RESEARCH ARTICLE

Assessing the extreme risk spillovers to carbon markets from energy markets: evidence from China

Ruirui Wu[1] · Zhongfeng Qin[1,2]

Abstract

Previous studies point to the impact of energy market on carbon market under normal market conditions, but little is known about the impact under extreme market conditions. Motivated by these concerns, we aim to investigate the extreme risk spillovers to carbon markets from traditional fossil energy and new energy markets in China. After using copula model to obtain nonlinear tail dependence structure between carbon and energy markets, we compute conditional Value-at-Risk (CoVaR) to quantify extreme risk spillovers. The results indicate that (i) the risk spillovers from both traditional fossil energy and new energy markets to carbon markets are obviously larger when extreme events cause large shocks to energy markets; (ii) there are risks in the opposite direction in carbon markets when carbon-intensive energy markets are under extreme market conditions, but the direction of risks in carbon markets is uncertain when low-carbon energy markets are under extreme market conditions; (iii) the extreme risk spillovers to carbon markets from energy markets are regionally heterogeneous not only in magnitude but also in direction; (iv) energy markets prefer to transmit extreme risks to more liquid carbon markets. These new findings have valuable implications for both policymakers and participating enterprises in carbon markets.

Keywords Extreme risk spillovers · China's regional carbon markets · Traditional fossil energy markets · New energy markets · Copula model · Conditional Value-at-Risk (CoVaR)

Introduction

Climate change that resulted from the emissions of greenhouse gases, mainly CO_2, has received a widespread concern (Jian et al. 2019). The carbon market is considered to be a vital instrument to reduce CO_2 emissions (Li et al. 2021; Wang and Yan 2022). Compared with other CO_2 emission reduction measures, the carbon market has advantages of high efficiency and low social cost (Zhu et al. 2021). As a policy-oriented market, the carbon market is a special energy commodity market (Tan et al. 2020). Theoretically, both traditional fossil and new energy markets have an impact on carbon markets. Carbon market is naturally affected by traditional fossil energy markets, since CO_2 emissions are largely attributed to fossil energy consumption (Zhang et al. 2019; Yang et al. 2020). More precisely, rising fossil energy prices decrease the demand for fossil energy and CO_2 emissions, leading to the decline in the demand for carbon allowances and carbon price (Wu et al. 2022a). Carbon market is also affected by new energy market. New energy including wind energy, solar energy, hydroelectricity, and biomass energy is an alternative to traditional fossil energy and plays an important role in reducing CO_2 emissions (Adebayo et al. 2022). Higher new energy price increases the cost of new energy consumption, which causes enterprises to purchase more carbon allowances to complete emission reduction tasks and thus drives higher carbon price (Lin and Chen 2019).

According to the International Carbon Action Partnership (ICAP), carbon markets had been established in 25 jurisdictions and had covered 17% of global greenhouse gas emissions by the end of 2021 (ICAP 2022). As the world's largest carbon emitter, China has also established eight regional carbon markets as the major means of reducing CO_2 emissions and achieving carbon neutrality targets (Wu et al. 2022b;

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✉ Zhongfeng Qin
  qin@buaa.edu.cn

[1] School of Economics and Management, Beihang University, Beijing 100191, China

[2] Key Laboratory of Complex System Analysis, Management and Decision (Beihang University), Ministry of Education, Beijing 100191, China

Zhu et al. 2022). Until the end of 2020, China's regional carbon markets had accumulated a turnover of 10.431 billion CNY by covering 445 million tons of CO_2 emissions.[1] With the development of China's regional carbon markets, the increasing traditional fossil energy and new energy companies are participating in carbon trading. Specially, traditional fossil energy has occupied a dominant position in China's energy consumption. In 2020, the proportions of coal, oil, and natural gas consumption were 56.8%, 18.9%, and 8.4%, respectively.[2] China is also a major consumer of new energy. For instance, China contributes around half of the global growth in wind energy and solar energy (Jiang and Chen 2022). Thus, understanding the impact of traditional fossil energy and new energy markets on carbon market is particularly relevant for China.

In recent years, some extreme events such as trade disputes between China and the United States have increased uncertainty and caused frequent large fluctuations in energy markets, resulting in extreme market conditions. Unlike normal market conditions, the risk transmission between markets under extreme market conditions is more disruptive and can cause unexpected losses, as in the case of the 2008 global financial crises (Uddin et al. 2020). Thus, the relationship between energy and carbon markets under extreme market conditions may be more complicated than under normal market conditions. Moreover, fluctuations in energy markets under extreme market conditions can lead to significant volatility in carbon market, which discourages participants in carbon market and thus weakens the effectiveness of carbon market in reducing emissions. In this context, it is meaningful to investigate how carbon market behaves when energy markets are under extreme market conditions. As extreme risk spillover can directly characterize the relationship between markets under extreme market conditions, this work aims to explore the extreme risk spillovers to carbon markets from energy markets.

In term of methods, existing literature focusing on the relationship between carbon and energy markets have some limitations. First, multivariate GARCH models (e.g., Zhang and Sun 2016; Chang et al. 2019), Diebold-Yilmaz spillover index (e.g., Dutta et al. 2018; Tan et al. 2020), and time-varying VAR model with stochastic volatility (e.g., Gong et al. 2021; Zhao et al. 2021) have been mainly employed to analyze time-varying spillovers. Although these methods are renowned for their meticulousness and practicality, they are based on conditional mean estimators, focus on normal market conditions, and assume that average shocks affect the relationship between markets. Actual shocks can be much larger than average shocks, especially under extreme market

conditions, and can cause severe risk contagion, showing the necessity of exploring large shocks under extreme market conditions. Second, linear methods are frequently used, mainly including ordinary least squares regression model (e.g., Alberola et al. 2008; Fan and Todorova 2017), vector autoregressive model (e.g., Kumar et al. 2012; Zeng et al. 2017), and quantile regression model (e.g., Hammoudeh et al. 2014; Ren et al. 2022). However, financial time series typically present volatility clustering and nonnormality under extreme market conditions, resulting in a complex nonlinear relationship between financial markets.

Existing literature has also discussed the extreme risk in carbon market by using Value-at-Risk (VaR). On this subject, extreme value theory (EVT) is often used to estimate marginal distribution to further compute VaR (Mi and Zhang 2011; Wang and Yan 2022). EVT assumes that samples are independent and identically distributed. However, many financial time series have autocorrelated and heteroscedastic characteristics and therefore cannot meet this assumption. Furthermore, VaR can only measure the isolated extreme risk in individual financial market, but cannot measure the extreme risk spillovers between multiple markets.

In light of the above, the methods used in this work are as follows. First, this work uses the autoregressive moving average (ARMA)-generalized autoregressive conditional heteroskedasticity (GARCH) model with Student-t innovations to estimate marginal distributions. This model can well capture characteristics of autocorrelation, heteroscedasticity, and fat-tail. Then, this work applies copula model based on marginal distributions to identify nonlinear tail dependence structure between carbon and energy markets. Finally, this work computes CoVaR to quantify the extreme risk spillovers to carbon markets from energy markets.

The contributions of this work mainly have three aspects. First, to the authors' best knowledge, this work is the first to measure the extreme risk spillovers to carbon markets from energy markets. Contrary to the previous research concentrating on normal market conditions, this work clarifies the risk transmission to carbon markets from energy markets under bullish and bearish market conditions, i.e., upward and downward risk spillovers, by computing CoVaR at the 95% and 5% confidence levels. It is beneficial for policymakers and participating enterprises in carbon markets that are mostly interested in tail risk management. Second, this work sheds light on the impact of traditional fossil energy and new energy markets on carbon markets, extending the widely examined impact of traditional fossil energy markets on carbon markets (e.g., Kim and Koo 2010; Marimoutou and Soury 2015; Duan et al. 2021). This research topic is of great importance, since traditional fossil energy and new energy markets have distinctive characteristics that may influence carbon markets in unique manners. Third, this work defines the relative extreme risk spillovers (%CoVaR)

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[1] Data comes from the China Emissions Trading website.
[2] Data comes from the National Bureau of Statistics of China.

to compare the extreme risk spillovers from the same energy market to different carbon markets. Since there are price differences among regional carbon markets, the introduction of %CoVaR is helpful to eliminate the influence of different carbon market dimensions and further obtain in-depth enlightenment for the stable development of carbon markets.

The structure of the rest of the work is summarized as follows. "Literature review" surveys the relevant literature on carbon markets. "Methodology" introduces marginal distribution and copula models as well as VaR and CoVaR measures. The data and descriptive statistics analysis are provided in "Data and descriptions". "Results and discussion" presents and analyzes the results. Finally, "Conclusions" provides the conclusions and policy implications.

