Heliyon 11 (2025) e41186

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Assessing the risk spillover effects between the Chinese carbon market and the US-China energy market

Jiale Yan [a,*], Cem Işık [b,c,d,e]

[a] College of Letters and Science, University of California Berkeley, 94720, USA
[b] Department of Economics, Faculty of Economics and Administrative Sciences Anadolu University, Eskisehir, Turkiye
[c] Western Caspian University, Economic Research Center (WCERC), Baku, Azerbaijan
[d] Baku Eurasian University, Economic Research Center (BAAU-ERC), Baku, Azerbaijan
[e] Azerbaijan State University of Economics (UNEC), Clinic of Economics, Baku, Azerbaijan

ARTICLE INFO

Keywords:
Risk spillover
China carbon market
US-China carbon market

ABSTRACT

Pollution caused by environmental problems has aggravated the problem of resource scarcity, and the destruction of the ecological environment by mankind has shown serious consequences. Countries around the world are actively launching various carbon emission reduction and energy transformation policies to face this predicament. This paper investigates the risk spillover effects of China's carbon trading market with China's energy market and the U.S. energy market from the first quarter of 2018 to the first quarter of 2022. This paper uses the optimal ARMA-GARCH to fit the marginal distribution of each market and selects the optimal Copula function for the calculation of CoVaR to obtain more accurate risk measurement results. The results of this paper are as follows. First, there is a bidirectional risk spillover effect between each market in China and the U.S. At the same time, the risk spillover is time-varying, and the extreme return brings more risk. Second, the overall trend of risk spillover from China's carbon market to the U.S.-China energy market has not increased significantly, but the risk of China's energy market to China's carbon market has increased significantly over time. Third, the risk spillover situation in China's carbon trading market is not smooth. Compared to the energy market, it is also more prone to violent reactions in the face of risks. This paper provides policy recommendations to promote the coordinated development of energy and carbon markets.

1. Introduction

Environmental pollution is a serious challenge facing the world. The loss of global forest cover and desertification of land have put many countries at risk of extinction [1,2,3]. How to cope with the various harms caused by environmental pollution is an urgent issue for mankind. To address this problem, the Chinese government has not only improved its environmental policies, but also started to gradually establish local carbon markets through market forces since 2011. In 2017, the national carbon emissions trading market also began to be established and perfected. The formation of a trading market for carbon emissions as a resource is conducive to the rational allocation of resources and the reduction of resource wastage [4,5]. Moreover, the existence of a carbon market is different from direct policy intervention and is conducive to the formation of a virtuous circle in which development and the environment complement each

* Corresponding author.
E-mail address: morningyjl@berkeley.edu (J. Yan).

https://doi.org/10.1016/j.heliyon.2024.e41186
Received 22 August 2024; Received in revised form 10 December 2024; Accepted 12 December 2024
Available online 13 December 2024

other [6]. Given the importance of the carbon market, it is essential to further explore the risk transfer mechanism.

In recent years, as the world's largest energy-consuming market, China has played an increasingly critical role in shaping the global energy landscape. Due to its huge demand for energy resources, the energy consumption pattern in China directly influences global trends. Therefore, the restructuring of China's energy market is crucial not only for its own sustainable development, but also for the broader global energy transition [7–9]. According to the BP World Energy Outlook 2023, it is expected that China's energy market will be transformed towards a decarbonized consumption structure and further optimized and upgraded [10]. This transition involves large-scale investments in renewable energy technologies and green infrastructure to mitigate energy-related problems. Against this background, China has gradually established a variety of financial hedging instruments to cope with the risk of large fluctuations in energy prices [11]. Energy prices fluctuate frequently as global energy markets are affected by geopolitical events, supply chain disruptions or changes in demand [12,13]. These measures help to protect the energy market in China from such volatility. They also help stabilize the market and provide greater certainty for energy producers, distributors and consumers. However, the energy market in China still faces significant challenges. Many energy prices, particularly for coal and electricity, remain heavily influenced by government regulations, subsidies and state-owned enterprises. This limited marketization can distort energy prices, impede the efficient allocation of resources, and slow the transition to clean energy. In addition, the rapid expansion of China's carbon market brings another layer of complexity to the energy market. Carbon markets have great potential to drive emissions reductions and facilitate the development of low-carbon technologies, but they also bring risks. The implementation of carbon pricing could lead to sudden changes in energy costs, affecting both industries and consumers [14].

The United States also faces significant risks. Due to the COVID-19, the U.S. energy market has been severely impacted by the willingness to consume, and there has been a significant decline in energy market demand [15,16,17]. This will severely limit the energy market sector's ability to invest in the energy transition and its efforts to reduce expenditures in the search for a new balance of payments [18]. Also, against the backdrop of global demand threats, the major U.S. crude oil producing regions have begun to consciously reduce their production activities to avoid the stagnation that would result from overproduction. According to the U.S. Energy Information Administration, U.S. crude oil production in 2021 will average 11 million barrels per day, down from 12.2 million barrels per day in 2019. Meanwhile, frequent wars and unrest in the Middle East have led to instability in Middle East oil production. The U.S. domestic energy market will certainly be affected by price shocks. In addition to the wars in the Middle East, the Russia-Ukraine conflict has also blocked Russia's channels for sending energy out of the country. This has led to a serious energy crisis in Europe, and energy prices have deviated significantly from market norms. This will also pose a serious threat to the U.S. energy market(Su et al., 2023; [19]). Therefore, under various extreme events, analyzing the two-way risk spillover of the carbon market to the US and China energy markets can provide important references for China's future development and reform.

In the field of risk spillover effects, based on the consideration of portraying correlation, systematic risk, most of the studies use Granger causality test, Vector Autoregressive model, GARCH (Generalized Auto Regressive Conditional) model, Copula function, DY spillover index model [20,21,22,23]. Cointegration and Granger causality tests can only characterize the low-dimensional structure, which makes it difficult to explain the complexity of the risk spillover network structure. The GARCH-BEKK model can only identify the direction of risk spillover. The DY spillover index, which is currently the most widely used model, is based on the rolling window method, which leads to the loss of research samples and the fitting effect is not smooth enough for a small number of samples. This paper uses the ARMA-GARCH-Copula-CoVaR method. In the process, different markets choose the optimal function within the permitted range for fitting, which is conducive to improving the accuracy of risk measurement.

