ORIGINAL RESEARCH

High-dimensional nonlinear dependence and risk spillovers analysis between China's carbon market and its major influence factors

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Abstract

In July 2021, China began its national emissions trading scheme, marking a new stage of development for the country's carbon market. This study analyzes the multidimensional correlation between carbon prices in the Guangdong pilot market and eight influencing factors from three perspectives (the international carbon market, energy prices, and China's economic situation), using the ARMA-GARCH-vine copula model. The CoVaR between the carbon price and each factor is then calculated using copula-CoVaR. The results show that the crude oil market plays the primary role in the vine structure, and that the carbon market is not strongly correlated with other markets. China's carbon market is still a regional market driven by government policy, and the international carbon and energy markets (especially the crude oil market) have upward risk spillover effects upon it. This indicates an asymmetric risk spillover between influencing factors and the carbon market. The findings of this study will help market participants prepare risk management strategies and make related investment decisions, and provide a reference for policy makers to formulate national emission trading scheme policies.

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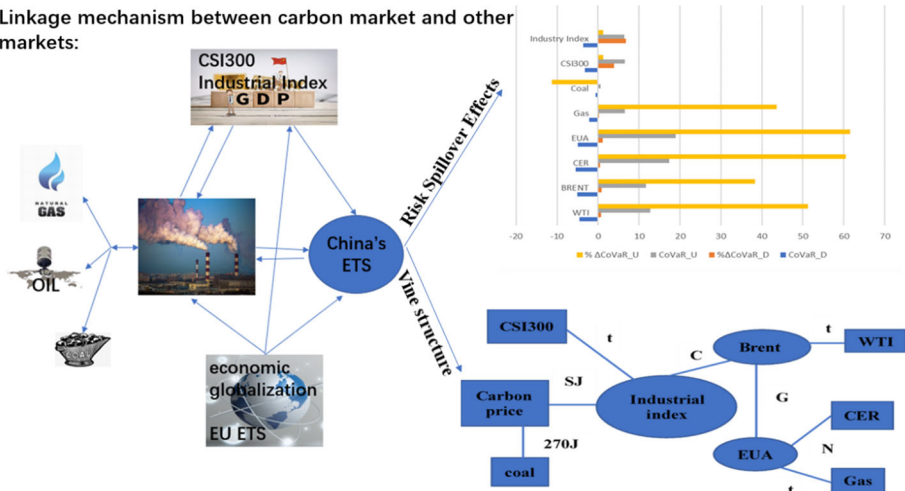 Shaobin Zhang
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Graphical abstract

Keywords High-dimensional nonlinear dependence · Risk spillovers · China's carbon market · Major influence factors

1 Introduction

COVID-19 has caused a serious recession in the global economy, which has implications for carbon dioxide (CO_2) emissions. Global emissions from the economic sector are projected to decrease by 3.9–5.6% from 2020 to 2024, compared with the non-pandemic baseline scenario (Shan et al., 2020). In 2020, China was the world's only major economy to achieve economic growth, with its gross domestic product (GDP) increasing by 2.3%.[1] Because this growth may lead to an increase in carbon emissions, in recent years the Chinese government has begun to focus on economic transformation and the development of the green economy. As the world's largest developing country, China is likely to maintain medium- to high-speed economic growth in the years to come, and its consequent energy demand will be substantial. Despite this, the Chinese government has promised to reach its CO_2 emissions peak by 2030 and achieve carbon neutrality before 2060,[2] and has already taken measures and implemented regulations to help it achieve this. Seven pilot carbon emission trading markets have been established in the country, to encourage the main sources of emissions to improve their efficiency and reduce emission intensity. In December 2017, China established a national carbon emission trading market for the power industry. This industry is expected to reach

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[1] 2.3%! China's economy grows against the trend in 2020, Xinhuanet, 2021-01-18, www.xinhuanet.com/2021-01/18/c_1126995039.htm.

[2] Central Economic Work Conference held in Beijing, Renminnet, 2020-12-19, www.politics.people.com.cn/n1/2020/1219/c1024-31971922.htm.

its CO2 emissions peak by 2023, except for the eastern region, which will reach it by 2030 (Tang et al., 2018). On July 16, 2021, the national carbon emission trading market officially opened. It is projected to grow into a large market with an annual transaction volume over 100 billion CNY, and to provide price signals and financial support for the carbon reduction behavior of society as a whole.[3]

Despite differences in their implementation, most carbon policies aim to achieve a similar outcome: to raise the price of carbon-intensive products relative to non-carbon-intensive ones (Choi et al., 2010). Hájek et al. (2019) used multiple panel regression to analyze whether the carbon tax policies of five European countries (Denmark, Finland, Ireland, Slovenia and Sweden) promoted development of the green energy industry. The results showed that increasing the carbon tax could effectively improve the efficiency of the energy industry and reduce its greenhouse gas emissions. A reasonable carbon pricing mechanism within a carbon emissions trading market is therefore key to achieving energy conservation and emission reduction without hindering economic growth. Market participants have raised concerns, however, as to whether appropriate risk management provisions are in place to cope with the fluctuations of time-varying allowance prices (Segnon et al., 2017). With the continuous opening up of China's market and the growth of its economy, the nation's carbon emission trading market will inevitably move towards internationalization. It is therefore critical to enterprise operation and risk avoidance that market participants understand which factors affect the carbon price, and how they relate to each other. Zeb et al. (2014) point out that increased energy production leads to an incremental rise in the GDP, which further contributes to carbon emissions. International markets (especially the crude oil market), have a direct or indirect impact on the production activities of all countries. We considered the potential influencing factors of this impact (including energy markets, the economic situation of China and international carbon markets), and detected a high-dimensional dependence between them and Chinese carbon markets (Hao & Tian, 2020; Zeng et al., 2021; Zhou & Li, 2019).

This study preprocesses the data with the ARMA-GARCH model to eliminate autocorrelation and heteroscedasticity, before applying the vine copula model to analyze the direct and indirect dependent structures between the pilot carbon market and the factors that affect it. It then uses the copula-CoVaR model to explore the risk spillover effect from other markets on the pilot carbon market. The risk transmission mechanism of each type of market is important to the theoretical research and sustainable development of the carbon market. This is a key basis for business investment and government policy. The study fills the research gap by analyzing the high dependence structure and risk spillover effect between the carbon market and other markets from a broader perspective. We find that China's carbon market is directly affected by domestic economic conditions with a small risk spillover effect, and indirectly affected by the oil market with a large upside risk. China's carbon market is still immature, regional and policy-oriented. The study contributes to the literature in two aspects. First, it uses the vine copula model to analyze the multiple structures between the Guangdong pilot carbon market and eight factors that affect it. Although the vine copula model performs well when dealing with multi-dimensional variables, few studies to date have used it to study the multi-dimensional structure between the carbon market and markets related to it. This study reflects the position of carbon markets and the risk transmission paths between them from a broader perspective. Second, it applies the copula-CoVaR model to analyze the risk spillover effect from other markets on the Guangdong pilot carbon market. The carbon premium in

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[3] The national carbon market "opened" for 6 days, full of highlights, Xinhuanet, 2021-07-24 www.gov.cn/xinwen/2021-07/24/content_5627095.htm.

stock returns increased after China's carbon emissions trading market was established, and companies participating in the carbon market have higher carbon exposure (Wen et al., 2020; Wen et al., 2020a, 2020b). The results achieved in this paper provide a reference with which enterprises can avoid carbon price risk and build carbon asset portfolios. The combination of high-dimensional structural analysis and risk spillover effect analysis clearly describes the risk transmission between the carbon market and other related markets. Based on these results, China should keep reasonable oil reserves to avoid a rise in carbon price caused by soaring international oil prices, which in turn increase the production cost for enterprises and impact the social economy.

This paper focuses on the current status of China's emission trading scheme (ETS), and analyzes its interaction mechanism with the domestic energy market and economy. Vine copula describes the high-dimensional correlation between China's carbon market and other markets, and copula-CoVaR quantifies the risk spillover between them. The combination of the two reveals the characteristics of China's ETS. The results between the model based on Guangdong carbon price and on the national average carbon price showed the similar conclusion that China's carbon market would be impacted by rising crude oil prices and a slowing industrial economy. To counter this, the Chinese government could loosen environmental regulations during times of economic downturn. The remainder of the paper is organized as follows: Sect. 2 reviews the literature; Sect. 3 describes the methodology; Sect. 4 presents descriptive statistics and results; Sect. 5 discusses the results, conducts a validity test, and proposes policy improvements; and Sect. 6 draws conclusions and identifies the limitations of the study.

