i is derived as f_i, and the optimal copula density function is denoted by c. Note that CoVaR_q^{ij} is the conditional risk of X^i as $X^j = \mathrm{VaR}_q^j$, we then obtain

$$\mathrm{CoVaR}_q^{ij} = F_{i|j}^{-1}\Big(q\Big|\mathrm{VaR}_q^j\Big) \tag{15}$$

In Eq. (15), $F_{i|j}^{-1}$ is the inverse function of $F_{i|j}$, namely a conditional quantile function. When solving for $F_{i|j}^{-1}$, it is often difficult to obtain analytic expressions. Note that

$$\int_{-\infty}^{x^i} c\Big(F_i(x^i),F_j\Big(\mathrm{VaR}_q^j\Big)\Big)f_i(x^i)dx^i = q \tag{16}$$

It is known that CoVaR_q^{ij} represents the conditional risk value of the affected stock market with quantile q. The median risk spillover is expressed as $\mathrm{CoVaR}_{0.5}^{ij}$, then the carbon market$j$ is in the extreme risk state α, and the risk contribution to the stock market is expressed as follows:

$$\Delta\mathrm{CoVaR}^{ij} = \mathrm{CoVaR}_\alpha^{ij} - \mathrm{CoVaR}_{0.5}^{ij} \tag{17}$$

Variable selection and data description. In order to study the spillover effect from the carbon market to stock market, we select five stock markets, namely electricity, finance, real estate, industry, and energy markets. The source of sample data is shown in Table 1 below, the data range is from May 11, 2015 to March 31, 2021. The sample size is 1774, and the logarithmic rate of return is $r_t = 100\times \ln(p_t/p_{t-1})$. The analysis of data is mainly realized by software R.

Table 2 shows the statistical characteristics of the return rate sequence for the carbon trading price index (THC), Huaneng International Stock daily closing price (HNGJ), Financial Index daily closing price (FI), Real Estate Index daily closing price (RE), Industrial Index daily closing price (IN), SSE Energy daily closing price (TE).

According to the descriptive statistical results of the return rate sequence shown in Table 2, we obtain the following conclusion: (1) From the perspective of standard deviation, the carbon market and financial market have a relatively large standard deviation, which means that there is greater volatility risk in the carbon and financial markets, while the average returns of the industrial and energy markets are relatively large. The maximum yield of the carbon market is larger than that of other markets, while the minimum yield of the financial market is smaller than that of

Table 2 Descriptive statistics of volatility of sample market.

Statistic	THC	HNGJ	FI	RE	IN	TE
Minimum	−5.136	−6.159	−6.610	−6.895	−5.872	−6.992
Maximum	8.192	7.931	7.661	6.040	6.172	6.022
Mean Value	0.029	0.017	−0.148	0.026	0.077	0.113
Standard Deviation	5.190	4.992	5.250	3.148	3.778	4.152
Skewness	0.189	0.235	−0.118	−0.483	0.152	0.194
Kurtosis	5.215	3.147	8.110	4.014	3.002	5.390
J-B Statistics	294.770*	512.209*	311.140*	433.984*	148.500*	248.401*

*significance at 1%.

Table 3 Estimations of Archimedes copula parameters.

Copula Type	Joe	Clayton	Gumbel	Frank	BB1	BB2	BB6	BB7
θ	1.3254**	0.2748*	1.4749*	1.7742*	0.1147*	1.4836*	1.0016*	1.1532*
p value	0.0177	0.0000	0.0095	0.0021	0.0042	0.0017	0.0023	0.0053
δ	—	—	—	—	1.2463*	1.1936*	0.5573*	0.3638*
p value	—	—	—	—	0.0000	0.0000	0.0000	0.0000
AIC	−215.24	−251.16	−273.75	−203.34	−293.17	−294.87	−278.98	−299.58

*significance at 1%, **significance at 5%.

other markets. (2) From the perspective of skewness and kurtosis, except for the financial and real estate markets where skewness is less than zero and shows a skew to the left, all other markets show a skew to the right. The kurtosis of all markets are greater than three, which indicates that the sequence is different from a normal distribution. The financial market has the largest value of kurtosis, which shows that the financial market is more prone to extreme risk events. (3) All sample sequences passed the J-B test at the significance level of 1%.