This paper explores the bidirectional risk spillover between the carbon trading market and the U.S.-China energy market from the first quarter of 2018 to the first quarter of 2022 based on the AMRA-GARCH-Copula-CoVaR methodology. The main innovations are as follows. First, most of studies examined the risk spillovers between China's domestic carbon trading market and a single energy market [24,25]. The United States is considered as an important energy market in the world. Therefore, we analyze the bidirectional risks. Second, this paper uses the ARMA-GARCH-Copula-CoVaR method. In both applications of the model, this paper uses ARMA to fit the GARCH to the optimal order to form the marginal distribution function, and then fits a variety of Copula functions to find the Copula with the smallest value of BIC for CoVaR calculation. This can obtain more accurate risk measurement results. Third, this paper compares and analyzes whether there is a difference in the risk spillover of China's carbon market to the two energy markets to promote the improvement of China's carbon market.

2. Literature review

The global energy landscape is being transformed by a variety of factors, including technologies, environmental concerns and geopolitical dynamics. The development of the global energy market faces many opportunities and challenges. For example, the rapid development of renewable energy has led to a significant reduction in the cost of energy, with solar and wind energy becoming more competitive with traditional fossil fuels. Despite the rapid development of renewable energy, fossil fuels (coal, oil and natural gas) remain the main source of energy globally. The global supply chain for fossil fuels is subject to geopolitical risks, and many countries are striving to reduce their dependence on fossil fuels. For example, Europe is accelerating the replacement of Russian gas with alternative energy sources such as liquefied natural gas, hydrogen and renewable energy, while some oil-rich countries are investing in clean energy technologies to ensure long-term economic sustainability. Many scholars have conducted a lot of research on energy development and the factors that influence it [26–30]. And many scholars focused on the carbon and energy markets. The enhancement of resource allocation efficiency in the energy market by the carbon market have been receiving extensive attention. Chen et al. [31] found an internal co-movement pattern in the energy market using the co-movement matrix transmission network approach. This demonstrates that the carbon market is able to influence trading prices in the energy market. Andersson and Karpestam

(2021) validate the long run cointegration and show that the coal market is clearly affected by carbon market price fluctuations. Ren et al. [32] explore the effect of crude oil prices on carbon prices over time through quantile regression.

At the same time, risk spillover is also the focus of long-term attention of market investors and government managers. Santiago et al. [33] found that economic volatility in United States has a negative impact on economic activity in Latin America and the Caribbean. This urges countries to adopt countercyclical instruments to hedge against potential risks and mitigate the severe consequences of economic downturns. Balcilar et al. [34] focus on exploring the magnitude of volatility propagation and their mechanisms in the oil, financial market risk and oil sectors. They find that all shocks related to the oil market have significant risk transmission effects. Kumar [35] provides evidence that uncertainty variables can have a significant impact on tourism and leisure equities. Analyzing and controlling risks is a popular topic among scholars. Cao and Xie [36] analyze spillovers between carbon and clean energy markets under extreme events using quantile vector autoregression. In addition, other scholars have explored the dynamic correlations between electricity prices, fossil energy markets, renewable energy markets, non-ferrous metal markets and shipping energy markets [21,22,37–40].

In this paper, the ARMA-GARCH-Copula-CoVaR method is used for the optimal selection, and the optimal function within the allowed range of different market selection conditions is fitted to improve the accuracy of risk measurement. By exploring the relationship between the U.S.-China energy market and China's carbon market, this paper hopes to provide investors and government policy makers with a more accurate measure of risk spillover.

3. Methodology and data

3.1. ARMA-GARCH model

The markets examined in this paper are all financial markets, and the time series of financial markets often have significant characteristics such as high frequency, sharp peaks and thick tails, and volatility aggregation. Therefore, this paper uses ARMA-GARCH model to establish the marginal distribution function. At the same time, we choose the optimal order to fit the ARMA-GARCH model in the ARMA ordering process, so as to achieve a more accurate marginal distribution function within the allowable range. The GARCH (1,1) model has been proved to be a good measure of financial time series in many literatures, and there is no need for optimal order selection[41–44]. It is expressed as follows.

$$r_t = \omega_0 + \sum_{i=1}^{p} \omega_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_i \varepsilon_{t-i} \tag{1}$$

$$\varepsilon_t = \mu_t \sqrt{\sigma_t^2} \quad \mu_t \sim skew_t(\vartheta, \tau) \tag{2}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3}$$

Equation (1) represents the logarithmic yield series of the market. Equation (2) represents the disturbance term in the GARCH model. Equation (3) is the expression of the GARCH(1,1) model. $\alpha_1 + \beta_1$ represents the degree of volatility clustering in the time series. Larger values represent greater time series volatility persistence.

We employ the standardized skewed Student's t (SST) distribution to represent the skewness and kurtosis characteristics separately. Let $X \sim SST(\xi, \nu)$ be the SST distribution, and its probability density function is

$$(\varepsilon_t|\xi, \upsilon) = \begin{cases} \dfrac{2}{\xi + \dfrac{1}{\xi}} \varrho f(\xi(\varrho\varepsilon_t + w)|\upsilon), \varepsilon_t \langle -\dfrac{w}{\varrho} \\ \dfrac{2}{\xi + \dfrac{1}{\xi}} \varrho f((\varrho\varepsilon_t + w)/\xi|\upsilon), \varepsilon_t \geq -\dfrac{w}{\varrho} \end{cases} \tag{4}$$

where $f(\bullet|\upsilon)$ in equation (4) is the PDF of the standardized Student's (ST) distribution:

$$f(\varepsilon_t|\upsilon) = \frac{\Gamma\left(\frac{\upsilon+1}{2}\right)\left(1 + \frac{\varepsilon_t^2}{\upsilon-2}\right)^{-(\nu+1)/2}}{\Gamma(\upsilon/2)\sqrt{\pi(\upsilon-2)}} \tag{5}$$

where $\Gamma(x)$ in equation (5) is the gamma function and $\upsilon > 2$ denotes the degree of freedom. The ratio of probability is equal to ξ^2. ξ is the skewness parameter, $w = \frac{\Gamma\left(\frac{\upsilon+1}{2}\right)\sqrt{\upsilon-2}}{\sqrt{\pi}\Gamma(\upsilon/2)}\left(\xi - \frac{1}{\xi}\right)$, and $\varrho^2 = \left(\xi^2 + \frac{1}{\xi^2} - 1\right) - w^2$.