2 Literature review

Extreme events driven by climate change have lasting effects on the global economy (Chen et al., 2020; Medina-Olivares et al., 2021; Shi et al., 2021). Energy conservation and emission reduction in response to climate change is a concern of governments around the world, and a challenge that all humanity must face together. In February 2021 the United States recognized this, and renewed its commitment to the Paris Agreement. Many other countries have already adopted energy taxes, such as carbon taxes, fuel taxes or carbon emission trading schemes, to control carbon emissions and promote a low-carbon economy. Scholars have used various methods to study the factors that affect carbon emissions, and have addressed the topic from multiple perspectives. Some have documented the impact of climate policy on carbon emissions, and found that different policies can reduce carbon emissions to varying degrees (Beck et al., 2015; Vera & Sauma, 2015; Zhu et al., 2018). In theory, an energy tax could raise the price of energy to curtail its demand, and an ETS could increase the cost of emissions for enterprises, forcing them to improve their energy efficiency. In China's Hubei Province, however, the ETS has had little demonstrable impact on industrial and household CO2 emissions, GDP or energy consumption, because of its irrational quota allocations (Wen, Hu, et al., 2020; Wen et al., 2020a, 2020b). Some scholars have compared the effects of climate policy on emission reduction. Dissanayake et al. (2020) compared the effects of three carbon emission mitigation strategies (carbon tax, fuel tax and ETS) in Indonesia, a high-emitting developing country. They found that while the fuel tax promoted economic growth, the carbon tax and ETS caused a decline in the GDP but contributed to high tax revenue and low inflation. Although China does not yet have a carbon tax, it has implemented a policy that reduces the capacity of coal, steel and other polluting industries, with good results. Li and Yao (2020) used a dynamic computable general equilibrium model to establish that

reducing China's coal production capacity reduced emissions more effectively than a carbon tax, but also resulted in greater economic loss. Further, they found that a combination of the two policies had a stronger effect. The factors that affect carbon emissions vary between countries, as does the role of environmental policy, and governments must choose strategies that are suitable for their own national situations. Luo et al. (2021) surveyed all the power companies that paid into the Guangdong ETS, and found that the scheme had a positive impact on company behavior in the form of carbon asset transactions, energy saving measures and emission reduction technologies. This shows that an ETS can encourage enterprises to adopt low-carbon behaviors, which is key to achieving a green economy. China's national ETS was established with this goal in mind.

Other studies have focused on the influencing factors of carbon emissions from a market perspective, and found that climate policy is more likely to affect emissions in the long term than in the short term, and capital accumulation is the main driver of long-term emissions (Andersson & Karpestam, 2013). It was also found that the alternative relationship between capital, energy and the labor force promoted the reduction of carbon emissions in China's commercial sector (Wang & Lin, 2020). Xie et al. (2021) evaluated the carbon emission efficiency of 59 countries from 1998 to 2016, and saw that technological progress led to a significant improvement. The rebound effect, however, meant that this improvement would encourage consumers and producers to use more energy. Scientific and technological advancements are the main drivers of reducing carbon emission intensity, but they do not guarantee a decrease in total emissions. To effectively reduce carbon emissions, it is therefore important to promote the transformation of economic structures (Yang & Li, 2017). President of the People's Bank of China, Yi Gang, believes that realizing carbon neutrality requires a large amount of investment, and the financial system should be guided to provide the necessary support in a market-oriented manner.[4] An increased share of wind and solar electricity production would contribute to reducing carbon intensity in the short and long term (Khan et al., 2021). The government should provide policy support (e.g., in taxation and finance) for the development of clean energy and related technologies.

In the carbon emissions trading market, carbon price is the key to controlling emissions and promoting the development of a low-carbon economy. The carbon prices of China's seven pilot markets are low, and fluctuate wildly. There is volatility clustering in the price of carbon in Hubei, Shanghai, Shenzhen and the European Union ETS. The latter, along with all China's pilot carbon markets, is deficient in terms of stability (Lyu et al., 2020). In Europe, emission prices are highly sensitive to the implied volatility of oil markets, and the impact of the crude oil volatility index on the EUA market appears asymmetric (Dutta, 2018). Ji et al. (2021) explain that the oversupply of allowances, low auction prices and the use of the CCER would lead to a remarkable decline in carbon prices, and the expansion of the carbon market and centralized trading would raise them. Among the factors that affect the carbon price in Europe, economic development has the largest magnitude and shortest duration. In comparison, the impact of black energy consumption is weaker, but its duration is longest. The impact of clean energy development on carbon prices is similar to that of black energy, but its magnitude and duration are lower (Li et al., 2020). Zhu et al. (2019) argue that the effects of electricity prices and the stock index appear relatively early. They drive carbon prices in the short term, and then continue to strengthen them at a steady rate, while the impacts of coal, oil and gas prices are lagged, and drive carbon prices in the medium and long term. Zhou and Li (2019) found a long-term equilibrium relationship between the price

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[4] The People's Bank of China and the International Monetary Fund held a joint high-level seminar on "Green Finance and Climate Policy", Sina, 2021-04-15, https://finance.sina.com.cn/roll/2021-04-15/doc-ikmxzfmk7055841.shtm.

of carbon emissions and the coal price, Industrial Index, CSI 300 and Air Quality Index. Wang et al. (2018) ranked the factors that affect carbon prices (including the price of natural gas, the futures price of Certified Emission Reduction [CER] and the crude oil future price) using an inscribed cored grey relational analysis model, and found that the most influential factor varied between China's pilot markets.

This analysis of the literature shows that while many studies have investigated pilot markets, there is a lack of research into the carbon price in China as a whole. Additionally, most studies analyzed the factors that influence carbon price and the links between them without examining the high-dimensional structure of carbon prices and its determining factors. There has been no research into the risk spillover effects of other markets on China's carbon market to date. This study contributes to the literature by analyzing the multiple structures between carbon price and its influencing factors using the vine copula model. It also studies the risk spillover effects from other markets on the Guangdong pilot carbon price through the copula-CoVaR model.

3 The vine copula and copula-CoVaR methodology

In order to capture the actual and pure interdependence of the considered markets, first we apply the ARMA-GARCH model to filter the data avoiding the influencing from the autocorrelation and heteroscedasticity, as documented in the literature (Ji et al., 2020; Ji, Wang, et al., 2019; Ji, Xia, et al., 2019; Jondeau & Rockinger, 2006). Then the residuals were transformed to a uniform distribution, and their high-dimensional dependence structure was analyzed with the vine copula approach. Finally, we applied the copula-CoVaR model to examine the risk spillover effect of each factor on the carbon market.

3.1 Vine copula model

Based on Sklar's (1959) theorem, if F is assumed to be an n-dimensional distribution function with the continuous marginal distribution functions F_1, F_2, ..., F_n, then there will be a unique n-dimensional copula function C:

$$F(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F_n(x_n)), \forall (x_1, \cdots x_n) \in R^n \tag{1}$$

An n-dimensional copula is a cumulative distribution function on $[0, 1]^n$ with uniform marginal distributions on [0,1]. By taking derivatives of both sides of Eq. (1), the joint density function of $(x_1, ..., x_n)$ can be expressed as:

$$f(x_1, \cdots, x_n) = \frac{\partial^n C(F(x_1), \cdots, F(x_n))}{\partial F(x_1) \cdots \partial F(x_n)} f(x_1) \cdots f(x_n)$$
$$= c(F_1(x_1), \cdots, F_n(x_n)) \prod_{i=1}^{n} f(x_i). \tag{2}$$