Literature review

Carbon markets established in Europe (EU), China, and elsewhere have made a great contribution in response to climate change. Extensive literature has therefore identified the characteristics of carbon market. Our research mainly relates to three strands of literature on (i) the impact of energy prices on carbon price, (ii) the measures of time-varying spillovers between carbon and energy markets, and (iii) the extreme risk of carbon market.

The impact of energy prices on carbon price

Existing literature has pointed out that the carbon price can be driven by traditional fossil energy and new energy prices. More focus has been paid to the impact of traditional fossil energy prices on carbon price. For example, Kim and Koo (2010) found that EU carbon price was only affected by coal price in the long term, but by coal, crude oil, and natural gas prices in the short term. Tan and Wang (2017) studied evolution of influence paths of fossil energy prices on EU carbon price, which showed that coal and gas prices generated the higher production restrain effect on carbon price in Phase I and presented the greater demand effect in Phase II. Zeng et al. (2017) considered Beijing carbon pilot and proved that its price was positively related to coal, crude oil, and natural gas prices. Meanwhile, some studies also confirmed that traditional fossil energy prices were the drivers of carbon price (e.g., Hammoudeh et al. 2014; Marimoutou and Soury 2015; Guo 2015; Duan et al. 2021). Research into the relationship between new energy price and carbon price is scarce. Several studies showed that the linkage between clean energy stock price and EU carbon price was not evident (Kumar et al. 2012; Dutta et al. 2018), while Alkathery and Chaudhuri (2021) argued that there was a correlation between EU carbon price and Global Clean Energy Index. Hanif et al. (2021) also found that there was

a stronger connectedness between EU carbon price and S&P clean energy index in the short run. By taking China as a case study, Tu and Mo (2017) and Mu et al. (2018) found that new energy price was related to carbon price. Some research further focused on specific industries of the new energy market in China. The results proved that there was an equilibrium relationship between carbon and renewable electricity certificates markets (Wang et al. 2021) or between carbon and new energy vehicle market (Nie et al. 2022). However, rare studies have simultaneously examined or compared the relationship between carbon and traditional fossil energy markets as well as between carbon and new energy markets.

The measures of time-varying spillovers between carbon and energy markets

The dynamic extreme risk spillover method employed in our research is related to a strand of literature on measuring time-varying spillovers between carbon and energy markets. With regard to the research methods, multivariate GARCH models have been most used due to the characteristics of capturing volatility correlation for mass data, including dynamic conditional correlation (DCC) GARCH model (Chang et al. 2019; Balclar et al. 2016; Lin and Chen 2019) and full Baba, Engle, Kraft, and Kroner (BEKK) GARCH model (Zhang and Sun 2016). Since multivariate GARCH models fail to measure the direction of time-varying spillovers, several studies have investigated the directional time-varying spillovers between carbon and fossil energy markets by employing Diebold-Yilmaz spillover index (Diebold and Yilmaz 2012, 2014). On this subject, Wang and Guo (2018) found that EU carbon market was a net receiver to fossil energy markets. For further details, Tan et al. (2020) examined and explored the structural breaks of spillovers. The results indicated that spillovers have three significant structural breaks and are most sensitive to the structural break in 2010. By taking China's regional carbon markets as a case study, Cui et al. (2020) showed that most regional carbon markets acted as information receivers. However, these methods have been limited to the analysis of time-varying spillovers under normal market conditions.

The extreme risk in carbon market

The extreme risk in carbon market has attracted increasing attention since actual carbon market has frequently experienced large negative or positive shocks under extreme market conditions. In terms of measuring extreme risk, VaR has been widely used. For instance, Mi and Zhang (2011) adopted the EVT to compute VaR to explore the extreme risk in EU carbon market. This study was extended by Zhang et al. (2020) to further investigate factors affecting VaR for

carbon market, including exchange rate and interest rate. Fang and Cao (2021) computed VaR for both carbon markets in EU and China. Their findings showed that the extreme risk in EU carbon market had two breaks, while there was no break in China's carbon market. VaR could only measure the isolated extreme risk in individual financial market and ignores the interaction of multiple markets. As a result, Adrian and Brunnermeier (2016) proposed CoVaR to measure extreme risk spillovers across financial markets. There are two methods to compute CoVaR, one is quantile regression method. For example, Zhu et al. (2020) used this method to take into account extreme risk spillovers between EU carbon and electricity markets. Another method is copula model, which can capture nonlinear relationship between markets compared to quantile regression method. Yuan and Yang (2020) applied this method to demonstrate that there were significant extreme risk spillovers from financial market uncertainty to EU carbon market. Xu (2021) extended this work by focusing on China's regional carbon markets. However, previous research has not revealed the extreme risk spillovers between carbon and energy markets through nonlinear method such as copula model.

Gap in the review

This work differs from the above research in various aspects. First, contrary to existing studies that have mainly explored the relationship between carbon and traditional fossil energy markets, we are particularly interested in the relationship between carbon markets and multiple types of energy markets (traditional fossil energy and new energy). Second, in contrast to previous works concentrating on the time-varying spillovers between carbon and energy markets under normal market conditions, we focus on the time-varying spillovers between carbon and energy markets under extreme market conditions, i.e., extreme risk spillovers.

Methodology

In this work, the copula model is used to compute CoVaR to quantify extreme risk spillovers, since it has an excellent property of describing nonlinear tail dependence compared to traditional quantile regression method (Reboredo et al. 2016; Uddin et al. 2020; Sun et al. 2020). Before constructing joint distribution between two markets by copula model, the marginal distribution model of each market should be obtained. Thus, in "Marginal distribution model and copula model", we first introduce the ARMA-GARCH models with Student-t innovations, which is used to obtain marginal distribution of each market. Then, we introduce copula model to construct bivariate distribution. In "Downside and upside

VaR and CoVaR", we present VaR and CoVaR to measure extreme risk and extreme risk spillover, respectively.

Marginal distribution model and copula model

Financial market returns usually have the features of autocorrelation, heteroscedasticity, and fat-tail. The $ARMA(p, q)$ model is used to fit returns with autocorrelation. The $GARCH(1,1)$ model has been proved to be suitable for fitting most of time series with heteroscedasticity, and it provides a simple and parsimonious description of time series properties (Bollerslev 1987). Student-t innovations can capture characteristics of fat-tail. Thus, the $ARMA(p, q)$-$GARCH(1,1)$ models with Student-t innovations are used in this work, which are often directly used to obtain marginal distributions of financial markets, such as electricity markets (Apergis et al. 2020) and stock markets (Reboredo et al. 2016). This model is defined as

$$y_t = \mu_t + \varepsilon_t, \tag{1}$$

$$\mu_t = \phi_0 + \sum_{p=1}^{n} \phi_p y_{t-p} + \sum_{q=1}^{m} \theta_q \varepsilon_{t-q}, \tag{2}$$

$$\varepsilon_t = z_t \sigma_t, \tag{3}$$

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{4}$$

where the return y_t is the logarithmic difference of market price with time-varying mean μ_t and residual ε_t. In Eq. (2), ϕ_0, ϕ_p, and θ_q represent the constant term, autoregressive (AR) coefficients, and moving average (MA) coefficients, respectively, whereas p and q are the corresponding orders. In Eq. (4), ω, α, and β are the constant term, autoregressive conditional heteroskedasticity (ARCH) coefficient, and GARCH coefficient, respectively, and σ_t is the conditional standard deviation. The sum of α and β is high, indicating the existence of persistent clustering in time series. And z_t of Eq. (3) obeys Student-t distribution with zero mean and unit variance, which implies that its probability density functions is denoted as

$$f(z_t; \nu) = \Gamma(\frac{\nu+1}{2}) / \sqrt{\pi(\nu-2)} \Gamma(\frac{\nu}{2}) \left(1 + \frac{z_t^2}{\nu-2}\right)^{-(\nu+1)/2}, \tag{5}$$

where ν represents the degree-of-freedom parameter ($\nu > 2$), and when $\nu \to \infty$, it converges to the Gaussian density distribution.