3.2. Copula function

Copula function can measure nonlinear correlation, and it is less restrictive on the marginal distribution function. Moreover, it can choose the appropriate marginal distribution function according to the characteristics of the time series, which can measure the tail risk more accurately [45,46,47]. The monotonic transformation of the marginal distribution function will not change the correlation of the Copula function and will not affect the results of CoVaR. In this paper, we take the optimum of each step in the construction to improve the CoVaR measurement. The specific expressions are as follows.

$$F(x_1, x_2, \cdots, x_n) = C(F_1(x_1), F_2(x_2), \cdots, F_n(x_n)) \tag{6}$$

$$C(\mu_1, \mu_2, \cdots, \mu_n) = F\left(F_1^{-1}(\mu_1), F_2^{-1}(\mu_2), \cdots, F_n^{-1}(\mu_n)\right) \tag{7}$$

Where $F_1(x_1), F_2(x_2), \cdots, F_n(x_n)$ in equation (6) represents the marginal distribution function for n variables and $F_1^{-1}(\mu_1), F_2^{-1}(\mu_2), \cdots, F_n^{-1}(\mu_n)$ equation (7) represents the marginal distribution inverse function for n variables.

3.3. Risk spillover model

Initially, risk was often measured using the VaR method, but it measures the maximum risk of a market or an asset with a certain probability. It has no way of measuring the impact of risk between markets. In order to accurately measure market-to-market risk spillovers, this paper adopts the CoVaR (conditional value-at-risk) approach. Since both extreme gains and extreme losses associated with upward and downward price fluctuations are risks, to obtain losses and gains under extreme risk conditions, downside and upside risk premiums are obtained by setting the CoVaR quartile at 5 % and 95 % To calculate CoVaR, we first calculate the VaR, which in finance is the maximum loss an asset over a specified period of time within a given confidence interval. The VaR value is useful for assessing market risk and is given in the following formula.

$$P\left(r_t^i \ll VaR_{\alpha t}^i\right) = \alpha \tag{8}$$

Equation (8) in which r_t^i represents the time series of the market's market's return. We further derive the specific meaning of CoVaR through VaR.

$$P\left(r_t^i \ll CoVaR_{\beta t}^{ji} r_t^i \ll VaR_{\alpha t}^i\right) = \beta \tag{9}$$

$$P\left(r_t^i \gg CoVaR_{(1-\beta)t}^{ji} r_t^i \gg VaR_{(1-\alpha)t}^i\right) = \beta \tag{10}$$

The $CoVaR_{\beta t}^{ji}$ in equations (9) and (10) represent the conditional value-at-risk of upside and downside risk spillovers. α and β typically take the value of 0.05, which represents at the 0.95 quantile level. Since this paper is a CoVaR calculation using Copula functions, we give the conditional value-at-risk of the downside and upside risk spillovers in the form of Copula functions.

$$P\left(r_t^i \ll CoVaR_{\beta t}^{ji} r_t^i \ll VaR_{\alpha t}^i\right) = \frac{P\left(r_t^i \ll CoVaR_{\beta t}^{ji} r_t^i \ , \ r_t^i \ll VaR_{\alpha t}^i\right)}{P\left(r_t^i \ll VaR_{\alpha t}^i\right)} = \frac{C(u_j, u_i)}{u_i} = \beta \tag{11}$$

Where u_j and u_i in equation (11) are the cumulative distribution functions of the returns of time series j and i, respectively. When $P\left(r_t^i \ll VaR_{\alpha t}^i\right) = u_i = \alpha$, we refer to Reboredo and Rivera[48] to derive a formula for the conditional insured value of the upside risk premium in equations (12) and (13).

$$1 - u_j - (1 - \alpha) + C\left(u_j, (1 - \alpha)\right) = \alpha\beta \tag{12}$$

$$CoVaR_{(1-\beta)t}^{ji} r_t^i = U_j^{-1}(u_i) \tag{13}$$

3.4. Data sources

China's carbon market is characterized by a short period of time since the establishment of the unified national market, a lack of market structure, and a lack of data availability. Therefore, this paper uses the daily data of the closing price of Hubei carbon market (HCM), which is the largest carbon trading market among China and is relatively well-developed. It has strong representativeness [49, 50].

In the area of energy, we consider the fact that oil is a strategically important energy and that the share of oil consumption has been on an upward trend [51]. To achieve the SDGs, China has been promoting the use of clean energy in recent years. The government is increasing its support for the clean energy market [52,53,54]. Therefore, we have chosen the daily closing prices of the Shanghai Crude Oil Futures (SCOF) and the China New Energy Index (CNEI) as a proxy for China's energy market. Correspondingly, we chose daily data from the U.S. Oil Fund's Crude Oil ETF (USO) and the NASDAQ Clean Green Energy(NCGE) closing price as a proxy for the U.S. energy market.

We selected data for the Shanghai crude oil futures contract, which has the shortest data length among the five markets, as the basis for the length. The specific time frame is data from April 2018 to April 2022. The source of Hubei carbon market data is the Hubei Carbon Emission Trading Center. The rest of the data are from Choice Financial Terminal.

3.5. Data processing

After the data are organized by R software, we get the same-day comparable data of five markets, and the length of the data is 1098. Descriptive statistics are shown in Table 1. Next, we algorithmize the data of the five markets to obtain the logarithmic return series, and the length of the series is 1096. The formula is as follows: $r_t^i = \ln(P_t) - \ln(P_{t-1})$.

The existence of positive and negative logarithmic returns in each market indicates that essential to examine the upward and downward risk spillover. The kurtosis and skewness indicate that all five markets have sharp peaks, thick tails and left skewed distributions, the ADF test is significant, so the log returns of all five markets are smooth time series, the Jarque-Bera test is significant, so the distribution of log returns of all five markets do not obey the normal distribution, and the Ljung-Box test is significant, so there is an autocorrelation among the series of all five markets. Finally, the results of ARCH effect test are also significant, and there is ARCH effect in all five markets.