Early discussions on the theory and application of the copula model were based mainly on binary situations. Joe (1997) defined the vine copula, and since then the theory has attracted attention in academic circles. It analyzes the correlation between multiple variables from a new perspective, and measures the correlation between all variables at the same time. A vine structure is generally composed of trees, nodes, and edges. There are $(n − 1)$ trees in an n-dimensional vine structure. The ith tree T_i has $(n + 1 − i)$ nodes and $(n − i)$ edges. The nodes
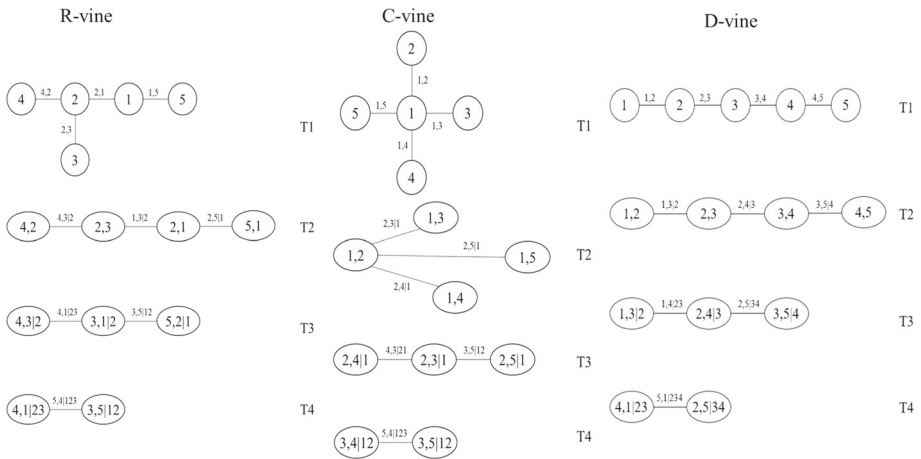
Fig. 1 Five-dimensional vine copula structures

and edges can represent the different uniform margins and bivariate copula density. There are therefore different ways to decompose an n-dimensional density. The number of decomposition methods increases rapidly as the number of dimensions increases. To describe the decomposition process, Kurowicka and Joe (2010) proposed a regular vine (R-vine), which can be represented by a graph. Multivariate density can be decomposed through the R-vine:

$$f(x_1, \cdots, x_n) = \prod_{i=1}^{n} f(x_i) \prod_{i=1}^{n-1} \prod_{e \in E_i} c_{e|D_e}\left(F_{e_a|D_e}, F_{e_b|D_e}\right), \tag{3}$$

where E_i is the set of edges associated with T_i, $e = \{a, b\}$ represents the edge connecting variables denoted by e_a and e_b in T_i,; and D_e denotes the edge e's conditioning set. The vine structure is not unique to multivariate density. Figure 1 illustrates possible R-vine, C-vine and D-vine structures for five-dimensional density. The R-vine has more diverse and flexible dependent structures than other structures.

3.1.1 Tail dependence coefficients

Tail correlation is used to describe the degree of correlation between two financial assets when extreme events occur. In the carbon market, it is necessary to analyze the correlation between the yield of carbon price and its influencing factors under extreme events. Tail dependence is represented as a conditional probability that one asset will incur a large loss (or gain), given the large loss (or gain) of another asset. Vine copula models with appropriate bivariate reflection asymmetric linking copulas can be used to assess tail asymmetries (Nikolouloupoulos, et al., 2012). In this article, λ_L and λ_u represent the lower and upper tail dependence coefficients respectively.[5]

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[5] Suppose there are two assets, X_1 and X_2, with joint continuous cumulative distribution function F, marginal distributions F_{X_1}, F_{X_2}, and corresponding copula C. $\lambda_L = \lim_{v \to 0^+} P\left(F_{X_1}(X_1) \le v | F_{X_2}(X_2) \le v\right) =$

3.2 The copula-CoVaR approach

We used value at risk (VaR) to measure the risk of each market under extreme conditions. The VaR is the maximum loss that investors can experience within a specific time horizon and confidence level. The downside and upside VaRs were defined respectively as:

$$\Pr\left(r_t \leq VaR_{\alpha,t}\right) = \alpha, \tag{4}$$

$$\Pr\left(r_t \geq VaR_{\alpha,t}\right) = \alpha. \tag{5}$$

We quantified the systemic impact of selected markets on carbon price using the CoVaR method (Adrian & Brunnermeier, 2011). The CoVaR of asset i is the VaR of asset i on the condition that asset j exhibits an extreme movement. The downside and upside CoVaRs were defined respectively as:

$$\Pr\left(r_t^i \leq CoVaR_{\beta,t}|r_t^j \leq VaR_{\alpha,t}\right) = \beta, \tag{6}$$

$$\Pr\left(r_t^i \geq CoVaR_{\beta,t}|r_t^j \geq VaR_{\alpha,t}\right) = \beta. \tag{7}$$

In this study, $\alpha\,and\,\beta$ of the downside CoVaR are both 0.05; and $\alpha\,and\,\beta$ of the upside CoVaR are both 0.95. Based on Sklar's (1959) theorem, we computed the two CoVaRs according to the following equations:

$$C\left(F_{r_t^i}\left(CoVaR_{\beta,t}^i\right), F_{r_t^j}\left(VaR_{\alpha,t}^j\right)\right) = \alpha\beta, \tag{8}$$

$$1 - F_{r_t^i}\left(CoVaR_{\beta,t}^i\right) - F_{r_t^j}\left(VaR_{\alpha,t}^j\right) + C\left(F_{r_t^i}\left(CoVaR_{\beta,t}^i\right), F_{r_t^j}\left(VaR_{\alpha,t}^j\right)\right) = \alpha\beta, \tag{9}$$

$$CoVaR_{\beta,t}^i = F_{r_t^i}^{-1}\left(F_{r_t^i}\left(CoVaR_{\beta,t}^i\right)\right). \tag{10}$$

We judged the direction of risk spillover according to the ΔCoVaR. In this article, the ΔCoVaR is the difference between the VaR of the carbon market return conditional on the extreme state of other returns ($CoVaR_{\beta,t}^i(VaR_{\alpha,t}^j)$), and the VaR of the carbon market return conditional on the normal state of other returns ($CoVaR_{\beta,t}^i(VaR_{0.5,t}^j)$). The systemic risk contribution of selected markets to the carbon market is given as %ΔCoVaR. The ΔCoVaR and the %ΔCoVaR are defined respectively as:

$$\Delta CoVaR = CoVaR_{\beta,t}^i\left(VaR_{\alpha,t}^j\right) - CoVaR_{\beta,t}^i\left(VaR_{0.5,t}^j\right), \tag{11}$$

$$\%\Delta CoVaR = \frac{\Delta CoVaR}{CoVaR_{\beta,t}^i(VaR_{0.5,t}^j)}. \tag{12}$$

Footnote 5 continued

$$\lim_{v \to 0^+} \frac{P\left(F_{X_1}(X_1) \leq v, F_{X_2}(X_2) \leq v\right)}{P\left(F_{X_2}(X_2) \leq v\right)} = \lim_{v \to 0^+} \frac{c(v,v)}{v}, \quad \lambda_u = \lim_{v \to 1^-} P\left(F_{X_1}(X_1) \geq v|F_{X_2}(X_2) \geq v\right) =$$

$$\lim_{v \to 1^-} \frac{P(F_{X_1}(X_1) \geq v, F_{X_2}(X_2) \geq v)}{P(F_{X_2}(X_2) \geq v)} = \lim_{v \to 1^-} \frac{1 - 2v + c(v,v)}{1-v}.$$

4 Empirical studies

4.1 Variables and data

Seven pilot carbon markets have been in operation in China since 2013. They form the basis of the country's current carbon trading system, which includes nearly 3000 companies and is the world's second largest carbon market by quota transactions. At the end of 2020, China's Central Economic Work Conference listed "carbon peaking and carbon neutralization" as one of its eight key tasks for 2021. The national carbon trading system officially began operation in 2021, marking a new stage in the construction of China's ETS. This study explores the main influencing factors of the carbon price in China, and researches the risk spillover effects of other markets on the carbon price. The Guangdong ETS has the largest cumulative trading volume and the province has a high degree of economic openness, as well as a developed financial market. It was selected as the research object for these reasons. As Figure 2 shows, monthly trading volumes in Guangdong are volatile, and the carbon price is relatively low.