Empirical results

Model fitting and parameter estimation. In the extreme value theory, the generalized Pareto distribution has a better effect on describing the tail data of yield. Therefore, in this section, we use the steps in Section "Model of extreme marginal distribution" to fit the upper and lower tails of sample data, while fitting the middle data by empirical distribution. Firstly, we calculate the upper and lower tail thresholds of yields according to 10% rule in Dumouchel, Waternaux (1983), and use the maximum likelihood method to estimate the parameters of generalized Pareto distribution, we obtain the estimations of the shape parameter ξ and scale parameter $\beta(\mu)$. Further, the estimations of parameters are taken back into $F(x)$ to obtain marginal distribution function of sample sequences. Secondly, after determining the marginal distribution of yields, we obtain the relevant structure of the carbon emission sequence and the stock sequence by using the dependent structure function. Thirdly, we calculate the parameters in the copula function according to the maximum likelihood principle. According to the AIC criterion, we select the optimal copula function from eight Archimedean copula function families introduced in Section "Functions of copula dependent structure". For example, we estimate parameters using carbon market and electricity market revenue sequences and obtain the results in Table 3, which can be found that the two parameters of BB7 copula function have passed the significant test and have the minimum AIC value, so BB7 copula is used to fit the function. In the same way, one can estimate the parameters of other stocks. Then, we substitute the estimations into BB7 copula function shown in formula (18), and further obtain the corresponding probability density function, one can also refer to Cao, Lei (2022).

$$C(u, v; \theta, \delta) = 1 - \left(\left\{\left[1-(1-u)^{\theta}\right]^{-\delta} + \left[1-(1-v)^{\theta}\right]^{-\delta} - 1\right\}^{1/\theta}\right), \theta \geq 1, \delta > 0 \tag{18}$$

Finally, we consider the dependent structure functions of return sequences for the carbon market and the stocks market, the parameter estimations, and upper and lower tail correlation coefficients and Kendall correlation coefficients. Note that the lower tail correlation coefficients are usually a concern in the research, according to Table 4, we obtain the conclusions as follows: (1) Spillover effect intensity. The spillover effect is the weakest for the financial index according to the carbon index, and its lower tail correlation coefficient with the carbon market is significantly lower than other indexes. The main reason may be that the environmental protection concept has not yet fully penetrated into the commercial banks daily operation and management, and banks should establish corresponding environmental financial risk management systems according to their own development. (2) Risk spillover direction. The lower tail correlation coefficient is positive, it can be seen that the carbon index has a positive spillover effect on other stock indexes, that is, when the carbon index faces extreme conditions, the potential risk probability of another stock index will also increase. Therefore, we complete the marginal distribution function calculation of sample sequences and obtain the dependent structure function between the return sequences of each stock and the carbon market.

Analysis of risk spillover effect. In order to examine the carbon market risk spillover effect intensity on other stock markets, in this section, we calculate each stock market upside and downside risk spillover ΔCoVaR under the carbon market by the method in

Table 4 Fitting results of the dependence structure between the yield sequences of carbon emission and the stock.

Sample Sequence	Optimal Copula	Parameter Estimate	Kendall Correlation Coefficient	Upper tail Correlation Coefficient	Lower Tail Correlation Coefficient
HNGJ	BB7 Copula	$\theta = 1.1532$ $\delta = 0.3638$	0.344	0.354	0.339
FI	BB7 Copula	$\theta = 1.3315$ $\delta = 0.5392$	0.069	0.077	0.041
RE	BB7 Copula	$\theta = 1.1250$ $\delta = 0.2672$	0.226	0.230	0.193
IN	BB7 Copula	$\theta = 1.1014$ $\delta = 0.1525$	0.201	0.185	0.191
TE	BB7 Copula	$\theta = 1.1143$ $\delta = 0.2618$	0.224	0.233	0.272

Table 5 Average of risk spillover effect for sample sequences.