4. Analysis of results

4.1. Marginal distribution model

The results in Table 1 demonstrate the existence of autocorrelation in all five markets. The larger (p, q) value of the ARMA (p, q) is selected according to the AIC, BIC minimization criteria, and the more widely used GARCH (1,1) model is chosen for the GARCH model. The computed optimal (p, q) value is (2,1), corresponding to a great likelihood estimate of 1632.46, an AIC value of −3254.91, and a BIC value of −3228.44. And we further fit marginal distributions to the five series. Table 2 presents the preliminary estimation results and Ljung-Box and ARCH tests for the Student-t distributions of the five-time series based on Eqs. (1)–(3). $\alpha + \beta$ values of less than 1 satisfy the coefficient constraints. Meanwhile, the Ljung-Box test and ARCH test are also insignificant.

4.2. Fitting copula functions

Before proceeding with CoVaR estimation, this paper estimates various copula models. Based on the AIC, we determine the optimal copula parameters for each payoff pair, and the corresponding parameter estimates are listed in Table 3. Among them, the Student t-Copula function has the smallest BIC value.

4.3. Analysis of VaR

In this paper, the dynamic VaR values for the five market categories are calculated by converting VaR to extreme losses at the 95 % confidence level. With the exception of the Chinese clean energy market and the U.S. clean energy market, where the trends in VaR are highly similar, the trends in VaR are quite different between the other markets. The Chinese crude oil market not only has the lowest extreme losses, but also has the weakest volatility. The carbon market has the highest extreme risk and the strongest volatility as a result of COVID-19 in early 2020.

Table 4 shows that China's crude oil market has the smallest extreme loss and the carbon trading market has the largest extreme loss. The probability that the daily loss in China's crude oil market exceeds 0.0761 % is 5 %. The carbon market has the smallest VaR of −19.4464, which is the largest extreme loss among the five types of markets. The standard deviation of carbon market is still the largest. The carbon market has the highest extreme VaR and the highest volatility of risk. This may be due to the high price volatility and the relatively homogenous nature of the trading community.

4.4. The results of CoVaR estimation

We used 0.05 and 0.95 confidence intervals for the CoVaR calculations. The CoVaR calculated with the 0.05 confidence interval represents the downside risk spillover and the CoVaR calculated with the 0.95 confidence interval represents the upside risk spillover. For the risky scenario of the Chinese carbon market, we performed CoVaR estimates for the energy markets. Additionally, we have

Table 1
Descriptive statistics.

	HCM	SCOF	USO	CNEI	NCGE
Min	−0.137	−0.229	−0.182	−0.147	−0.455
Max	0.187	0.242	0.135	0.082	0.136
Mean	0.005	0.002	0.003	0.002	0.001
Kurtosis	3.438	23.429	17.390	5.293	103.134
Skewness	−0.042	−3.341	−2.782	−0.562	−5.526
ADF	−40.474***	−29.398***	−35.732***	−38.421***	−26.372***
Jarque-Bera	635.325***	1350.621***	757.290***	191.455***	6287.380***
Ljung-Box	206.312***	89.545***	130.842***	213.378***	268.261***
ARCH	117.875***	20.994***	55.970***	63.864***	131.107***

Note: *** means rejection of the null hypothesis at the 1 % level.

Table 2
Estimates for GARCH model''

	HCM	SCOF	USO	CNEI	NCGE
φ_1	−0.188***	−0.229***	−0.182***	−0.147***	−0.455***
	(3.292)	(3.779)	(3.154)	(2.853)	(5.079)
φ_2	−0.060**	0.242**	0.135***	0.082***	0.136***
	(2.026)	(2.113)	(2.970)	(5.672)	(3.007)
ω	0.005***	0.002**	0.003**	0.002*	0.001
	(3.243)	(2.171)	(2.249)	(1.633)	(0.531)
α	0.438***	0.429***	0.390***	0.293***	0.134***
	(2.738)	(2.652)	(3.115)	(3.470)	(2.839)
β	0.860***	0.780***	0.779***	0.817***	0.905***
Lj (1)	0.497 [0.481]	1.290 [0.256]	0.156 [0.693]	0.836 [0.361]	0.679 [0.410]
Lj (5)	2.271 [0.883]	2.519 [0.769]	3.719 [0.130]	2.299 [0.872]	1.857 [0.979]
Lj (9)	7.062 [0.122]	3.848 [0.726]	7.133 [0.116]	5.166 [0.417]	7.731 [0.072]
Shape	4.325***	4.621***	4.290***	4.455***	4.380***
LLH	−2902.247	−2818.685	−2821.787	−2814.289	−2791.905
AIC	117.875***	20.994***	55.970***	63.864***	131.107***

Note: P values are reported in square brackets, and ***, ** and * indicate significance levels of 0.01, 0.05 and 0.1.

Table 3
Fitting copula.

	Statistics	Clayton	Rotated Gumbel	Student t-Copula	Frank Copula
HCM	$\hat{\delta}$	3.447	3.310	3.472	4.250
	LLF	3631	4186	4300	3581
	AIC	−7260	−8370	−8598	−7160
SCOF	$\hat{\delta}$	1.492	1.743	2.026	2.329
	LLF	1584	1834	1907	1528
	AIC	−3166	−3666	−3812	−3054
USO	$\hat{\delta}$	1.581	1.732	2.139	2.429
	LLF	1691	1960	2115	1634
	AIC	−3380	−3918	−4228	−3266
CNEI	$\hat{\delta}$	1.566	1.783	2.120	2.410
	LLF	1671	1931	2081	1616
	AIC	−3340	−3860	−4160	−3230
NCGE	$\hat{\delta}$	2.759	1.307	1.398	1.415
	LLF	4290	1900	2061	2097
	AIC	−3578	−3798	−4207	−4192

Table 4
Descriptive statistics of dynamic VaR.

	SCOF	CNEI	USO	NCGE	HCM
Mean	−0.0761	−2.6556	−0.1034	−2.8562	−4.0176
Max	−0.0171	−1.2407	0.1482	−1.1734	−2.0322
Min	−0.7683	−5.6964	0.0796	−7.2933	−19.4464
Std	0.0069	0.9141	1.1280	1.1155	2.5799

calculated CoVaR under a dangerous scenario for the US and Chinese energy markets.