Next, the copula model proposed by Sklar (1959) is used to connect marginal distributions of two random variables X and Y to a multivariate distribution function, which is defined as

Table 1 The functions of copula specifications in this work

Copula	Distribution function	Parameter
Gaussian	$C_N(u_1, u_2; \rho) = \Phi_\rho[\Phi^{-1}(u_1), \Phi^{-1}(u_2)]$	$\rho \in (-1, 1)$
Student-t	$C_T(u_1, u_2; \rho, f) = T_{\rho, f}[T_f^{-1}(u_1), T_f^{-1}(u_2)]$	$\rho \in (-1, 1)$ $f \in (2, \infty)$
Clayton	$C_C(u_1, u_2; \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-1/\theta}$	$\theta \in (0, \infty)$
Gumbel	$C_G(u_1, u_2; \theta) = \exp[-\{(-\ln u_1)^\theta + (-\ln u_2)^\theta\}^{\frac{1}{\theta}}]$	$\theta \in [1, \infty)$
Frank	$C_F(u_1, u_2; \theta) = -\frac{1}{\theta}\ln(1 - \frac{(1-e^{-\theta u_1})(1-e^{-\theta u_2})}{1-e^{-\theta}})$	$\theta \in \mathbb{R}\{0\}$
180-degree rotated Clayton	$C_{RC}(u_1, u_2; \theta) = ((1-u_1)^{-\theta} + (1-u_2)^{-\theta} - 1)^{-1/\theta}$	$\theta \in (0, \infty)$
180-degree rotated Gumbel	$C_{RG}(u_1, u_2; \theta) = C_G(1-u_1, 1-u_2; \theta) + u_1 + u_2 - 1$	$\theta \in [1, \infty)$

Φ_ρ, $T_{\rho, f}$, and T_f are the bivariate standard normal, bivariate t, and univariate t cumulative distribution functions, respectively

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)), \qquad (6)$$

where $C(., .)$ is the copula function and $F_X(x)$ and $F_Y(y)$ obey the uniform distributions u_1 and u_2. Thus, we have $C(F_X(x), F_Y(y)) = C(u_1, u_2)$. Accordingly, the joint probability density function is given as

$$f_{XY}(x, y) = c(u_1, u_2)f_X(x)f_Y(y), \qquad (7)$$

where $c(u_1, u_2) = \partial^2 C(u_1, u_2)/\partial u_1 \partial u_2$ and $f_X(x)$ and $f_Y(y)$ represent the probability density functions of X and Y, respectively.

In order to find the best-fit copula to describe the best dependence structure, this work uses seven typical copula specifications. Specifically, there are two elliptic copulas in this work, including Gaussian and Student-t copulas. Both copulas capture symmetric linear tail dependence characteristics, but Student-t copula can capture a thicker tail. Sine many financial time series are nonlinearly correlated, this work selects five Archimedes copulas to effectively capture nonlinear relationship, including Clayton, Gumbel, Frank, 180-degree rotated Clayton, and 180-degree rotated Gumbel copulas. Clayton and 180-degree rotated Gumbel copulas are suitable for modeling structures with lower tail dependence characteristics, while Gumbel and 180-degree rotated Clayton copulas are suitable for depicting upper tail dependence characteristics. Frank copula has a "U"-shaped density distribution, which is used to describe relationships with symmetric thick-tailed characteristics. Thus, these various copula specifications offer a great modeling flexibility, and their functions are presented in Table 1.

Downside and upside VaR and CoVaR

VaR is a common and effective method to quantify extreme risks in financial markets. It can represent the maximum loss over a given confidence level and time horizon · Specifically, downside risk brings losses to investors for long position

and upside risk brings losses to investors for short position. Downside risk $\text{VaR}_{\alpha,t}^{y,D}$ and upside risk $\text{VaR}_{\alpha,t}^{y,U}$ for return y_t at $1 - \alpha$ confidence level are given as $P(y_t \leq \text{VaR}_{\alpha,t}^{y,D}) = \alpha$ and $P(y_t \geq \text{VaR}_{\alpha,t}^{y,U}) = \alpha$, respectively. VaR can be computed from the estimated marginal distribution model in "Marginal distribution model and copula model".

However, VaR can only measure the isolated extreme risk in an individual market, instead of measuring the co-movements and extreme risk contagion across multiple markets. As a result, Adrian and Brunnermeier (2016) proposed CoVaR to measure extreme risk spillovers between markets. Further, some co-movements in financial markets are in same directions, while others are in opposite directions. With this in mind, we introduce downside and upside CoVaR following Liu et al. (2017), which enables us to measure extreme risk spillovers based on positive or negative relationships between markets. Specifically, if return x_t and return y_t show positive tail dependence, downside and upside CoVaR ($\text{CoVaR}_{\alpha,t}^{y|x,D}$, $\text{CoVaR}_{\alpha,t}^{y|x,U}$) for y_t at $1 - \alpha$ confidence level conditional x_t at $1 - \beta$ confidence level are measured by lower-lower and upper-upper tail and are defined as

$$P(y_t \leq \text{CoVaR}_{\alpha,t}^{y|x,D} | x_t \leq \text{VaR}_{\beta,t}^{x,D}) = \alpha, \qquad (8)$$

$$P(y_t \geq \text{CoVaR}_{\alpha,t}^{y|x,U} | x_t \geq \text{VaR}_{\beta,t}^{x,U}) = \alpha. \qquad (9)$$

If x_t and y_t show negative tail dependence, $\text{CoVaR}_{\alpha,t}^{y|x,D}$ and $\text{CoVaR}_{\alpha,t}^{y|x,U}$ are measured by lower–upper and upper-lower tail and are defined as

$$P(y_t \leq \text{CoVaR}_{\alpha,t}^{y|x,D} | x_t \geq \text{VaR}_{\beta,t}^{x,U}) = \alpha, \qquad (10)$$

$$P(y_t \geq \text{CoVaR}_{\alpha,t}^{y|x,U} | x_t \leq \text{VaR}_{\beta,t}^{x,D}) = \alpha. \qquad (11)$$

Let F_{y_t} and F_{x_t} be marginal distributions of y_t and x_t, respectively, and $F_{y_t x_t}$ is the joint distributions of y_t and x_t.

Then, Eq. (8) is equivalent to $\frac{F_{y_t x_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}, \mathrm{VaR}_{\beta,t}^{x,D}\right)}{F_{x_t}\left(\mathrm{VaR}_{\beta,t}^{x,D}\right)} = \alpha$. Since Eq. (6) in "Marginal distribution model and copula model" is formulated as

$$C\left(F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right), F_{x_t}\left(\mathrm{VaR}_{\beta,t}^{x,D}\right)\right) = F_{y_t x_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}, \mathrm{VaR}_{\beta,t}^{x,D}\right) \quad (12)$$

and $F_{x_t}\left(\mathrm{VaR}_{\beta,t}^{x,D}\right) = \beta$, Eq. (8) is rewritten as.

$$C\left(F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right), \beta\right) = \alpha\beta. \quad (13)$$

Similarly, Eqs. (9)–(11) are re-expressed as Eqs. (14)–(16)

$$F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U}\right) - C\left(F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U}\right), 1-\beta\right) = (1-\alpha)\beta, \quad (14)$$

$$F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right) - C\left(F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right), 1-\beta\right) = \alpha\beta, \quad (15)$$

$$C\left(F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U}\right), \beta\right) = (1-\alpha)\beta. \quad (16)$$

The two-step procedure of Reboredo and Ugolini (2015) is used to compute CoVaR. First, once copula function $C(.,.)$ as well as α and β are given, we can solve the estimated values of $F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right)$ and $F_{y_t}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U}\right)$ as $\widehat{F_{y_t}}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right)$ and $\widehat{F_{y_t}}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U}\right)$. Next, $\mathrm{CoVaR}_{\alpha,t}^{y|x,D}$ and $\mathrm{CoVaR}_{\alpha,t}^{y|x,U}$ are computed as $F_{y_t}^{-1}\left(\widehat{F_{y_t}}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D}\right)\right)$ and $F_{y_t}^{-1}\left(\widehat{F_{y_t}}\left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U}\right)\right)$.

We can now examine asymmetry of downside and upside risk spillovers with null hypothesis as H0: $\frac{\mathrm{CoVaR}_{\alpha,t}^{y|x,D}}{\mathrm{VaR}_{\beta,t}^{y,D}} = \frac{\mathrm{CoVaR}_{\alpha,t}^{y|x,U}}{\mathrm{VaR}_{\beta,t}^{y,U}}$ referring to Reboredo et al. (2016). To test this hypothesis, we use the bootstrapped two-sample Kolmogorov–Smirnov (KS) test proposed by Abadie (2002). The KS test does not consider any underlying distribution function and is defined as

$$\mathrm{KS}_{mn} = \left(\frac{mn}{m+n}\right)^{1/2} \sup_x \left|F_m(x) - G_n(x)\right|, \quad (17)$$

where m and n are sizes of two samples and $F_m(x)$ and $G_n(x)$ are cumulative distribution functions of left and right side variables of null hypothesis, respectively.