Direction of Risk Spillover	Downside Risk Spillover	Upside Risk Spillover
Carbon Market → Electricity Stock Market	−0.863	0.274
Carbon Market → Financial Stock Market	−0.578	0.099
Carbon Market → Real Estate Stock Market	−0.650	0.173
Carbon Market → Industrial Stock Market	−0.631	0.141
Carbon Market → Energy Stock Market	−0.778	0.266

Carbon market → electricity stock market represents the direction of risk spillover from the carbon market to the electricity stock market, other representations explain similarly.

Section "Model of EV-Copula CoVaR". The average results are shown in Table 5 as follows.

Note that the greater the absolute value of risk spillovers, the stronger the contagiousness of risk between markets. From Table 5, the following conclusions can be obtained: (1) Downside risk spillovers. The carbon market has the greatest risk spillover effect on the electricity stock market, that is, when the carbon market has an extremely bad event, the risk probability of the electricity stock market will significantly increase. On the contrary, the carbon market has the smallest risk spillover effect on the financial stock market, which means that the financial stock market will be less affected when the carbon market has an extremely bad event. (2) Upside risk spillovers. The result for upside risk spillover is similar to that of the downside risk spillover. Therefore, when an extremely favorable event occurs, the electricity stock market is most affected by the carbon market, and the financial stock market is least affected by the carbon market. (3) Even the financial market with the smallest risk spillover effects has a risk spillover intensity of 57.8%, therefore extreme events in carbon market have a strong spillover effect on other stock markets. Once extreme events in the carbon market occur, the risk of other stock markets will increase rapidly. (4) According to the AIC principle, the BB7 copula function is mainly aimed at the lower tail dynamic dependence, which leads to the weak upper tail dependence between the carbon market and the stock market. From the results of the spillover effect, we can also find that the upside risk spillover effect has small values.

Figure 1 shows a fitting diagram of risk spillover for the carbon market to five stock markets at a significance level of 5%. We conclude from Fig. 1 that the return of each market fluctuates around zero, and there is a "volatility cluster" in the sequences of yields. It is known that China proposed energy supply-side reform in 2015, and began structural adjustments to the coal industry in 2016, which caused severe fluctuations in prices and spilled to other markets. The fitting results of risk spillovers slightly underestimate market risk at some extreme values of yields, however, the five figures as above can better depict the trend of yield risk.

In order to test the accuracy of the measurement results of spillover effects, we apply Kupiec (1995) failure rate test for back-testing analysis. The formula of LR statistic is as follows:

$$LR = -2\ln\left[P^N(1-P)^{T-N}\right] + 2\ln\left[(N/T)^N(1-N/T)^{T-N}\right] \tag{19}$$

where P is significance level, N is day number of the failure (that is, the actual number of days exceeding the overflow risk value), T is the total number of days.

Table 6 gives the test results of failure rate test, it can be seen that the five groups of spillover effect results have passed the failure rate test, indicating that the carbon index has a significant impact on the index of each stock.

Note that the smaller the significance level, the greater the own risk of market. In order to explore the relationship between the spillover risk and market self risk, Fig. 2 shows the varying of ΔCoVaR between the carbon market and the stock markets at different significance levels.

According to Fig. 2, due to significant differences in development levels and internal structures among different industries, carbon trading price fluctuations have varying degrees of impact on stock prices in other industries, which leads to different spillover effect risks of carbon markets on other markets. First, ΔCoVaR of the electricity industry is the largest at different significance levels, which indicates that the carbon trading market and the electricity stock market are most closely connected. With the proposal of the "dual carbon" target, the activity of the carbon emissions trading market has increased, which has caused fluctuations in the stock markets of related industries. Second, the risk spillover intensity of the carbon index to other stock indexes is positively correlated with the carbon index self-risk, that is, the smaller the significance level, the greater the carbon index self-risk. Therefore, the greater the ΔCoVaR according to the analysis, hence there is a positive correlation between them.