The result shows the spillover from the HCM to the SCOF and CNEI. Both the upward and downward CoVaR change over time, and the risk changes according to the different external conditions. Moreover, the upside risk spillover from the HCM to the SCOF and CNEI is higher than the downside risk spillover. This implies that when extraordinary returns happen, the carbon market affects the Chinese energy market more. The overall trend of upside risk premium and downside risk premium is significantly higher in June 2019, 2021, and February 2022, which may the price of carbon trading market has been increasing in the past few years, but it is also due to the price of carbon trading market has been increasing. This could be brought on by the notable swings in the price of carbon at those times.

The upside risk spillover from SCOF and CNEI to HCM is greater than the downside risk spillover. Meanwhile, when the risk spillover from HCM to SCOF and CNEI increases significantly, the risk spillover from SCOF and CNEI to HCM does not change significantly. The degree of risk spillover shows an increasing trend, which indicates that the risk contagion of energy market to carbon trading market is increasing. The reason may be that the energy market is more mature and more risk resistant. The risk contagion does not increase significantly as the degree of market linkage increases. Finally, we find that the risk spillover is more drastic, with more frequent upward and downward fluctuations in the line.

The U.S. energy market varies with external conditions, and the CoVaR is time-varying. Compared to the negative risk spillover, there is a greater positive risk spillover. The Chinese carbon market has a bigger effect on the US energy market when there are extreme returns. There is a significant increase in risk premiums around June 2019, 2021, and February 2022, which can be attributed to the sharp fluctuations in carbon market prices at the corresponding times. This can be attributed to the sharp price fluctuations in the carbon market at the corresponding times. The risk increases at the same time during this period. However, the contagion of risk spillover did not increase significantly in most of the time, and the market influence still needs to be improved.

There is no substantial change from the U.S. energy market to the Chinese carbon market. It shows a variable trend. Except for 2020, when the risk increases significantly due to sharp stock price fluctuations, the risk contagion from the U.S. energy market to carbon market is small. Finally, the instability of risk spillover caused by market instability due to imperfections in carbon market is reflected in both the US and Chinese energy markets.

4.5. Diversified benefit analysis

To further explore the practical significance of volatility spillover, this paper uses the conditional diversification benefit (CDB) to measure the impact of China's carbon trading market on portfolio returns. This method is based on the subadditivity of expected shortfall.

$$ES_t^q\left(r^i\right) = -E\left[r^i < F_i^{-1}(q)\right] \tag{14}$$

$$ES_t^q(r^p) \leq \sum_{i=2}^{N} w_i ES_t^q\left(r^i\right) \tag{15}$$

Where $F_i^{-1}(q)$ in equation (14) is the inverse function of the distribution function of portfolio i, and portfolio p in equation (15) is a combination of N portfolios with weight w_i. The portfolio consists of carbon and commodities, and the conditional diversification benefit (CDB) is:

$$CDB_t(w_t, q) = \frac{w_t\, ES_t^q(r^i) + (1 - w_t)ES_t^q(r^g) - ES_t^q(r^P)}{w_t\, ES_t^q(r^i) + (1 - w_t)ES_t^q(r^g) - VaR_t^q(q)} \tag{16}$$

Where $w_t\, ES_t^q\left(r^i\right) + (1 - w_t)ES_t^q(r^g)$ in equation (16) can be regarded as the upper bound, the lower bound is $VaR_t^q(q)$, and the expected loss and subadditivity are combined to obtain the value of CDB_t in the interval [0,1]. The higher the diversification of the portfolio, the higher the value. This indicator measures the degree of dispersion of the portfolio returns. The marginal distribution estimated above is a t-distribution, so the expected loss can be calculated as follows:

$$ES_t^q\left(r^i\right) = -\mu_t^i + \frac{\sigma_t^i}{q} h\left(H^{-1}(q)\right)\left(\frac{\nu + H^{-1}(q)^2}{\nu - 1}\right. \tag{17}$$

$$VaR_t^q(q) = -\mu_t^P + \sigma_t^P H^{-1}(q) \tag{18}$$

where h(.) and H(.) in equations (17) and (18) are the density function and distribution function of the t distribution with ν degrees of freedom.

We construct a passive portfolio based on actual data. The weight of each asset is fixed at 0.5 and does not change over time. At the same time, we use the 5 % and 50 % quantiles to measure the dispersion of the portfolio's returns.

The diversification benefits of a diversified portfolio are all greater than 0, which shows that adding carbon trading to a commodity portfolio can bring diversification benefits. However, compared with the diversification benefits of different quantiles, the diversification benefit of the 0.05 quantile is less than that of the median (See Table 5). This shows that in extreme cases, a portfolio that does not include carbon trading can generate greater diversification benefits. If the market has a greater downside risk, less carbon trading in the portfolio can reduce portfolio risk and obtain diversification benefits.

The diversification benefits of different portfolios also vary. Specifically, the diversification benefits are higher for crude oil and lower for clean energy commodities. This further lays the foundation for the practical significance of the risk spillover study. In markets

Table 5
Risk diversification of the portfolio.

	Q-Value	Mean	Max	Min
HCM ↔ SCOF	0.05	0.0396	0.2601	0.0162
	0.5	0.1296	0.2986	0.0381
HCM ↔ CNEI	0.05	0.0775	0.2840	0.0160
	0.5	0.1083	0.2426	0.0559
HCM ↔ USO	0.05	0.1956	0.4258	0.0837
	0.5	0.2031	0.3292	0.1277
HCM ↔ NCGE	0.05	0.1070	0.3049	0.0219
	0.5	0.1814	0.3560	0.0839

with low correlation, the diversification benefits are greater, while in markets with high correlation, the diversification benefits are lower.