The factors affecting China's carbon price in previous studies mainly include coal, natural gas, crude oil, macroeconomy and international carbon price (Han et al., 2019; Hao & Tian, 2020; Zeng et al., 2017). Based on theoretical analysis and China's actual situation, this study selected eight factors that might affect China's carbon price from the following three perspectives. (1) The international carbon market: Having completed three stages of development, the EU ETS is the world's largest and most effective carbon emission trading market (Zeng et al., 2021). We used CER and EUA futures prices to analyze the linkage between Chinese and international carbon markets. (2) Energy prices: Production activities use a lot of energy, especially from fossil fuels, which emit large amounts of carbon dioxide. The fluctuation of energy prices has an impact on their supply and demand. Adekoya (2021) proved carbon allowance prices can be significantly predicted by energy prices (oil, coal, natural gas). In China's current energy structure, coal accounts for the largest proportion, followed by crude oil and natural gas. In recent years, the proportion of coal has been declining, and the proportion of oil and gas has been increasing, showing a substitution effect. Natural gas is the cleanest of the three energy sources. We selected WTI and Brent crude oil futures prices, the Chinese Coal Price Index and Chinese natural gas prices to analyze the impact of energy prices on China's carbon markets. (3) China's economic situation: Macroeconomic activities have a particular influence on the carbon emission rights market (Zhou & Li, 2019), because
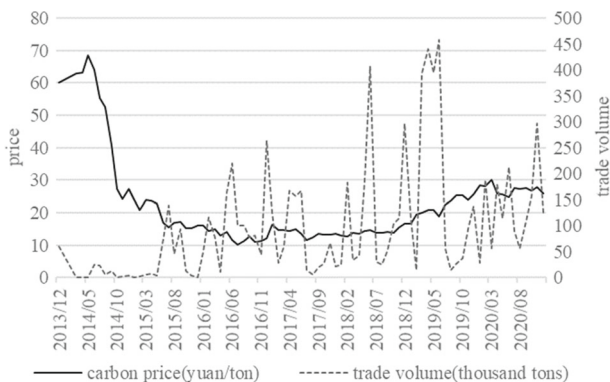

Fig. 2 Monthly price and monthly trade volume of Guangdong pilot carbon market

economic activities, especially industrial production, require a lot of energy. We used the CSI 300 and Industry Index of China to indicate national economic situation of China. The weekly data from March 2014 to December 2020 contained 318 observations after excluding no trading days and holidays, and the dataset was taken from the WIND and Choice databases. To exclude the interference of exchange rate fluctuations, we converted units of all variables into CNY based on the corresponding exchange rates. The weekly log return is calculated as $r_t = 100 \times log\left(\frac{P_t}{P_{t-1}}\right)$, where P_t and P_{t-1} are carbon emission prices, and are considered influence factors at time points t and $t - 1$ respectively. Table 1 displays a summary of statistics for asset returns.

The means of some returns are close to zero, while their standard deviations are relatively large. This indicates a degree of volatility. The average yield of WTI and BRENT was negative, probably because of geopolitical conflicts during the analysis period. The CSI 300 and Industry Index benefited from the growth of China's economy, and consequently showed positive average returns. In addition, the values of the excess kurtosis are all significantly larger than zero, especially for CER and WTI, which indicates that these returns have thicker tails than those of the normal distribution. Consequently, they are often affected by extreme events. The p values of the Jarque–Bera statistics also provided strong evidence of non-normality. The result of the Ljung-Box test shows that autocorrelation exists in most returns except the CSI 300 and Industry Index, while the ARCH test demonstrates that heteroscedasticity exists in most returns except CER and EUA. The augmented Dicky-Fuller unit root test indicated that all returns series are stationary.

4.2 Dependent structural analysis with the vine copula model

To obtain a purely dependent structure among the variables, we first adopted a univariate ARMA-GARCH model for each series, to remove autocorrelation and heteroscedasticity. According to the test results in Table 1, we selected appropriate types and order based on the AIC. The results show that the residuals of each model had no autocorrelation or heteroscedasticity.[6] The copula model can therefore be used for further research.

We explored the multidimensional dependent structure of all variables based on the results of the vine copula model, and used it to analyze the transmission paths of price risk among variables. As shown in Fig. 3, each node represents the uniform margin of a corresponding variable; and each edge represents a pair copula model for the connected nodes. Tree 1 shows the direct correlation between variable pairs, and the other trees reflect the indirect relationship between variables. EUA, Brent crude oil and the Industry Index are the key nodes in Tree 1, and connect other variables. The EUA and Industry Index are connected through Brent crude oil, which makes the latter crucial to direct and indirect transmission among variables. These three variables play a vital role in the entire structure. In Tree 2, the Industry Index-BRENT and EUA-BRENT pairs play major roles, as they connect with other pairs. In the whole structure, the energy market, the international carbon market and the Chinese economic situation all play key roles.

The parameters of the vine copulas, corresponding bivariate copula types, upper and lower tail dependence coefficients (λ_U and λ_L), and associated Kendall's τ for each level are summarized in Table 2. In the unconditioned copula structure of Tree 1, Kendall's τ coefficients are positive, except the pairs EUA-Natural Gas and WTI-Coal. This indicates that the majority of variables may change in the same direction. The Kendall's τ of WTI-Brent

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[6] Interested readers can contact the author for the results of ARMA-GARCH model.

Table 1 Descriptive statistics of the assets returns

	Cpr	WTI	BRE	CER	EUA	Gas	Coal	CSI	Ind
Mean	− 0.30	− 0.13	− 0.22	− 0.04	0.54	− 0.03	0.01	0.23	0.16
Median	0.00	0.37	0.12	− 0.45	0.66	− 0.24	− 0.07	0.28	0.42
Max	64.26	139.01	19.49	279.63	25.46	24.57	5.22	10.66	8.55
Min	− 54.67	− 163.08	− 36.27	− 52.33	− 32.12	− 30.82	− 2.24	− 14.02	− 14.77
S. D	11.78	12.73	4.92	17.35	5.82	4.82	0.85	3.22	3.33
Skewness	0.25	− 2.38	− 1.51	12.48	− 0.23	0.32	2.31	− 0.71	− 1.08
Kurtosis	5.36	125.27	14.33	205.21	7.55	16.33	13.53	5.58	6.36
J.B.(p)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LB-Q (12)	0.00	0.01	0.00	0.03	0.00	0.00	0.00	0.78	0.65
ARCH-LM (12)	0.00	0.00	0.00	1	0.73	0.00	0.00	0.00	0.00
ADF(p)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Cpr represents the carbon price of Guangdong ETS, WTI represents WTI crude oil futures prices, Bre. represents the brent oil futures prices, CER represents CER futures price, EUA represents EUA futures price, Gas represents Chinese natural gas prices, Coal represents Chinese coal price prices, CSI represents Chinese coal price index, Ind represents Industry Index of China. J.B. is the p-value of Jarque–Bera statistics, LB-Q is the p-value of Ljung-Box test with lagged order 12, ARCH-LM is the p-value of ARCH test with lagged order 12, ADF is the p-value of the augmented Dicky-Fuller unit root test
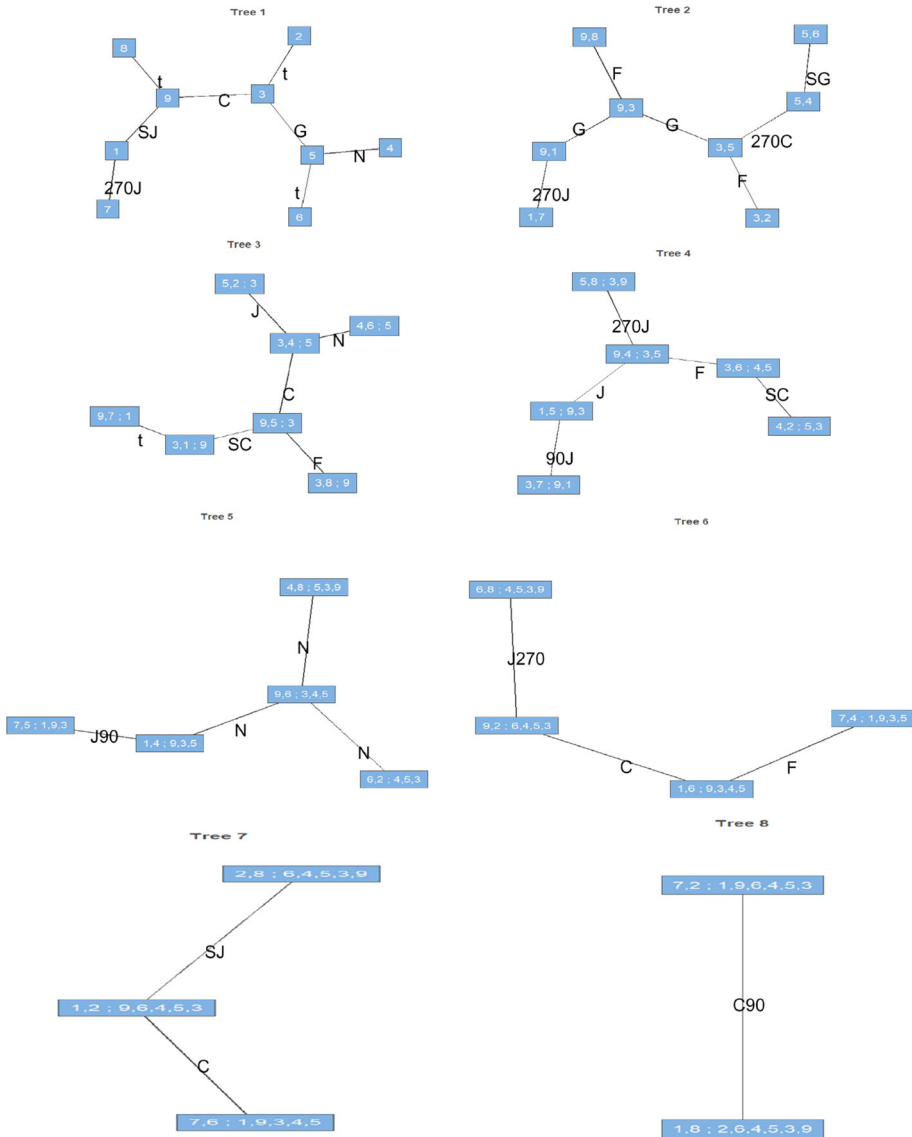
Fig. 3 Vine structures of Guangdong pilot carbon market. *Note:* each node denotes the marginal distribution of the corresponding variable, each edge represents a bivariate copula for two connected nodes, and the label is the family of corresponding bivariate copula. 1 = carbon price of Guangdong ETS, 2 = WTI, 3 = BRENT, 4 = CER, 5 = EUA, 6 = Natural Gas, 7 = Coal, 8 = CSI300, 9 = Industry Index