In the empirical analysis, due to the price gap among different regional carbon markets, this work selects three carbon markets with relatively high transaction days. To compare the degree of extreme risk spillovers to different carbon markets from energy market, we introduce %CoVaR, which reflects the relative extreme risk spillovers from energy markets to carbon markets after eliminating the dimensional impact of different carbon markets. Downside

Table 2 The trading days in sample period

Market	The observations of day without zero trading volume	The proportion of days without zero trading volume
Hubei	1585	90.68%
Shenzhen	1483	84.84%
Guangdong	1400	80.09%
Beijing	1022	58.47%
Shanghai	983	56.24%
Tianjin	569	32.55%

and upside %CoVaR ($\%\mathrm{CoVaR}_{\alpha,t}^{y|x,D}$, $\%\mathrm{CoVaR}_{\alpha,t}^{y|x,U}$) for y_t at $1-\alpha$ confidence level conditional x_t at $1-\beta$ confidence level are defined as

$$\%\mathrm{CoVaR}_{\alpha,t}^{y|x,D} = 100 \times \left(\mathrm{CoVaR}_{\alpha,t}^{y|x,D} - \mathrm{VaR}_{\beta,t}^{y,D}\right)/\mathrm{VaR}_{\beta,t}^{y,D}, \quad (18)$$

$$\%\mathrm{CoVaR}_{\alpha,t}^{y|x,U} = 100 \times \left(\mathrm{CoVaR}_{\alpha,t}^{y|x,U} - \mathrm{VaR}_{\beta,t}^{y,U}\right)/\mathrm{VaR}_{\beta,t}^{y,U}. \quad (19)$$

Data and descriptions

Data sources

This work uses daily data from April 23, 2014, to December 31, 2020. The detailed description of data is as follows.

1. Carbon markets: this work chooses Guangdong (GD), Hubei (HB), and Shenzhen (SZ) pilots to represent China's regional carbon markets, as they are more active than other carbon pilots. The portion of days without zero trading volume in carbon pilots is shown in Table 2.

   We only make reports on the pilots established before the beginning of the sample.

2. Traditional fossil energy markets: this work selects coal (COAL), crude oil (OIL), and natural gas (GAS) markets to stand for traditional fossil energy markets. Specifically, the coal market is represented by the thermal coal futures of Zhengzhou Commodity Exchange, as thermal coal is the main raw material for thermal power generation (Lin and Chen 2019). The crude oil market is represented by China South Sea crude oil as Chang et al. (2019). Compared with the price trend of Daqing and Shengli crude oil, the price trend of China South Sea crude oil is closer to that of international crude oil. Meanwhile, the market price is transformed with the exchange rate of USD to RMB because it is

Table 3 Descriptive statistics of market returns

	GD	HB	SZ	COAL	OIL	GAS	NEW
Mean	− 0.0004	0.0001	− 0.001	0.0001	− 0.0005	− 0.0003	− 0.0004
Std. Dev	0.0456	0.0308	0.0383	0.0118	0.0307	0.0119	0.0456
Skewness	− 0.025	− 0.326	− 0.0799	− 1.9799	− 1.0646	− 1.4417	− 0.0250
Kurtosis	11.0076	32.1797	5.2139	36.5941	36.445	18.5951	11.0076
JB	4665.0629***	61,974.1497***	358.4261***	83,243.7624***	81,705.6017***	18,298.1553***	1241.3189***
PP	− 46.9510***	− 54.0700***	− 46.8530***	− 36.8124***	− 40.7299***	− 25.2203***	− 39.4878***
ADF	− 44.2434***	− 51.8089***	− 46.8530***	− 30.3226***	− 15.6236***	− 18.9553***	− 39.2428***
$Q(20)$	33.4091*	116.7705***	65.3106***	90.1875***	151.2347***	633.9774***	29.4522*
$Q^2(20)$	279.8830**	392.5678**	724.7439**	645.2966***	1438.0534***	271.6295***	1397.1583***
ARCH	224.1596***	248.1821***	253.3065***	210.19***	522.7401***	173.0419***	361.8608***

The $Q(20)$ and $Q^2(20)$ are the Ljung-Box statistics in the residuals and squared residuals with 20 lags, respectively. The ARCH(20) is the LM test of Engle (1982) for testing the presence of the ARCH effect (conditional heteroscedasticity) in the residuals up to 20th order

***, **, *Null hypothesis is rejected at 1%, 5%, and 10% significance levels, respectively

priced in dollars. The market price of liquefied natural gas is the indicator of natural gas price. Since this price is affected by domestic offshore, imports, and unconventional sources together, it shows better marketization than the price of natural gas dominated by the government (Chang et al. 2019).

3. New energy market (NEW): this work selects CNI new energy index as the indicator of new energy market as Wen et al. (2014) and Zeng et al. (2018). This index consists of 70 enterprises of Shanghai and Shenzhen stock exchanges, far exceeding those of CSI new energy index. Moreover, it includes a wide range of fields like new energy (such as wind energy, solar energy, nuclear energy, and biomass energy), new energy vehicle, and cleaner energy technologies.

Additionally, the data of energy markets and exchange rate are derived from the WIND database. The data of carbon markets are from the China Emissions Trading website (http://www.tanpaifang.com).

Descriptive statistical analysis

Table 3 presents the descriptive statistics of daily returns for carbon and energy markets in China. It can be seen from the results of standard deviations that crude oil and three carbon markets are more volatile than other financial markets. We also can see that the values of skewness are negative and kurtosis are greater than three, which implies that all series exhibit the characteristics of left-skewed, sharp-peak, and fat-tail. According to the Jarque–Bera (JB) test, each series is not normally distributed at 1% significance level. Phillips and Perron (PP) and augmented Dickey-Fuller (ADF) unit root tests show that all series are stationary at

1% significance level. The results of the $Q(20)$ and $Q^2(20)$ show that all series have autocorrelation. Finally, ARCH tests indicate that each series has heteroscedasticity.

Results and discussion

In our empirical analysis, we first exhibit estimates for the marginal distribution of each market in "Empirical estimates for marginal distribution models". To obtain the best dependence structure between carbon and energy markets, we estimate copula models to construct joint distribution between two markets in "Empirical results for copula models". In "Downside and upside VaR and CoVaR results", we further compute downside and upside VaR and CoVaR to analyze the extreme (downside and upside) risk spillovers to carbon markets from energy markets and perform asymmetry and robust tests of downside and upside risk spillovers. Finally, we compute %CoVaR to compare the degree of extreme risk spillovers to different carbon markets from energy markets in "Downside and upside %CoVaR results".

Empirical estimates for marginal distribution models

Here, we employ ARMA(p, q)-GARCH(1,1) models with Student-t innovations to estimate the marginal distribution of each market. The modeling process of this model is strictly divided into two steps. p and q are firstly selected according to Akaike information criterion (AIC) ($0 \leq p, q \leq 2$), which are shown in Table 9. Then, the ARMA(p, q)-GARCH(1,1) model with Student-t innovation is estimated in Table 4. As can be seen from Table 4, although some coefficients in the mean equation are not significant, all coefficients in the variance equation are

Table 4 The estimates of ARMA-GARCH-Student-t model

	GD	HB	SZ	COAL	OIL	GAS	NEW
Mean							
ϕ_0	0.001*	0.000	0.000	0.000	0.000	0.000*	0.004*
	(1.852)	(0.000)	(0.037)	(−0.962)	(0.072)	(1.768)	(2.691)
ϕ_1	−0.238	0.644**	1.453***		−0.304***	0.121	0.999***
	(−1.515)	(2.031)	(5.517)		(7.224)	(0.535)	(2.083e+03)
ϕ_2		0.113	−0.651**		−0.936***	0.222**	
		(1.426)	(−2.148)		(−22.459)	(2.021)	
θ_1	0.086	−0.879***	−1.459***	0.173***	−0.294***	0.351	−0.996***
	(0.521)	(−2.759)	(−5.574)	(7.114)	(−5.837)	(1.551)	(−3.873e+04)
θ_2		0.064	0.697**	−0.002	0.914***		
		(0.596)	(2.413)	(−0.081)	(18.788)		
Variance							
ω	0.000***	0.000	0.000	0.000	0.000***	0.000***	0.000
	(4.792)	(0.000)	(1.299)	(0.663)	(2.929)	(4.250)	(0.623)
α	0.509***	0.342***	0.239***	0.163***	0.157***	0.306***	0.081***
	(12.117)	(8.877)	(3.176)	(3.677)	(5.361)	(14.996)	(2.375)
β	0.490***	0.656**	0.760***	0.830***	0.832***	0.693***	0.915***
	(14.523)	(22.211)	(9.034)	(12.486)	(44.854)	(11.978)	(25.461)
ν	3.189***	3.227***	4.526***	3.284***	6.730***	2.581***	4.454***
	(24.006)	(30.988)	(7.871)	(6.339)	(6.098)	(25.981)	(7.186)
Residual test							
LogLike	3590	4337	3507	5749	4282	6021	4832
$Q(20)$	17.367	0.719	8.983	21.749	29.894	25.995	16.744
	[0.629]	[0.999]	[0.641]	[0.297]	[0.072]	[0.166]	[0.770]
$Q^2(20)$	22.274	0.112	20.251	2.216	3.520	16.904	9.439
	[0.326]	[0.999]	[0.443]	[0.999]	[0.999]	[0.659]	[0.977]
ARCH(20)	22.877	0.012	16.918	2.479	3.458	20.824	9.843
	[0.249]	[0.999]	[0.658]	[0.999]	[0.999]	[0.408]	[0.977]