5. Discussion

Table 6 shows the average value of the risk premiums. On average, the upside risk of the Chinese carbon market to the Chinese energy market is greater than the downside risk. This implies that the risk impact of upward price movements is greater than the risk impact of downward oscillations. Chinese government should be more alert to the risks that may be induced by upward price volatility. On average, the upside risk is greater than the downside risk. This implies that investors should be more alert to the risks that may be induced by upward price swings in the other markets [55]. The upside risk from the Chinese energy market and the US energy market is on average greater than the downside risk. This implies that the risks associated with upward price fluctuations in the Chinese and U.S. energy markets are likely to be greater than the risks associated with downward price oscillations in both markets. This paper argues that managers should be more vigilant about the risks that may be induced by upward fluctuations in the market prices. Meanwhile, investors in the Chinese carbon market should be more alert to the investment risks that may be induced by the upward price fluctuations in the energy markets.

We further compare the risk spillover with the CoVaR results. There is a clear risk spillover when prices in China's carbon market move upwards in large swings. This creates the potential for risk. The transmission of risk from the Chinese carbon market to the Chinese energy market is stronger than to the U.S. energy market. We also find that the contagion of risk from the Chinese carbon market to the US and Chinese energy markets is not stable. The contagion strength fluctuates over time, but the trend is similar. This suggests that the risk impacts on the energy markets of the two countries are homogeneous and homogeneous, even though China's carbon market has extreme returns. This may be related to the clear trend of globalization of energy markets [56,57]. At the same time, we find that the risk transmission from the U.S. energy market to the carbon market is on average greater than the risk transmission from the Chinese energy market to the carbon market, both in the extreme gain scenario and in the extreme loss scenario. This suggests that the Chinese government can take more risk-control measures against risk spillovers as the energy market becomes more internationalized and interconnected.

There are significant risk spillovers when the Chinese carbon trading market is in extreme loss. The risk contagion to the U.S. energy market is stronger than the contagion to the Chinese energy market. It is different from the stronger risk contagion to the Chinese energy market at extreme returns. Meanwhile, although the contagion strength to the U.S. and China's energy markets fluctuates over time when China's carbon market is at extreme losses, the trend is roughly the same. This suggests that the risk impacts on the energy markets of the two countries when the Chinese carbon market experiences extreme losses are also homogeneous and homogeneous.

6. Conclusions and recommendations

6.1. Conclusions

This paper focuses on the bidirectional risk spillover between China's carbon market and the U.S.-China energy market and explores the risk contagion relationship through ARMA-GARCH-Copula-CoVaR. The conclusions are as follows. First, there are obvious two-way risk spillovers between the Chinese carbon market and the Chinese energy market, and between the Chinese carbon market and the U.S. energy market. Second, the risk spillover is greater on the upside than on the downside. Risk contagion is stronger when extreme returns occur. Third, the general trend of risk spillover from the Chinese carbon market to the US and Chinese energy markets has not increased significantly over time, but the risk spillover from the Chinese carbon market has not been stable.

6.2. Recommendations

First, policymakers should consider the impact on the energy market when constructing mechanism, so as to facilitate the development of the carbon trading market in the transformation process of the energy market. A well-functioning carbon market can incentivize a shift in energy consumption and production towards low-carbon alternatives. For example, by incorporating a carbon pricing mechanism into the energy market, carbon emissions in energy production can be priced appropriately, thereby encouraging a shift from fossil fuels to renewable energy sources such as wind, solar and hydro. In turn, an increase in demand for low-carbon energy can support the growth of the carbon market by raising the overall price of carbon allowances, thereby enhancing the incentive for industry to reduce emissions. In addition, policymakers should ensure that carbon markets are closely linked to energy market policies. For example, governments can incentivize energy companies to innovate and adopt greener technologies through carbon pricing. And carbon trading mechanisms can reduce emissions by providing clear financial incentives for companies to reduce their carbon footprint.

Second, the Chinese government and carbon market managers should improve the risk response procedures. It is essential to control management and enhance the risk-resistant ability. In the risk prevention and control of carbon market, pay more attention to the market volatility of China's energy market than that of the U.S. energy market is necessary, and to be more alert to the risks brought by China's energy market. In addition, mechanisms to mitigate market volatility risk are necessary. This could include implementing price floors or ceilings to ensure that the market does not experience extreme price fluctuations that could destabilize the economy or discourage investment in clean technologies. Furthermore, governments could establish stabilization reserves, use a portion of carbon credits during market downturns, or set up contingency funds to buffer market shocks. In addition, policymakers should regularly

Table 6
Average of risk spillover across markets.

	Uplink CoVaR average	Row CoVaR average
HCM → SCOF	0.054637	−0.027428
HCM → CNEI	0.049419	−0.182902
SCOF → HCM	0.047213	−0.402868
CNEI → HCM	0.038208	−0.190277
HCM → USO	0.043439	−0.207635
HCM → NCGE	0.042557	−0.218502
USO → HCM	0.050822	−0.253868
NCGE → HCM	0.039026	−0.214229

assess the health of the carbon market and adjust interventions according to current market dynamics.

Third, governments need to consider restructuring the existing energy market to meet the needs of environmental protection under sustainability context [58–63]. Government departments should also make greater efforts to promote the transformation and optimization of the energy market structure, vigorously develop clean energy with low carbon emissions, and vigorously support the new energy industry. Promoting a higher share of new energy sources in the energy market is important for optimization.

CRediT authorship contribution statement

Jiale Yan: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Cem Işık:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Data and code availability statement

Data will be made available on request.