is 0.68, and their λ_u and λ_L are 0.42, respectively. This means that WTI and Brent crude oil futures prices are highly likely to change in the same direction, and to respond to the impact of extreme events from different directions (positive and negative) in a similar way. The WTI and Brent crude oil futures prices can both reflect the changes of international oil prices to a significant extent. It can therefore be deduced that there is a strong linkage in the same

Table 2 The estimation result of vine copula model of Guangdong pilot carbon market

Tree	Edge	Copula	Par.1	Par.2	τ	λ_u	λ_L
1	5,6	t-copula	− 0.11 (0.06)	5.28 (1.58)	− 0.07	0.03	0.03
	3,2	t-copula	0.88 (0.02)	7.19 (2.99)	0.68	0.42	0.42
	9,8	t-copula	0.91 (0.01)	6.51 (2.33)	0.73	0.57	0.57
	5,4	Gaussian copula	0.27 (0.06)	–	0.18	–	–
	3,5	Gumbel copula	1.24 (0.06)	–	0.20	0.25	–
	1,7	rot270 Joe copula	− 1.16 (0.06)	–	− 0.08	–	–
	9,1	survival Joe copula	1.08 (0.04)	–	0.08	–	0.10
	9,3	Clayton copula	0.31 (0.10)	–	0.13	–	0.11
2	3,8;9	Frank copula	− 0.12 (0.33)	–	− 0.01	–	–
	5,2;3	Frank copula	− 0.31 (0.34)	–	− 0.03	–	–
	4,6;5	survival Gumbel copula	1.09 (0.05)	–	0.08	–	0.11
	3,4;5	rot270 Clayton copula	− 0.06 (0.08)	–	− 0.03	–	–

Table 2 (continued)

Tree	Edge	Copula	Par.1	Par.2	τ	λ_u	λ_L
	9,5;3	Gumbel copula	1.06 (0.04)	–	0.05	0.07	–
	9,7;1	rot270 Joe copula	– 1.06 (0.06)	–	– 0.03	–	–
	3,1;9	Gaussian copula	0.05 (0.06)	–	0.03	–	–
3	5,8;3,9	Frank copula	– 0.14 (0.37)	–	– 0.01	–	–
	4,2;5,3	Joe copula	1.07 (0.06)	–	0.04	0.08	–
	3,6;4,5	Gaussian copula	– 0.01 (0.06)	–	– 0.01	–	–
	9,4;3,5	Clayton copula	0.05 (0.08)	–	0.03	–	0.00
	1,5;9,3	survival Clayton copula	0.10 (0.09)	–	– 0.05	0.00	–
	3,7;9,1	t-copula	0.01 (0.06)	7.83 (4.09)	0.00	0.02	0.02
4	4,8;5,3,9	rot270 Joe copula	– 1.02 (0.05)	–	– 0.01	0.00	–
	6,2;4,5,3	survival Clayton copula	0.12 (0.09)	–	0.06	0.00	–
	9,6;3,4,5	Frank copula	0.05 (0.35)	–	0.01	–	–
	1,4;9,3,5	Joe copula	1.05 (0.05)	–	0.03	0.06	–
	7,5;1,9,3	rot90 Joe copula	– 1.03 (0.06)	–	– 0.02	–	–

Table 2 (continued)

Tree	Edge	Copula	Par.1	Par.2	τ	λ_u	λ_L
5	6,8;4,5,3,9	Frank copula	0.56 (0.34)	–	0.06	–	–
	9,2;6,4,5,3	survival Clayton copula	0.01 (0.08)	–	0.00	0.00	–
	1,6;9,3,4,5	Gaussian copula	1.02 (0.04)	–	0.02	0.03	–
	7,4;1,9,3,5	rot90 Joe copula	– 1.05 (0.06)	–	– 0.03	–	–
6	2,8;6,4,5,3,9	rot270 Joe copula	– 1.01 (0.05)	–	– 0.01	–	–
	1,2;9,6,4,5,3	Clayton copula	0.03 (0.08)	–	0.01	–	0.00
	7,6;1,9,3,4,5	Frank copula	0.45 (0.35)	–	0.05	–	–
7	1,8;2,6,4,5,3,9	Gaussian copula	0.01 (0.06)	–	0.00	–	–
	7,2;1,9,6,4,5,3	Clayton copula	0.07 (0.08)	–	0.03	–	0.00
8	7,8;1,2,6,4,5,3,9	rot90 Clayton copula	– 0.02 (0.08)	–	– 0.01	–	–

1 = cprice, 2 = WTI,3 = BRENT, 4 = CER, 5 = EUA, 6 = Natural Gas, 7 = Coal, 8 = CSI300, 9 = Industry Index. The table reports parameter estimates for vine copula models and their standard errors (in brackets). For t-copula, Par.1 denotes correlation ρ and Par.2 represents degree of freedom v, respectively. And τ, λ_u and λ_L denote the Kendall coefficients, upper tail dependence coefficient and lower tail dependence coefficient, respectively

direction between WTI and Brent crude oil futures prices. The Kendall's τs of EUA-Natural Gas and WTI-Coal are negative, but small. The correlation of negative changes between them is not strong, and the tail correlation is similar. Crude oil and coal are two of China's main energy sources, and there may be a substitution effect between them. The Kendall's τ of CSI 300-Industry Index is 0.73, and their λ_u and λ_L are 0.58, which shows a very high similar trend and tail correlation. The CSI 300 reflects the development trend of China's financial market to an extent, and the Industry Index embodies the country's industrial situation. The continuous improvement of the Chinese industrial sector and the rapid growth of its output value are important drivers of national economic growth, which means that the CSI 300 has a strong positive correlation with the Industry Index. The Kendall's τ coefficients for EUA-BRENT, BRENT-Industry Index and CER-EUA are 0.20, 0.13, and 0.18 respectively. CER and EUA are the two major derivative products of the EU ETS, and there exists a positive correlation between them. In Tree 1, the gaussian copula connects CER and EUA, and there is no upper or lower tail correlation between them. The other Kendall's τ coefficients are all less than 0.1, indicating that the correlation between them is small. In addition, the high-dimensional copula structure reflects the indirect correlation of variables and the transmission path of influence. In the second copula structure, the Kendall's τ coefficients are not more than 0.1. In the higher copula structures, all Kendall's τ coefficients are less than 0.1 and some variables are independent of each other, which demonstrates that there is no obvious correlation in the high-dimensional copula structure. There is therefore an obvious direct correlation between the variables in this study, and the indirect correlation and conduction relationship are not strong.

In Tree 1, Coal and the Industry Index are directly linked to the carbon price in the Guangdong pilot ETS. The carbon price is not directly linked to the crude oil market, but is linked to it indirectly, through the Industry Index. The international carbon price of the EUA is directly related to the crude oil market, and indirectly related to the Industry Index through it. In Tree 2, the carbon price is correlated with the WTI crude oil futures price, on the condition of the Industry Index. On the condition of carbon price, the Industry Index is correlated with Coal. The Chinese industrial sector accounts for a large percentage of the country's coal use, and is a key area in its carbon emission reduction plan. Consequently, many of China's enterprises have signed up to the ETS. At present, China is the world's largest oil importer, and the crude oil market has an indirect impact on the carbon price in the Guangdong pilot ETS through its direct impact on China's industrial production. The risks in the crude oil market are transmitted directly to the international carbon market. This shows that compared to the international carbon market, the Guangdong pilot ETS is currently a regional market, and has a less direct correlation with the international crude oil market. It is notable that China's natural gas price is directly linked to the EUA in Tree 1. Their Kendall's τ coefficient is -0.07, and their tail dependence coefficients (λ_U and λ_L) are both 0.03.