Values in parentheses and brackets denote t-statistics and p values, respectively. In addition, *, **, and *** represent $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. LogLike is the log-likelihood value. The $Q(20)$ and $Q^2(20)$ are the Ljung-Box statistics in the residuals and squared residuals with 20 lags, respectively. The ARCH(20) is the LM test of Engle ([1982]) for testing the presence of the ARCH effect (conditional heteroscedasticity) in the residuals up to 20th order

statistically significant. As for the mean equation, there are some significant coefficients on either AR or MA for all markets except GD pilot, indicating the serial dependence in all markets except GD pilot. With regard to the variance equation, both α and β are significant at 1% level, and the sum of α and β is high for each series, showing the persistent volatility clustering. The degree-of-freedom parameter ν is significant at 1% level for each series. It implies that Student-t distribution can well fit the disturbance of the ARMA(p,q)-GARCH(1,1) models and confirms that all series have the characteristics of fat-tail. In terms of residual tests, the results of $Q(20)$ and $Q^2(20)$ represent that there are no autocorrelations on the residuals and squared residuals, respectively. The results of ARCH(20) reveal no ARCH effects on the residuals. These residual tests mean that the ARMA(p,q)-GARCH(1,1) model with Student-t innovations is suitable for estimating the marginal distribution of each market.

Empirical results for copula models

Next, we apply copula model to connect marginal distributions obtained in "Empirical estimates for marginal distribution models". To ensure that the standardized residual of each marginal distribution is uniformly distributed, we convert them to pseudo-sample observations in advance by probability integral transformation. Then, we employ Gaussian, Student-t, Clayton, Gumbel, Frank, 180-degree rotated Clayton, and 180-degree rotated Gumbel copulas to identify the best dependence structure between carbon and energy markets. According to the minimum of AIC values for each pair in Table 5, the optimal bivariate copula model

Table 5 The AIC values for each pair

Pair	Gaussian	Student-t	Clayton	Gumbel	Frank	180-degree rotated Clayton	180-degree rotated Gumbel
GD-COAL	1.41	**−0.26**	0.03	1.37	1.32	1.82	−0.05
GD-OIL	2	**0.43**	2	1	2	1.49	2
GD-GAS	1.94	5.56	2	2.01	**0.67**	2	2.02
GD-NEW	0.8	**−5.7**	2	1.98	−0.22	2.01	1.68
HB-COAL	0.76	**−3.68**	2.02	0.41	−0.26	1.56	2.02
HB-OIL	**0.51**	9.25	2.01	2.04	1.87	2.01	2.02
HB-GAS	0.45	**−6.74**	0.95	−3.69	0.37	−1.85	0.25
HB-NEW	−0.15	−0.43	2.02	2	**−2.25**	2	2.03
SZ-COAL	**0.94**	3.12	2.01	2.02	1.7	2.01	2.03
SZ-OIL	**−0.84**	2.43	2.02	2.05	0.12	2.02	2.03
SZ-GAS	0.17	**−0.06**	2.01	2.02	0.65	2.01	2.01
SZ-NEW	2.92	5.1	2.01	1.67	2.43	**1.11**	2.01

The minimum AIC values are shown in bold

Table 6 Parameter estimates of optimal bivariate copula model for each pair

Pair	Optimal copula	Tail dependence parameter	Degree-of-freedom parameter
GD-COAL	Student-t	−0.026	15.31
GD-OIL	Student-t	−0.005	13.728
GD-GAS	Frank	−0.141	
GD-NEW	Student-t	−0.018	14.705
HB-COAL	Student-t	−0.033	16.243
HB-OIL	Gaussian	−0.026	
HB-GAS	Student-t	0.043	10.821
HB-NEW	Frank	−0.17	
SZ-COAL	Gaussian	−0.021	
SZ-OIL	Gaussian	−0.016	
SZ-GAS	Student-t	0.02	30.538
SZ-NEW	180-degree rotated Clayton	0.037	

Student-t copula has two parameters, while other copulas have one parameter, as shown in Table 1

specification is selected. The corresponding parameter estimates are presented in Table 6. This evidence reveals that HB-GAS, SZ-GAS, and SZ-NEW pairs have positive tail dependence, while other carbon-energy pairs show negative tail dependence. In addition, we can find that Gaussian, Student-t, and Frank bivariate copulas are the best copula specifications for carbon-energy pairs in addition to SZ-NEW pair. It indicates that there is the symmetric dependence structure between carbon and energy markets. This finding is similar to Liu and Chen (2013) and Wang and Guo (2018) who stress the symmetric relationship between carbon and energy markets.

However, the best fit for SZ-NEW pair is 180-degree rotated Clayton copula, which depicts the upper tail dependence between Shenzhen pilot and new energy market. That is, the interdependence between Shenzhen pilot and new energy market is greater when positive information comes. This phenomenon is not difficult to explain. First, Shenzhen pilot plays a vital role in promoting the development of new energy industry since it covers a large number of tertiary industry enterprises based on the local economic development structure (Wu and Qin 2021). Second, since both markets are significantly influenced by national policy, investors will be willing to take full advantage of the market mechanism of Shenzhen pilot to invest new energy industry if policymakers release favorable news to further reduce CO_2 emissions and support new energy industry (Xiao et al. 2022). This ultimately causes an obvious increase in the interdependence between two markets. Therefore, an in-depth understanding in tail dependence structure suggests that policymakers should focus on the price discovery function of Shenzhen pilot, in order to effectively guide the investment behavior of new energy industry and thus achieve the goals of emission reduction.

Downside and upside VaR and CoVaR results

This work computes downside and upside VaR and CoVaR (VaR(D), VaR(U), CoVaR(D), and CoVaR(U)) at the 5% and 95% confidence levels as Sun et al. (2020). This difference between confidence levels allows us to differentiate between bearish and bullish market conditions. Figure 1 displays dynamic downside and upside VaR and CoVaR for carbon markets conditional on energy markets. It can be found that the values of CoVaR(U) for carbon markets conditional on various types of energy markets are
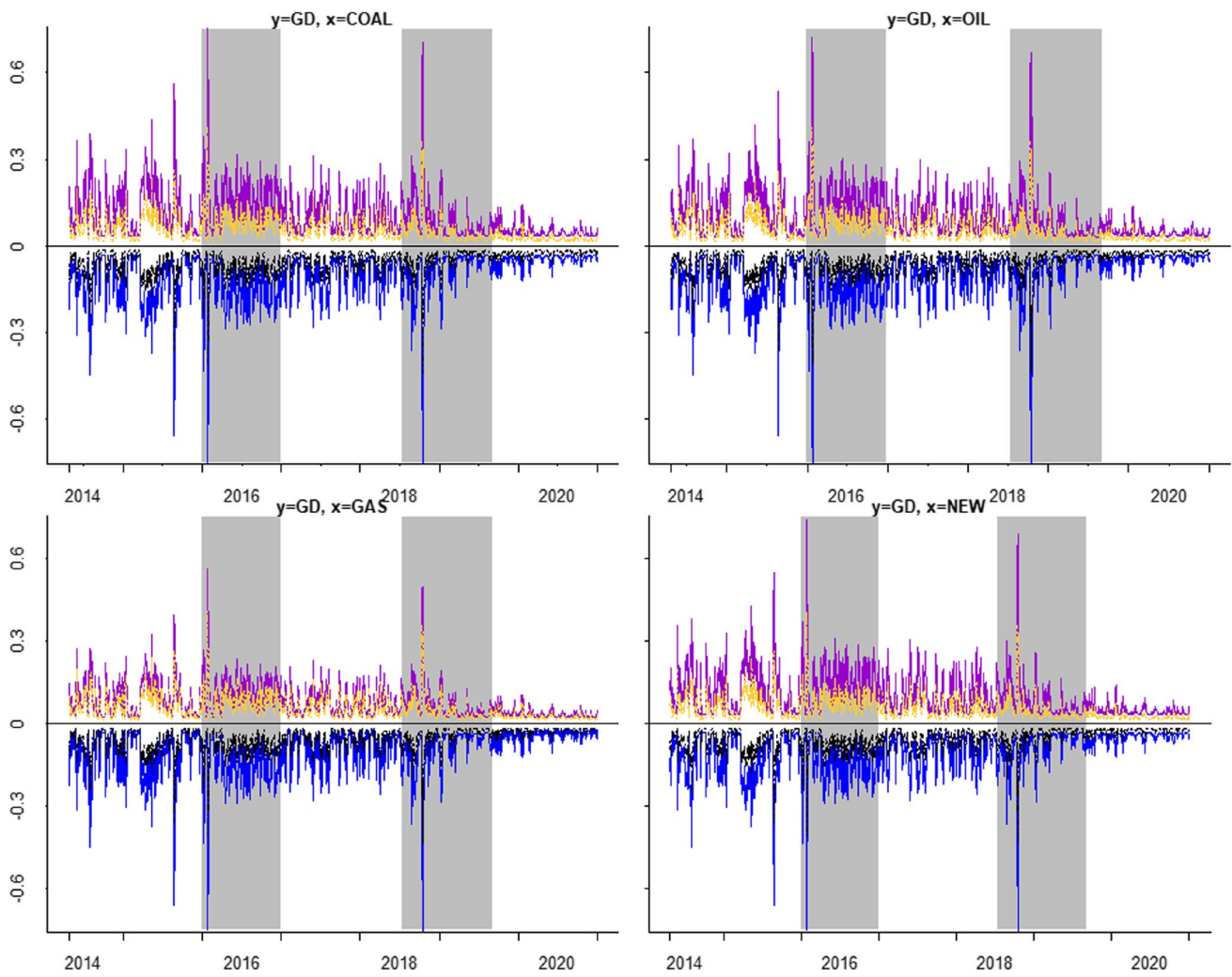
Fig. 1 Downside and upside VaR and CoVaR for carbon markets conditional on energy markets. Downside and upside $CoVaR^{HB|GAS}$ (y=HB, x=GAS), $CoVaR^{SZ|GAS}$ (y=SZ, x=GAS), and $CoVaR^{SZ|NEW}$ (y=SZ, x=NEW) are computed based on Eqs. (8) and (9), while others are computed based on Eqs. (10) and (11). The gray shadows are the periods when extreme events occur