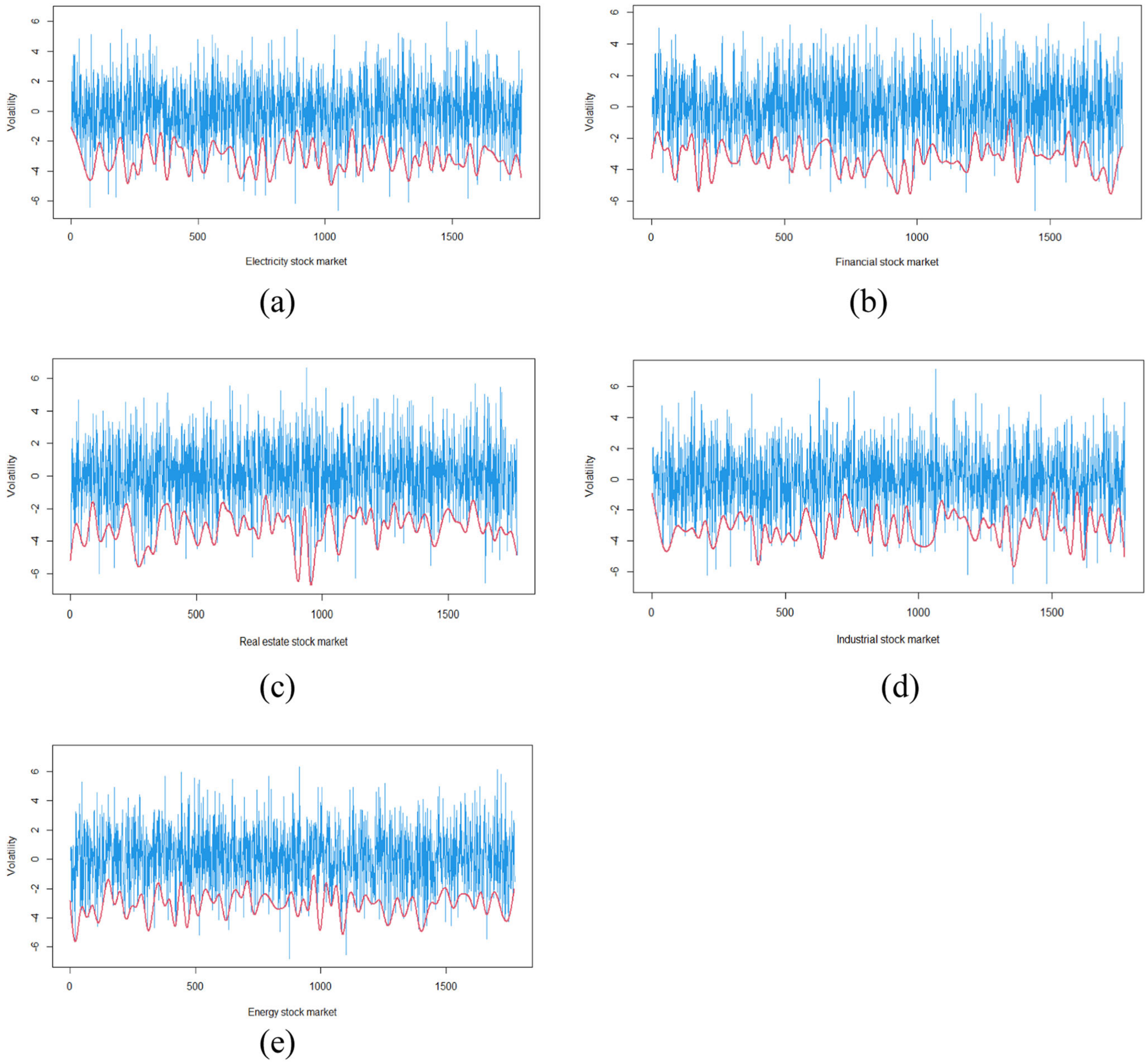

Fig. 1 Fitting results of risk spillovers carbon market to stock markets. a Electricity stock market (**b**) financial stock market (**c**) real estate stock market (**d**) industrial stock market (**e**) energy stock market accepts carbon market.