4.3 Risk spillover from other markets to the Guangdong pilot market

Table 3 shows the upside VaR at the 95% quantile, and the downside VaR at the 5% quantile for each return series. The absolute value of VaR is much higher in the Guangdong pilot market than in other markets, indicating that it is relatively high risk. A plausible reason for this is that, as the previous analysis shows, the carbon price in China is relatively low but highly volatile. This also indirectly indicates that the pricing mechanism and trading system of China's carbon market need to be further improved.

Table 3 The upside VaR (95 percent quantile) and the downside VaR (5 percent quantile) of returns

	Cpr	WTI	BRE	CER	EUA	Gas	Coal	CSI	Ind
VaRup	15.26	− 5.88	6.23	8.98	8.94	4.34	0.81	5.13	4.93
VaRdown	− 16.68	− 7.98	− 7.41	− 9.97	− 8.15	− 4.24	− 0.87	− 4.88	− 4.95

Table 4 The bivariate copula and corresponding parameters

	type	AIC	par1	par2	τ	λ_u	λ_L
cprice-WTI	Gumbel copula	0.65	1.05***(0.04)	–	0.04	0.06	–
cprice–BRENT	Gumbel copula	0.18	1.05*** (0.04)	–	0.05	0.07	–
cprice-CER	Gumbel copula	− 2.03	1.04 *** (0.04)	–	0.04	0.05	–
cprice-EUA	Gumbel copula	− 1.95	1.08*** (0.04)	–	0.07	0.10	–
cprice-Gas	Gumbel copula	1.13	1.03*** (0.04)	–	0.03	0.04	–
cprice-Coal	t-copula	0.51	− 0.13** (0.06)	10.00** (4.31)	− 0.08	0.00	0.00
cprice-CSI300	Clayton copula	− 1.09	0.15* (0.08)	–	0.07	–	0.01
cprice-Industry Index	Clayton copula	− 2.50	0.17* (0.09)	–	0.08	–	0.02

cprice represents carbon price of Guangdong ETS, *** Statistical significance at the 1% level, ** Statistical significance at the 5% level, * Statistical significance at the 10% level

To analyze the risk spillover from other markets to China's carbon market, we calculated the conditional VaR (CoVaR) based on the bivariate copula. This study uses Reboredo and Ugolini's (2016) definition of CoVaR as the VaR of carbon price, conditional on other markets experiencing an extreme movement. We chose the appropriate bivariate copula from the basic copula families, and the corresponding rotation copula according to the value of AIC.[7] The fitted optimal copula and their parameter estimation are reported in Table 4. The absolute value of Kendall's τs is less than 0.1, indicating that the correlation between the carbon market and other markets is relatively small. Interestingly, the Kendall's τ of cprice-Coal is less than zero, but the other Kendall's τs are greater. Coal is still the main energy source in China, and its carbon emissions are substantial. If coal prices are increased, companies' running costs will be higher, and they will look for alternative clean energy sources. This will reduce both emissions and the demand for carbon emission rights. An increase in the ETS' carbon price will also raise the costs of carbon emissions for enterprises, encouraging them to reduce their coal use. From these aspects, a definite negative correlation between the prices of carbon and coal emerges. Further, there is a low and asymmetric tail dependence between the carbon market and other markets, according to the tail dependence coefficients. China's carbon market has small upper tail correlations with the international carbon, crude oil, and natural gas markets, but no lower tail correlation. The largest upper tail coefficient of cprice-EUA is 0.10, which shows that there is co-movement between the extreme rise of both EUA futures prices and carbon prices in the Guangdong pilot ETS. In addition, the carbon price in the Guangdong ETS has small lower tail correlations with the CSI 300 and Industry Index, but no upper tail correlation. The Chinese carbon emissions market (represented by the Guangdong pilot carbon market) is therefore relatively independent, and exhibits regional and policy-driven characteristics.

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[7] Basic copula families include Clayton, Gaussian, Gumbel, Frank and Student's t.

This study calculated the upward CoVaR at the 5% quantile and the downward CoVaR at the 95% quantile. Using Eq. (12), the degree of risk spillover from other markets to the carbon market was analyzed according to the size of %ΔCoVaR. Figure 4 and Table 5 display the respective dynamic and static CoVaRs of carbon price, conditional on other markets showing extreme movement. They show an asymmetric risk spillover from other markets to the carbon market, with varied effects. The %ΔCoVaR-U of cprice-WTI, cprice-BRENT, cprice-CER, cprice-EUA and cprice-Gas are 51.32%, 38.32%, 60.47%, 61.60% and 43.55% respectively, indicating that the crude oil, natural gas and international carbon markets have significant upside risk spillover effects on the pilot carbon market in Guangdong. Soaring international crude oil, carbon and natural gas prices are likely to lead to a rise in carbon prices in China. The %ΔCoVaR-D of cprice-WTI, cprice-BRENT, cprice-CER, cprice-EUA and cprice-Gas are, however, 0.75%, 0.85%, 0.45%, 1.07% and 0.25% respectively: much smaller than their %ΔCoVaR-U. The crude oil, natural gas and international carbon markets have a weak downside risk spillover effect on the Guangdong pilot carbon market. The cprice-CSI 300 and cprice-Industry Index's %ΔCoVaR-U are both 1.23%, indicating a small upside risk spillover effect. The %ΔCoVaR-D of cprice-CSI 300 and cprice-Industry Index are 3.88% and 6.76% respectively. Factors that reflect China's economic situation are therefore seen to have asymmetric and limited risk spillover effects on the Guangdong ETS, and the downside risk spillover effect is greater than the upside. The %ΔCoVaR-U of cprice-Coal is negative at − 11.21%, which shows that the coal market has an upward risk hedging effect on the Guangdong ETS. An extreme rise in the coal price will hinder an extreme rise in the carbon price, which is consistent with the theoretical analysis that the carbon market is negatively correlated with the coal market. The %ΔCoVaR-U of cprice-Coal is − 0.084. From the perspective of absolute value, the upward risk spillover effect of the coal market on the carbon market is very small. But the CoVaR-U between them is also small, which makes the %ΔCoVaR-U relatively large. The characteristics of other markets' risk spillover to the carbon market are similar to their tail dependence characteristics.