systematically above the values of unconditional VaR(U) for carbon markets. And the values of CoVaR(D) for carbon markets conditional on various types of energy markets are systematically below the values of unconditional VaR(D) for carbon markets. It proves that there are the upside and downside risk spillovers from both traditional fossil energy and new energy markets to carbon markets. This finding can be also confirmed by the statistics in Table 10. Notably, the risk spillovers are obviously larger when extreme events cause large shocks to energy markets. For instance, we can see that downside and upside CoVaR for carbon markets exhibited a jump in 2016. In this stage, dramatic changes were taking place in energy markets due to a series of supply-side reforms, such as resolving excess capacity in the coal industry, reforming the oil and gas regime, and improving the development of new energy. CoVaR for

carbon markets also showed great changes from the second half of 2018 to the first half of 2019. This may be attributed to the intensified trade disputes between China and the United States, which led to significant volatility in energy markets. Specifically, in this period, international oil price experienced severe volatility, and domestic coal export, new energy export, and liquefied gas import substantially declined. Large shocks in energy markets significantly alter energy price, energy consumption, and CO_2 emissions, which in turn greatly affect carbon price and eventually cause higher risk spillovers. This concords with Wu et al. (2022a), Jiang and Chen (2022), and Ji et al. (2020) who point out the impact of large shocks on risk spillovers between financial markets.

According to the results in "Empirical results for copula models", HB-GAS, SZ-GAS, and SZ-NEW pairs have
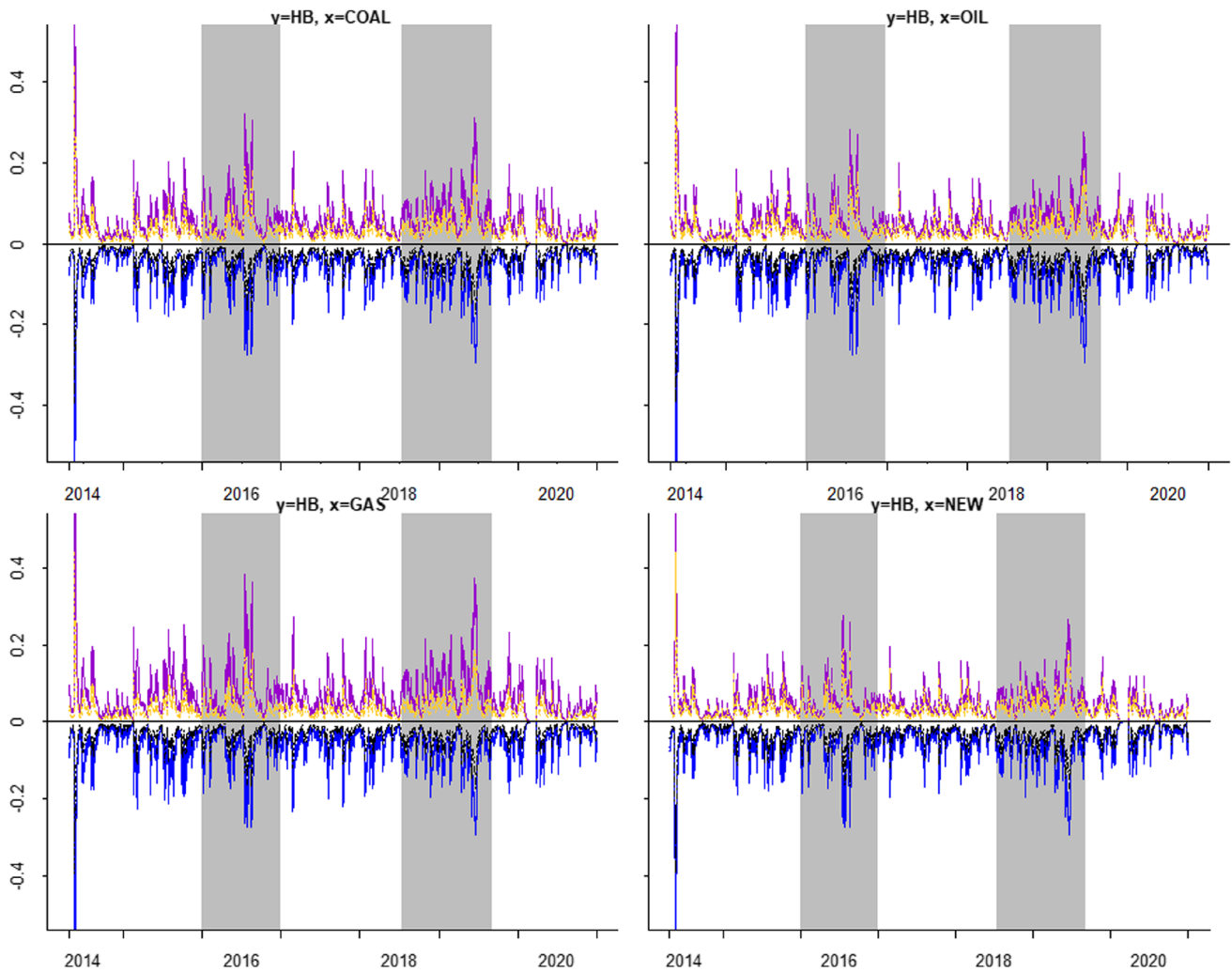
Fig. 1 (continued)

positive tail dependence and other pairs have negative tail dependence. Thus, we compute CoVaR(D) and CoVaR(U) for Hubei pilot conditional natural gas market, Shenzhen pilot conditional natural gas market, and Shenzhen pilot conditional new energy market based on Eqs. (10) and (11). In this case, CoVaR(D) measures the downside risk in carbon market when energy market is under bullish market conditions. CoVaR(U) measures the upside risk in carbon market when energy market is under bearish market conditions. And we compute CoVaR(D) and CoVaR(U) for other pairs based on Eqs. (8) and (9). In this case, CoVaR(D) measures the downside risk in carbon market when energy market is under bearish market conditions. CoVaR(U) measures the upside risk in carbon market when energy market is under bullish market conditions. In other words, there are upside risks in all carbon markets when coal or crude oil markets are under bullish market conditions, while there are upside or downside risks in carbon markets when natural gas or new energy

markets are under bullish market conditions and vice-versa. From the above analyses, it is not difficult to find that there are risks in the opposite direction in carbon markets when carbon-intensive energy markets (coal and crude oil) are under extreme market conditions, but the direction of risks in carbon markets is uncertain when low-carbon energy markets (natural gas and new energy) are under extreme market conditions.