Declaration of competing interest

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

References

[1] N.K. Arora, T. Fatima, I. Mishra, et al., Environmental sustainability: challenges and viable solutions, Environmental Sustainability 1 (2018) 309–340.
[2] S.M. Vicente-Serrano, S.M. Quiring, M. Peña-Gallardo, et al., A review of environmental droughts: increased risk under global warming? Earth Sci. Rev. 201 (2020) 102953.
[3] P. Roy, S.C. Pal, R. Chakrabortty, et al., Climate change and geo-environmental factors influencing desertification: a critical review, Environ. Sci. Pollut. Control Ser. (2024) 1–14.
[4] B. Wang, M. Yu, Y. Zhu, et al., Unveiling the driving factors of carbon emissions from industrial resource allocation in China: a spatial econometric perspective, Energy Pol. 158 (2021) 112557.
[5] J. Yan, Y. Sheng, M. Yang, et al., Local government competition, new energy industry agglomeration and urban ecological total factor energy efficiency: a new perspective from the role of knowledge, J. Clean. Prod. 429 (2023) 139511.
[6] G.L. Simon, A.G. Bumpus, P. Mann, Win-win scenarios at the climate–development interface: challenges and opportunities for stove replacement programs through carbon finance, Global Environ. Change 22 (1) (2012) 275–287.
[7] P. Nejat, F. Jomehzadeh, M.M. Taheri, et al., A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries), Renew. Sustain. Energy Rev. 43 (2015) 843–862.
[8] S. Yin, Z. Zhao, Energy development in rural China toward a clean energy system: utilization status, co-benefit mechanism, and countermeasures, Front. Energy Res. 11 (2023) 1283407.
[9] T.B. Nadeem, M. Siddiqui, M. Khalid, et al., Distributed energy systems: a review of classification, technologies, applications, and policies: current Policy, targets and their achievements in different countries (continued), Energy Strategy Rev. 48 (2023) 101096.
[10] B. Yu, D. Fang, K. Xiao, et al., Drivers of renewable energy penetration and its role in power sector's deep decarbonization towards carbon peak, Renew. Sustain. Energy Rev. 178 (2023) 113247.
[11] Y. Zhang, A. Farnoosh, Analyzing the dynamic impact of electricity futures on revenue and risk of renewable energy in China, Energy Pol. 132 (2019) 678–690.
[12] X. Wang, Y. Gan, Y. Zhou, et al., Country-level risk and green energy transition: evaluating political risk and human capital in OECD economies, Polit. Ekon. (2024).
[13] C. Zhang, M. Zhang, Y. Zhan, et al., Political risk and sustainable development: digitization and environmental policy stringency, Polit. Ekon. (2024).
[14] J. Tian, L. Yu, R. Xue, et al., Global low-carbon energy transition in the post-COVID-19 era, Appl. Energy 307 (2022) 118205.
[15] A.T. Hoang, S. Nižetić, A.I. Olcer, et al., Impacts of COVID-19 pandemic on the global energy system and the shift progress to renewable energy: opportunities, challenges, and policy implications, Energy Pol. 154 (2021) 112322.
[16] J. Lazo, G. Aguirre, D. Watts, An impact study of COVID-19 on the electricity sector: a comprehensive literature review and Ibero-American survey, Renew. Sustain. Energy Rev. 158 (2022) 112135.
[17] G. Cassetti, B. Boitier, A. Elia, et al., The interplay among COVID-19 economic recovery, behavioural changes, and the European Green Deal: an energy-economic modelling perspective, Energy 263 (2023) 125798.
[18] I. Sotnyk, T. Kurbatova, O. Kubatko, et al., Energy security assessment of emerging economies under global and local challenges, Energies 14 (18) (2021) 5860.
[19] R. Karkowska, S. Urjasz, How does the Russian-Ukrainian war change connectedness and hedging opportunities? Comparison between dirty and clean energy markets versus global stock indices, J. Int. Financ. Mark. Inst. Money 85 (2023) 101768.