5 Discussion

5.1 Comparison and contrast

Energy prices, the international carbon price and the international carbon market are the main factors that affect the carbon market, and some previous studies have focused specifically on the relationship between the energy sector and the carbon market (Fleschutz et al., 2021; Ji, Wang, et al., 2019; Ji, Xia, et al., 2019). In the correlation structure between the carbon market and other markets, the crude oil market, international carbon market and China's macroeconomy are all important. In the vine structure, BRENT, EUA and the Industry Index are crucial factors. The carbon price is directly linked to the Industry Index, and through it indirectly linked to the crude oil market. The result is the same as previous study that the energy market affects the carbon market through the intermediary effect of the stock market (Wang & Zhao, 2021). The Kendall's τs and tail correlation coefficients between the carbon price and other factors are small, and the impact of other markets on the carbon market may have a time lag. In different timescales, the effects of electricity prices and the stock index appear comparatively early, but the impacts of coal, oil and gas prices lag behind (Zhu et al., 2019). CSI300 and the Industry Index have asymmetric and limited risk spillover effects on the carbon market, and the upside risk spillover effect is smaller than the
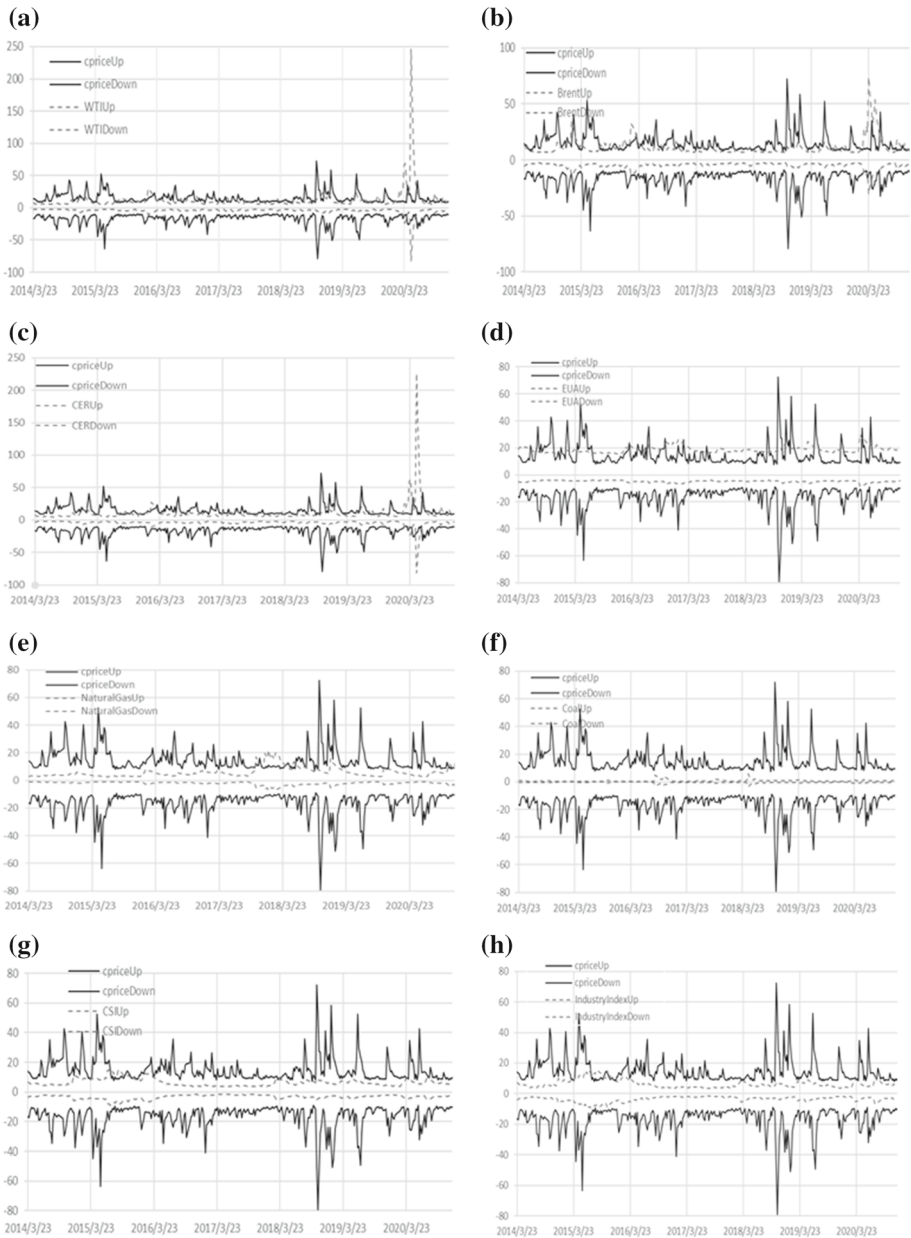
Fig. 4 Dynamic VaR of carbon price and CoVaR conditional on other markets. *Note:* cprice represents the VaR of carbon price in Guangdong ETS, and subfigures A, B, C, D, E, F, G, H show the VaR of carbon price conditional on the fact that WTI, Brent, CER, EUA, Natural Gas, Coal, CSI300, Industry Index markets experienced an extreme movement

Table 5 Risk spillover from other markets to the Guangdong pilot carbon market

	Cprice-WTI	Cprice-BRENT	Cprice-CER	Cprice-EUA	Cprice-Gas	Cprice-Coal	Cprice-CSI300	Cprice-Industry Index
CoVaR_D	– 4.560	– 5.029	– 5.465	– 4.948	– 2.189	– 0.579	– 3.254	– 3.551
Δ CoVaR_D	0.034	0.043	0.024	0.052	0.005	0.000	0.122	0.225
%ΔCoVaR_D	0.75	0.85	0.45	1.07	0.25	0	3.88	6.76
Rank	5	4	6	3	7	8	2	1
CoVaR_U	12.705	11.649	17.379	18.987	6.592	0.663	6.514	6.397
ΔCoVaR_U	4.309	3.228	6.520	7.238	2.000	– 0.084	0.079	0.076
% ΔCoVaR_U	51.32	38.32	60.47	61.60	43.55	– 11.21	1.23	1.23
Rank	3	5	2	1	4	8	6	7

The order is based on the value of %ΔCoVaR, cprice represents carbon price of Guangdong ETS

downside. The characteristics are similar to those of the European market. In Europe, the uncertainty of the crude oil market has greater influence on the carbon market than stock market uncertainty does, and its upper tail risk spillover is greater than the lower tail risk spillover in terms of absolute value (Yuan & Yang, 2020). Wen et al. (2020a, b), Wen & Hu et al. (2020)found significantly negative long- and short-term asymmetric relationships between the carbon emission trading market and stock market in China, but no significant effects passing from the stock index to the carbon emission trading price. This is a somewhat different from our conclusion. The plausible reason maybe that the pilot market studied is different. There is a small negative correlation between coal and the carbon market. The influence of the carbon market on the coal market is reliant on policy, and lasts for about one month, and there is a weak synchronization in the short term (Yin et al., 2021). Other energy markets have had significant upside risk spillover effects and weak downside risk spillover effects on the Guangdong pilot carbon market. Dai et al. (2021) also found that spillovers in the higher-order instances were strong when the carbon and energy markets had a bullish status. The absolute values of the impact of oil prices are much greater than those of gas prices (Duan et al., 2021). Oil prices are positively correlated with carbon prices, and coal prices are negatively correlated, which shows that financial markets have a limited effect on carbon prices (Ji et al., 2021). Our article further verifies these conclusions from a broader perspective by combining copula model and CoVaR approach. According to the results of this paper, we can not only grasp the transmission mechanism between carbon market and other markets as a whole, but also understand the specific characteristics of risk spillover between carbon market and other markets.

5.2 Validation test

We chose the Guangdong pilot market as our research object because of its large trading volume and mature financial market. To prove the generality of our results, a validation test was carried out using China's national average carbon price, which this article calculated from the transaction prices of the seven pilot markets using their transaction volume as the weight. There are some differences in vine structure between the national carbon market and the Guangdong pilot market. BRENT and EUA are the key nodes in the vine structure of the national carbon price, which is directly connected to the crude oil market. Although there are some changes in the vine structure, the correlations between variables are similar to those in the previous results. The Kendall's τ coefficients are all less than 0.1, and there is a low tail dependence between national average carbon prices and other markets according to the tail dependence coefficients. We therefore reached the same conclusion: China's carbon market is regional and policy oriented.

Table 6 shows the static CoVaR of the national average carbon price on the condition that extreme events are occurring in other markets. There is an asymmetric risk spillover from other markets on the national carbon market. The values of %ΔCoVaR-D are smaller than those of %ΔCoVaR-U. Most %ΔCoVaR-D values are close to zero. The decline of the price in other markets will not lead to a sharp drop in the national average carbon price. The %ΔCoVaR-Us of Cprice-WTI, Cprice-BRENT and Cprice-CER, are 64.53 percent, 30.87 percent and 14.77 percent respectively. Evidently, an extreme rise in the crude oil and international carbon prices will cause a rise in the national average carbon price. This is the same result as that of the Guangdong pilot market. The %ΔCoVaR-U of Cprice-Natural Gas is, however, small at 2.56 percent and there is little upward risk spillover from the natural

Table 6 The risk spillover from other markets to the national average carbon price

	Cprice-WTI	Cprice-BRENT	Cprice-CER	Cprice-EUA	Cprice-Gas	Cprice-Coal	Cprice-CSI300	Cprice-industry index
CoVaR-D	− 5.03	− 5.05	− 5.84	− 4.80	− 2.36	− 0.58	− 3.10	− 3.22
Δ CoVaR-D	0.00	0.00	− 0.01	0.00	− 0.03	− 0.00	− 0.02	− 0.01
%ΔCoVaR-D	0.00	0.00	0.12	0.00	1.14	0.51	0.53	0.30
ranked	6	7	5	8	1	3	2	4
CoVaR-U	13.61	10.28	12.25	10.65	4.54	0.96	7.99	6.72
ΔCoVaR-U	5.34	2.43	1.58	0.02	0.11	0.01	0.00	0.60
% ΔCoVaR-U	64.53	30.87	14.77	0.19	2.56	0.71	0.00	9.82
Ranked	1	2	3	7	5	6	8	4

Cprice is the national average carbon price

gas price to the national average carbon price. There is also little risk spillover from CSI300 and the Industry Index to the national average carbon price.