The above findings are worthy of in-depth discussion. Since the risk transmission mechanisms from energy markets to carbon markets under bullish and bearish market conditions are exactly reversed, we only discuss bullish market conditions as follows. A key concept is that energy prices are largely upward when energy markets are under bullish market conditions. Coal and crude oil are both carbon-intensive fossil energy. These largely upward prices greatly reduce the consumption of coal and crude oil as well as CO_2 emissions. This further lowers the demand
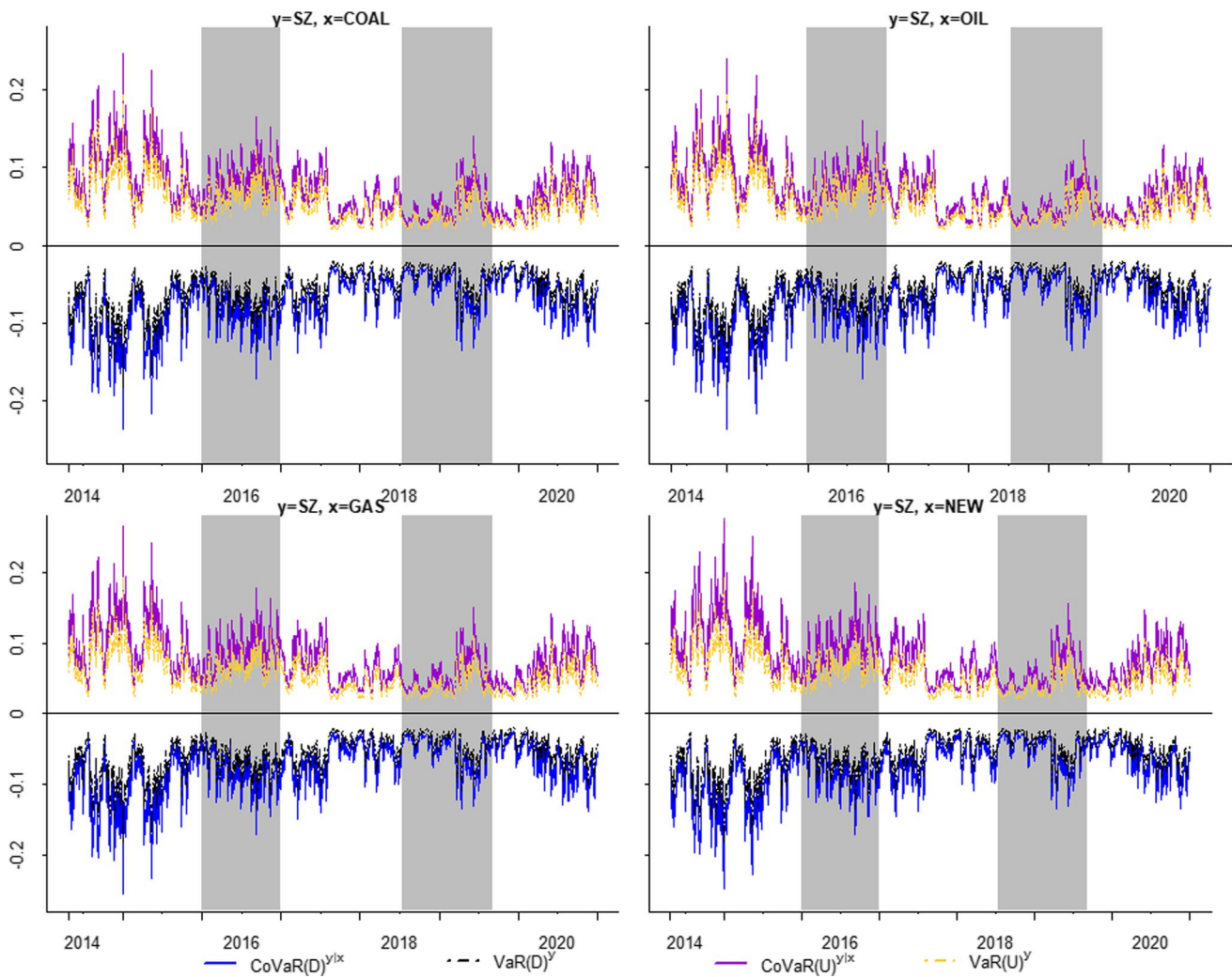
Fig. 1 (continued)

for carbon allowances and carbon prices and thus drives up the downside risks in carbon markets. This finding is somewhat consistent with previous research showing that coal and crude oil prices have a positive impact on carbon price (Guo et al. 2022; Zeng et al. 2017). Natural gas is low-carbon fossil energy and its consumption helps reduce CO_2 emissions. On the one hand, the largely upward natural gas price decreases natural gas consumption. On the other hand, since the largely upward natural gas price increases the consumption cost of natural gas, the government increases fiscal subsidies and reduces tax to promote natural gas consumption (Lin and Xu 2021). Thus, changes in natural gas consumption and CO_2 emissions are uncertain, resulting in that changes in carbon prices and the direction of risks in carbon markets are also uncertain. New energy index is a vital indicator to reflect investor expectations of the new energy market. The largely upward new energy price represents the boom development

prospect of new energy industry, promoting enterprises to expand new energy consumption to decrease CO_2 emissions. Besides, the largely upward new energy price is always accompanied by the growth of low-carbon willingness. This enhanced environmental willingness is related to higher CO_2 emissions in the environment (Lin and Chen 2019). Accordingly, changes in CO_2 emissions and carbon prices are unclear. Hence, the direction of risks in carbon markets are also uncertain when new energy markets is under bullish market conditions.

One striking result is that there is regional heterogeneity not only in magnitude but also in direction of the extreme risk spillovers to carbon markets from energy markets. In terms of the magnitude of extreme risk spillovers, as can be seen from Fig. 1 and Table 10, the absolute values of CoVaR for Guangdong pilot conditional on coal market are greater than other energy markets. The absolute values of CoVaR for Hubei pilot conditional on nature gas market

Table 7 The asymmetric tests of downside and upside risk spillovers from energy markets to carbon markets

x y	COAL	OIL	GAS	NEW
GD	0.276***	0.276***	0.276***	0.276***
HB	0.031	0.032	0.032	0.032
SZ	0.092***	0.092***	0.092***	0.930***

The tests are based on null hypotheses as H0: $\frac{\text{CoVaR}(D)^{y|x}}{\text{VaR}(D)^y} = \frac{\text{CoVaR}(U)^{y|x}}{\text{VaR}(U)^y}$

*** $p < 0.01$

are higher, while the values of CoVaR(U) for Shenzhen pilot conditional on new energy market are larger. The result indicates that there is regional heterogeneity in the magnitude of extreme risk spillovers to carbon markets from energy markets. To investigate the direction of the extreme risk spillovers, we perform the KS tests to examine the asymmetry of downside and upside risk spillovers in Table 7. The results show that the null hypotheses are rejected at the 1% level in addition to Hubei pilot. This implies that there is no distinct difference between the upward and downward risk spillovers to Hubei pilot from energy markets. Conversely, with regard to Guangdong and Shenzhen pilots, there are asymmetric downside and upside risk spillovers from energy markets. Due to the difference of local economic development, energy consumption structure, and policy incentives, the operation mechanism of carbon markets in different regions is highly diverse, including allowance allocation mechanism and Monitoring Reporting Verification (MRV) supervision mechanism (Wu and Qin 2021). Owing to the above reasons, three carbon pilots analyzed in this work eventually exhibit different price characteristics referring to Fig. 3. Therefore, both the magnitude and direction of the extreme risk spillovers to carbon markets from energy markets present regional heterogeneity. Our findings expand the relevant studies of Chang et al. (2019) and Cui et al. (2020) who prove the magnitude of heterogeneity in spillovers from energy markets to carbon markets in different regions.

Finally, to test the robustness of our results, we apply the KS tests following Abadie (2002) to access the significance of downside and upside risk spillovers from energy markets to carbon markets in Table 8. The null hypotheses are CoVaR(D)$^{y|x}$ ≤ VaR(D)^y and CoVaR(U)$^{y|x}$ ≥ VaR(U)^y, respectively, which implies that there are no significant downside and upside risk spillovers. One can evidently find from Table 8 that all null hypotheses are rejected at the 1% significant level. It demonstrates that there exist significant downward and upward risk spillovers to three carbon pilots from different energy markets at the 1% significant level. Thus, our results about extreme risk spillovers from energy markets to carbon markets are robust.