Table 6 Results of failure rate test for sample sequences.

Direction of Risk Spillover	Sample Capacity	Number of Failures	Failure Frequency	*LR* Statistics
Carbon → Electricity	1774	86	0.048	3.583(0.000)
Carbon → Finance	1774	83	0.047	3.315(0.000)
Carbon → Real Estate	1774	90	0.051	3.430(0.000)
Carbon → Industry	1774	88	0.050	3.702(0.000)
Carbon → Energy	1774	87	0.049	3.626(0.000)

The values in brackets represent the corresponding p values.

Conclusion and suggestions

This paper investigates the risk spillover effect of carbon trading market to the stock market by EV-Copula CoVaR model. First, the regional carbon prices are synthesized to obtain carbon trading price index according to the regional heterogeneity of the carbon trading market. Then, the EV-Copula CoVaR model is established to measure the risk spillover of carbon trading market to the stock market. The results show that the risk spillover effect of the carbon trading market to the stock market is significant, and the spillover effect to the electricity market is the largest. We study the relationship between the significant level and the risk spillover intensity, it is found that the smaller the significant level,

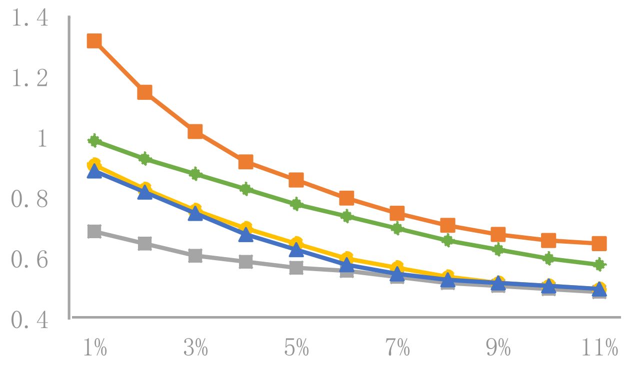

Fig. 2 Varying of ΔCoVaR for each sample sequence under different significance levels.

the greater the risk of carbon market itself, and the larger the ΔCoVaR value. We find that there is a positive correlation between the risk of the carbon market itself and the spillover risk.

In view of the above research, this paper puts forward the following suggestions:

(1) In terms of evaluation system. It should accelerate the establishment and improvement of the risk evaluation system of carbon market. At present, the development of carbon market and relevant research in China are not perfect. In addition, the risk assessment system is still based on a static VaR model, which is difficult to meet the actual needs of market risk regulation and risk losses. The dynamic EV-Copula CoVaR model proposed in this article has a simple calculation process and can reasonably measure risk spillover situations.

(2) In terms of government and regulatory agencies. Due to the lag nature of investor investment behavior, there will be a positive feedback loop caused by flow lag, which will lead to serious losses. Therefore, regulatory authorities can use this model to measure risks and conduct appropriate risk monitoring and intervention to reduce risk transmission. This can effectively stabilize investors' confidence and prevent investment stampede.

(3) For investors. It should provide them with good education and management, which is beneficial for market risk prevention and control. It is recommended that investors optimize the allocation of asset structure and investment direction, measure the pros and cons between risk and return, establish a sound investor risk evaluation system, and update and manage investment behavior in real-time according to different investment environments.

The method proposed in this article can be used to analyze the risk effect of the carbon market in other countries, it also can be extended to other fields, such as hedge funds and futures hedging. It is difficult to choose the optimal copula model, which is undoubtedly a current challenge. However, we can try to optimize the copula model, such as considering the problem of structural node changes between variables or using Markov copula models, etc., these are the research contents we need to consider in the future.

Data availability

The datasets generated during and analyzed during the current study are available from the corresponding author upon reasonable request.

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Author contributions
YZ contributed the idea of this study, wrote and revised the paper. WX collected and analyzed the data, wrote the manuscript.

Competing interests
The authors declare no competing interests.

Ethical approval
This article does not contain any studies with human participants performed by any of the authors.

Informed consent
Informed consent was obtained from all authors. All authors have read and agreed to the published version of the manuscript.

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