5.3 Policy implications

The analysis in this study shows that China's carbon market, represented by the Guangdong pilot market, currently exhibits regional characteristics, and is more policy-oriented than market-driven. There is no significant risk spillover effect among pilot carbon markets in China (Zhu et al., 2020). The change of carbon price is closely related to emission allocation policies and the announced policies are expected to raise future carbon price (Song et al., 2018). The quota system and pricing mechanism are still in the process of being improved, meaning that there is relatively poor transmission between China's carbon market and other markets. Effective carbon pricing and emissions trading instruments would be helpful to reduce carbon abatement costs and sustaining long-term economic development (Nassani et al., 2019). China's government should strengthen the linkage among the pilot projects and lay a solid foundation for establishing a carbon market for diverse industries. Through a series of policies release, the trading system of China's carbon market is being improved, however, it still suffers from a lack of sufficient liquidity (Song et al., 2019). If China wants to further dominate international cooperation in emission reduction, it must establish a more transparent, reasonable and fair international carbon trading market. Additionally, China's main energy source is still coal, moreover the energy consumption played an important role in agricultural production (Qureshi et al., 2016). Hence, the use of fossil energy cannot be blindly prohibited, and it should be gradually replaced by other cleaner energy sources. An appropriate carbon price plays an important role in this process.

Haxhimusa and Liebensteiner (2021) found that, during full lockdown periods, COVID-19 reduced more carbon emissions than electricity demand, indicating that a reduction in demand can offset large emissions by marginal displacing coal. The decline in carbon emissions from COVID-19 is, however, temporary, and the global economy will slowly recover. Countries should seize the opportunity to promote a green and low-carbon structural transformation of the economy. Adjusting the price gap between fossil and renewable energy sources (e.g., by adopting more stringent carbon pricing) and providing residents with appropriate tax relief, are ways in which the impact of this could be alleviated, and this should be a key part of environmental policy in the post-COVID-19 era (Jia et al., 2021). The authorities should adopt policies to encourage residents to engage in carbon reduction activities (Khan et al., 2016).

The Chinese government should support renewable energy while curbing the development of carbon-intensive industries. Investors began to consider low-carbon assets as an appealing investment opportunity after the Paris Agreement, but have not yet penalized carbon-intensive assets (Monasterolo & de Angelis, 2020). The policies that guide investors to invest in low-carbon green industries need to be improved. The crude oil market has significant upward risk spillover effects on China's carbon market. The national oil industry should therefore improve its oil reserve to prevent both an unreasonable rise in the carbon price if the oil price rises rapidly, and the knock-on effect of greatly increased production costs for enterprises.

6 Conclusion

As of August 2020, the 7 pilot carbon markets covered nearly 3000 key emission enterprises in more than 20 industries (including electricity, steel and cement production), with an accumulated trading volume of more than 4 billion tons and a cumulative turnover of more than 9 billion CNY.[8] In February 2021, the administrative measures for carbon emission rights trading (Trial) issued by the Ministry of Ecology and Environment were put into effect, officially opening the national carbon market for business. With the country's signing of the Regional Comprehensive Economic Partnership (RECP), China's market will further integrate with other global markets, including the carbon market. International institutional investments and enterprises will also pay close attention to, and participate in, China's carbon market. Driven by the Chinese government's goal of carbon neutrality, the country's carbon emission trading markets should develop rapidly. To reduce the risk associated with price volatility, investors and enterprises must therefore pay attention to the factors that influence carbon prices, and the relationship structure that exists between them.

Few studies have, however, analyzed the high-dependence structure and risk spillover effects of the carbon market from the perspective of multiple other markets, and this study fills that gap. Based on 2014–2020 trading data, the study analyzed the multi-dimensional correlation structure between carbon prices in the Guangdong pilot market and eight influencing factors from three perspectives (the international carbon market, energy prices and Chinese economic conditions) using the ARMA-GARCH-vine copula model. The results indicated that EUA, BRENT and the Industry Index are the key nodes in the vine structure, as they connect other variables. The crude oil and international carbon markets, as well as the Chinese economic situation, all play important roles in the structure as a whole. The former has an indirect impact on carbon price through its direct impact on industrial production, and its risks can be transmitted directly to the international carbon market. This shows that the Guangdong carbon market is, to an extent, regional. The weak correlation between the Guangdong pilot market and other markets also shows that China's ETS has regional and policy-driven characteristics. Finally, we analyzed the risk spillover from other markets to the Guangdong pilot carbon market, using the copula-CoVaR model, and found that other markets have clear asymmetric risk spillover effects. Compared to the downside spillover, the upside risk spillover effects of WTI, Brent, CER, EUA and natural gas on the Guangdong pilot carbon market were relatively large. The CSI 300 and Industrial Index, which reflect China's overall economic conditions, have relatively small upward and downward risk spillover effects on the Guangdong pilot carbon market, indicating that the latter is not closely linked to the social economy.

By applying the methodology mentioned previously, this study has reached the following findings. China's carbon market is directly affected by domestic economic conditions and industrial production, but the risk spillover between them is small, and the downward effect is greater than the upward. This further validates the conclusion that the Guangdong market is regional and policy-driven. If faced with downward pressure from the economy, the government may loosen the regulation of the carbon market. The international crude oil market has a great upward risk spillover effect on China's carbon price, mainly because it affects the production cost for enterprises. The international crude oil market, however, has a direct impact on the international carbon market. The international carbon market has an upward risk spillover effect on China's carbon market, but the correlation is small. Interestingly, the

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[8] Measures for the administration of Carbon Emission Trading (for Trial Implementation), xinhuanet, 2021–01-01, http://www.xinhuanet.com/energy/2021-01/07/c_1126954718.htm.

rise in coal prices leads to substitution with other energy sources, which reduces carbon prices. The correlation between China's carbon market and other markets is very small; the former is still regional and policy-driven, and needs to be improved. Other influencing markets can be divided into three categories, according to their risk spillover effect characteristics. The first contains the crude oil (WTI and Brent), natural gas, and international carbon (CER and EUA) markets, which have clear upward risk spillover effects on the pilot market, but a small downward risk spillover effect. The second is the factors that reflect China's economic situation (the CSI 300 and Industrial Index). These markets have small risk spillover effects on the pilot market, with the downward effect greater than the upward. The third is the coal market, which shows a negative correlation between the ETS carbon price and the coal price index.

This study makes several key contributions. The high-dimensional structure of the vine copula can effectively reflect the dependence structure and risk transmission path between the carbon price and eight other factors. This can help investors and policy makers understand the relationship between the carbon market and other related markets from a broader perspective, so they can make informed investment decisions and policies. According to the risk spillover characteristics, we divided the main factors affecting the carbon market into three categories, and undertook a theoretical analysis. The reasons behind the three different risk spillover characteristics summarized previously, and the risk transmission path between carbon markets and other markets, still need to be studied further, and are of great significance to the theoretical research and practical development of carbon markets. Our results also provide several suggestions for enterprises and policy makers. First, enterprises with a large carbon emission demand should establish a system to manage it, and schedule carbon emission for different time periods where possible. This paper can help carbon asset managers understand the dependence structure and risk transmission path of the carbon market and other related markets. Second, carbon prices are highly volatile, so enterprises should try to prevent price risk. This study provides a basis for risk aversion and asset portfolio construction for participants in the Chinese carbon market, which many improved risk management models such as the support vector machine can build upon (Abedin et al., 2019). Third, in the construction of China's national carbon market, a fairer and more concise trading mechanism should be established on the basis of efficiency, so as to attract more domestic and foreign investors and build a global carbon emission market that has benign interaction with other markets. To mitigate risk spillover effects, the government should maintain reasonable oil reserves and guard against the sharp increase in carbon price caused by high oil prices, which in turn lead to a sharp rise in enterprise costs and an inevitable impact on the social economy.

Our research is a valuable reference for the in-depth study of China's carbon market, and the unresolved problems and creative discussions it raises provide direction for future research. First, the mechanism of three kinds of influencing factor needs more profound theoretical discussion and research. Second, fossil fuels (especially oil) will continue to account for a high proportion of China's energy mix in the coming decades. This creates the practical problem of how to establish a mechanism at both market and regulatory levels, to prevent carbon price hikes and economic instability caused by abnormal oil price increases. Green and low-carbon development is the future, but it is difficult to balance long-term climate goals with short-term economic development. Because our research object is limited to the Guangdong pilot carbon market, the national average price in the validation test may not reflect the situation of the national carbon market, because each pilot market differs according to the local economic structure and market characteristics. To confirm the generality of the results obtained in this paper, we will further analyze the national carbon market in China. We

will also investigate specific risk aversion methods and reasonable asset portfolio building for carbon assets in the future.

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