[20] C. Baumeister, J.D. Hamilton, Structural interpretation of vector autoregressions with incomplete identification: revisiting the role of oil supply and demand shocks, Am. Econ. Rev. 109 (5) (2019) 1873–1910.
[21] A.K. Tiwari, E.J.A. Abakah, A.O. Adewuyi, et al., Quantile risk spillovers between energy and agricultural commodity markets: evidence from pre and during COVID-19 outbreak, Energy Econ. 113 (2022) 106235.
[22] A.K. Tiwari, E.J.A. Abakah, D. Gabauer, et al., Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: implications for hedging and investments strategies, Global Finance J. 51 (2022) 100692.
[23] X.L. Gong, M. Zhao, Z.C. Wu, et al., Research on tail risk contagion in international energy markets—the quantile time-frequency volatility spillover perspective, Energy Econ. 121 (2023) 106678.
[24] Y. Wang, Z. Guo, The dynamic spillover between carbon and energy markets: new evidence, Energy 149 (2018) 24–33.
[25] J. Tang, Z.Y. Ren, H.H. Chen, et al., Multidimensional risk spillover among power, coal, and carbon markets: empirical evidence from China, Environ. Sci. Pollut. Control Ser. 31 (1) (2024) 1244–1259.
[26] L. Xia, L. Wan, W. Wang, et al., Energy accessibility via natural resources: do natural resources ensure energy accessibility in low income countries? Resour. Pol. 86 (2023) 104145.
[27] J. Yan, C. Işık, X. Gu, The nexus between natural resource development, trade policy uncertainty, financial technology and poverty in China: contributing to the realization of SDG 1, Resour. Pol. 95 (2024) 105154.
[28] T. Long, X. Cui, J. Yan, et al., Natural resource development, economic policy uncertainty and urban residents' consumption in China: a nonlinear ARDL and time-varying parameter vector autoregressive with stochastic volatility approach, Stoch. Environ. Res. Risk Assess. (2024) 1–17.
[29] F. Li, J. Yan, How e-government and green technology innovation affect carbon emissions: evidence from resource-rich countries in the Shanghai Cooperation Organization, Energy Rep. 12 (2024) 4026–4033.
[30] L. Hou, L. Hao, W. Wang, et al., Clean energy, food, water and environment: examining COP27 targets for China's economy, Land Degrad. Dev. 35 (16) (2024) 4726–4740.
[31] W. Chen, S. Xiong, Q. Chen, Characterizing the dynamic evolutionary behavior of multivariate price movement fluctuation in the carbon-fuel energy markets system from complex network perspective, Energy 239 (2022) 121896.
[32] X. Ren, Y. Dou, K. Dong, et al., Information spillover and market connectedness: multi-scale quantile-on-quantile analysis of the crude oil and carbon markets, Appl. Econ. 54 (38) (2022) 4465–4485.
[33] R. Santiago, J.A. Fuinhas, A.C. Marques, The impact of globalization and economic freedom on economic growth: the case of the Latin America and Caribbean countries, Econ. Change Restruct. 53 (1) (2020) 61–85.
[34] M. Balcilar, S. Hammoudeh, E.A. Toparli, On the risk spillover across the oil market, stock market, and the oil related CDS sectors: a volatility impulse response approach, Energy Econ. 74 (2018) 813–827.
[35] D. Kumar, European travel and leisure sector and uncertainties: a risk spillover analysis, Tourism Econ. 29 (1) (2023) 48–67.
[36] G. Cao, F. Xie, Extreme risk spillovers across energy and carbon markets: evidence from the quantile extended joint connectedness approach, Int. J. Finance Econ. 29 (2) (2024) 2155–2175.
[37] X. Gong, R. Shi, J. Xu, et al., Analyzing spillover effects between carbon and fossil energy markets from a time-varying perspective, Appl. Energy 285 (2021) 116384.
[38] M.E. Hoque, L. Soo-Wah, M. Billah, Time-frequency connectedness and spillover among carbon, climate, and energy futures: determinants and portfolio risk management implications, Energy Econ. 127 (2023) 107034.
[39] M.A. Naeem, N. Arfaoui, Exploring downside risk dependence across energy markets: electricity, conventional energy, carbon, and clean energy during episodes of market crises, Energy Econ. 127 (2023) 107082.
[40] Q. Xie, Y. Bai, N. Jia, et al., Do macroprudential policies reduce risk spillovers between energy markets?: evidence from time-frequency domain and mixed-frequency methods, Energy Econ. 134 (2024) 107558.
[41] A. Angabini, S. Wasiuzzaman, GARCH models and the financial crisis-A study of the Malaysian, The International Journal of Applied Economics and Finance 5 (3) (2011) 226–236.
[42] O.B. Sezer, M.U. Gudelek, A.M. Ozbayoglu, Financial time series forecasting with deep learning: a systematic literature review: 2005, Appl. Soft Comput. 90 (2019) 106181, 2020.
[43] M.H. Doroudyan, S.T.A. Niaki, Pattern recognition in financial surveillance with the ARMA-GARCH time series model using support vector machine, Expert Syst. Appl. 182 (2021) 115334.
[44] L. Rubio, A. Palacio Pinedo, A. Mejía Castaño, et al., Forecasting volatility by using wavelet transform, ARIMA and GARCH models, Eurasian Economic Review 13 (3) (2023) 803–830.
[45] E.W. Frees, E.A. Valdez, Understanding relationships using copulas, North Am. Actuar. J. 2 (1) (1998) 1–25.
[46] I. Gijbels, N. Veraverbeke, M. Omelka, Conditional copulas, association measures and their applications, Comput. Stat. Data Anal. 55 (5) (2011) 1919–1932.
[47] Y. Zhao, Q.Y. Liu, J. Kuang, et al., Modeling multivariate dependence by nonparametric pair-copula construction in composite system reliability evaluation, Int. J. Electr. Power Energy Syst. 124 (2021) 106373.
[48] J.C. Reboredo, M.A. Rivera-Castro, A wavelet decomposition approach to crude oil price and exchange rate dependence, Econ. Modell. 32 (2013) 42–57.
[49] Y. Liu, X.J. Tan, Y. Yu, et al., Assessment of impacts of Hubei Pilot emission trading schemes in China–A CGE-analysis using Term CO2 model, Appl. Energy 189 (2017) 762–769.
[50] Y. Chen, S. Ba, Q. Yang, et al., Efficiency of China's carbon market: a case study of Hubei pilot market, Energy 222 (2021) 119946.
[51] C. Zou, Q. Zhao, G. Zhang, et al., Energy revolution: from a fossil energy era to a new energy era, Nat. Gas. Ind. B 3 (1) (2016) 1–11.
[52] H. Peng, Y. Liu, How government subsidies promote the growth of entrepreneurial companies in clean energy industry: an empirical study in China, J. Clean. Prod. 188 (2018) 508–520.
[53] J. Du, Z. Shen, M. Song, et al., The role of green financing in facilitating renewable energy transition in China: perspectives from energy governance, environmental regulation, and market reforms, Energy Econ. 120 (2023) 106595.
[54] S. Chai, Q. Liu, J. Yang, Renewable power generation policies in China: policy instrument choices and influencing factors from the central and local government perspectives, Renew. Sustain. Energy Rev. 174 (2023) 113126.
[55] X. Sun, W. Fang, X. Gao, et al., Complex causalities between the carbon market and the stock markets for energy intensive industries in China, Int. Rev. Econ. Finance 78 (2022) 404–417.
[56] L. Bai, Y. Wei, J. Zhang, et al., Diversification effects of China's carbon neutral bond on renewable energy stock markets: a minimum connectedness portfolio approach, Energy Econ. 123 (2023) 106727.
[57] W. Jiang, L. Dong, X. Liu, How does COVID-19 affect the spillover effects of green finance, carbon markets, and renewable/non-renewable energy markets? Evidence from China, Energy 281 (2023) 128351.
[58] C. Işık, S. Ongan, H. Islam, A. Sharif, D. Balsalobre-Lorente, Evaluating the effects of ECON-ESG on load capacity factor in G7 countries, J. Environ. Manag. 360 (2024) 121177, https://doi.org/10.1016/j.jenvman.2024.121177.
[59] C. Işık, S. Ongan, H. Islam, D. Balsalobre-Lorente, A. Sharif, ECON-ESG factors on energy efficiency: fostering sustainable development in ECON-growth-paradox countries, Gondwana Res. 135 (2024) 103–115.
[60] C. Işık, S. Ongan, H. Islam, G. Jabeen, S. Pinzon, Is economic growth in East Asia pacific and South Asia ESG factors based and aligned growth? Sustain. Dev. (2024) 1–14, https://doi.org/10.1002/sd.2910.

[61] C. Işık, S. Ongan, H. Islam, S. Pinzon, G. Jabeen, Navigating sustainability: unveiling the interconnected dynamics of ESG factors and SDGs in BRICS-11, Sustain. Dev. (2024) 1–15, https://doi.org/10.1002/sd.2977.
[62] C. Işık, S. Ongan, D. Ozdemir, J. Yan, O. Demir, The sustainable development goals: theory and a holistic evidence from the USA, Gondwana Res. (2024), https://doi.org/10.1016/j.gr.2024.04.014.
[63] C. Işık, et al., Renewable energy, climate policy uncertainty, industrial production, domestic exports/re-exports, and CO2 emissions in the USA: a SVAR approach, Gondwana Res. (2024), https://doi.org/10.1016/j.gr.2023.08.019.