Table 8 The robust tests of extreme risk spillovers from energy markets to carbon markets

| y	x	H0:CoVaR(D)$^{y|x}$ ≤ VaR(D)^y	H0:CoVaR(U)$^{y|x}$ ≥ VaR(U)^y
GD	COAL	0.432***	0.432***
	OIL	0.405***	0.411***
	GAS	0.275***	0.282***
	NEW	0.420***	0.424***
HB	COAL	0.302***	0.310***
	OIL	0.241***	0.236***
	GAS	0.387***	0.392***
	NEW	0.221***	0.216***
SZ	COAL	0.190***	0.191***
	OIL	0.169***	0.170***
	GAS	0.245***	0.245***
	NEW	0.229***	0.270***

*** $p < 0.01$

Downside and upside %CoVaR results

In this section, we proceed to analyze %CoVaR for carbon markets conditional on energy markets, to compare the degrees of extreme risk spillovers to different carbon markets from energy markets. Figure 2 plots the networks about the mean values of downside (Panel (a)) and upside (Panel (b)) %CoVaR, which shows that both downside and upside risk spillovers to Guangdong and Hubei pilots are greater than those to Shenzhen pilot from energy markets. This may be attributed to the liquidity of three pilots. Guangdong pilot has always played a leading role in China's efforts to tackle climate change, which results in this pilot having high market liquidity (Wen et al. 2022). By December 2020, the cumulative trading volume had reached 172 million tons and the cumulative transaction values had reached 3.561 billion Yuan, which account for 38% and 34% of the national, respectively, ranking first in China' regional carbon markets.[3] Similarly, Hubei pilot has great market liquidity along with excellent transaction continuity and active market participation (Fan et al. 2019). The proportion of days with trading in this pilot is 90.68% in our sample period, which is the highest among China's regional carbon markets (see Table 2). While Shenzhen pilot is the first regional carbon market launched in China, its price fluctuates violently and frequently due to the decline in the trading volume and oversupply of carbon allowances (see Fig. 3). This price phenomenon leads to the low liquidity of Shenzhen pilot (Guo and Feng 2021). An important concept is that low liquidity in one market can lead investors to move their funds to other more liquid markets in order to hedge their risk, resulting in a low level of financialization in this market. Hence, the extreme risk spillovers to Shenzhen

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[3] The data is from the China Emissions Trading website.

Fig. 2 The %CoVaR networks for carbon markets conditional on energy markets. Note: blue, green, and gray nodes represent carbon, traditional fossil energy, and new energy markets, respectively. And black, red, and orange edges correspond to the large, medium, and small extreme risk spillovers to different carbon markets from the same energy market, respectively
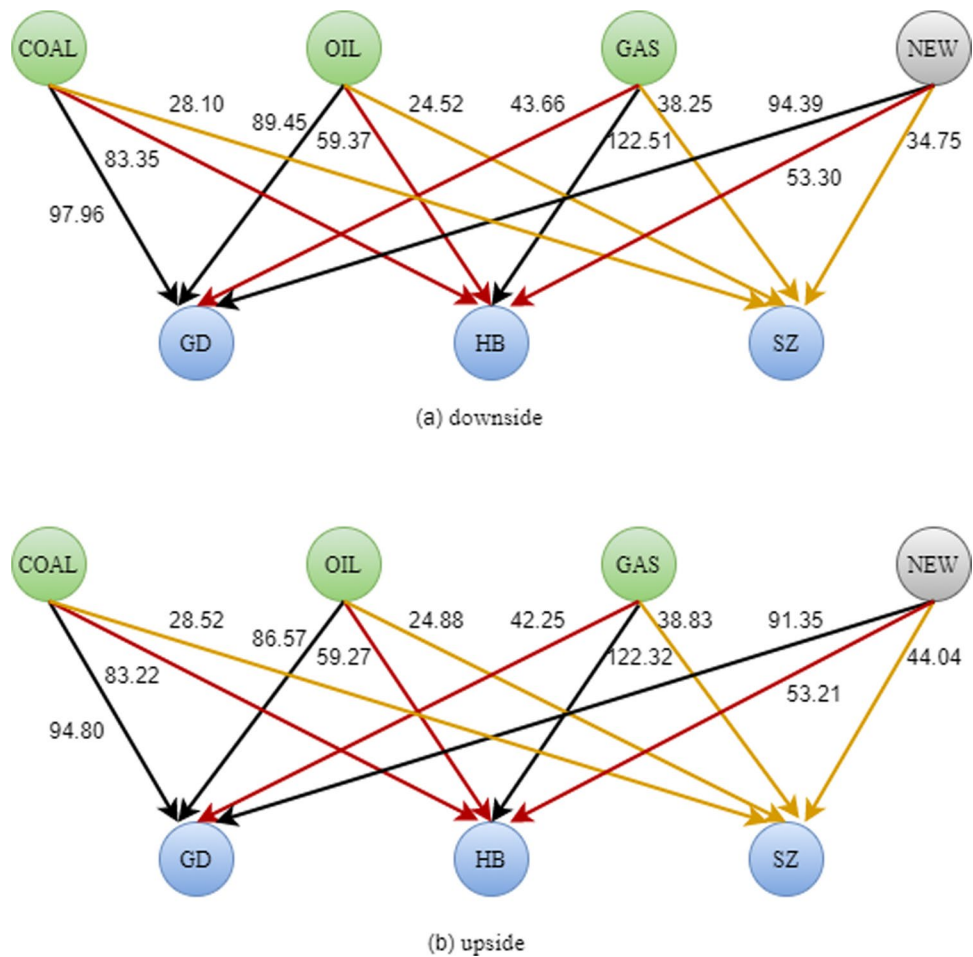
pilot from energy markets are the least. This finding verifies that energy markets prefer to transmit extreme risks to more liquid carbon markets.

Conclusions

The carbon market is regarded as an efficient instrument to reduce CO_2 emissions. However, under extreme market conditions, large shocks from energy markets may affect the effectiveness of carbon markets in reducing emissions. Thus, it is meaningful to investigate the extreme risk spillovers to carbon markets from energy markets. To our knowledge, this work is the first one to investigate the extreme risk spillovers to carbon markets (Guangdong, Hubei, and Shenzhen pilots) from energy markets (fossil energy and new energy). To achieve our objective, this work first combines the ARMA-GARCH model with copula models to select the best tail dependence structure between carbon and energy markets and then compute the downside and upside CoVaR and %CoVaR for carbon

markets conditional on energy markets to quantify extreme risk spillovers.

The main findings can be summarized as follows. First, Gaussian, Student-t, and Frank bivariate copulas are the best copula specifications for most carbon-energy pairs, which indicates the predominantly symmetric dependence structure between carbon and energy markets. Second, there are the downside and upside risk spillovers from both traditional fossil energy and new energy markets to carbon markets. Notably, the risk spillovers are obviously larger when extreme events, such as trade disputes between China and the United States, cause large shocks to energy markets. Third, there are risks in the opposite direction in carbon markets when carbon-intensive energy markets (coal and crude oil) are under extreme market conditions, but the direction of risks in carbon markets is uncertain when low-carbon energy markets (natural gas and new energy) are under extreme market conditions. Fourth, the CoVaR values indicate that the extreme risk spillovers to carbon markets from energy markets are regionally heterogeneous in magnitude. And the asymmetry tests of downside and upside risk spillovers reveal that the extreme risk spillovers are

also regionally heterogeneous in direction. Finally, both the upside and downside risk spillovers from the energy markets to Guangdong and Hubei pilots are greater than those to Shenzhen pilot, which reveals that energy markets prefer to transmit extreme risks to more liquid carbon markets due to the illiquidity of Shenzhen pilot.

Further, some implications are proposed through the above findings. First, our findings can provide references for policymakers. (i) Not only traditional energy markets but also new energy market should be monitored to reduce the severe fluctuations in carbon markets under extreme market conditions. (ii) On account of the differences in the extreme risk spillovers from carbon-intensive and low-carbon energy markets to carbon markets, the impact of changes in energy structure on carbon markets should be valued. Furthermore, to stabilize the extreme risk spillovers from low-carbon energy markets to carbon markets, production and consumption of natural gas and new energy should be further encouraged. For instance, the government can strengthen the construction of natural gas storage facilities and new energy power plants. (iii) As the liquidity of carbon markets continues to increase, the relationship between carbon trading mechanisms and energy policy needs to be further coordinated to safeguard against the extreme risk spillovers to carbon markets from energy markets.

Second, our findings also have insights for enterprises involved in carbon markets. (i) In addition to the change in carbon price, the fluctuations in both traditional fossil energy and new energy markets under extreme market conditions should be taken seriously to improve risk management capabilities of carbon assets. (ii) Risk awareness of market participants should be raised, especially when extreme events cause large shocks to energy markets. (iii) Regional differences in both the magnitude and direction of extreme risk spillovers to carbon markets from energy markets should be fully comprehended to avoid designing identical carbon reduction strategies. In particular, it is recommended that enterprises involved in Guangdong and Shenzhen pilots need to focus on the asymmetry of downside and upside risk spillovers from energy markets.

Nevertheless, there are limitations to our study. One of the limitations is that the inferences from this study may not be applicable to other countries, as the data come from one country. Another limitation is that this study only explores the extreme risk spillovers to carbon markets from energy markets. Other nonenergy financial markets may also transmit risks to carbon markets. Therefore, future studies can focus on the extreme risk spillovers to carbon markets from nonenergy markets for a deeper analysis.

Appendix

Table 9 The AIC values of ARMA(p, q) model

	GD	HB	SZ	COAL	OIL	GAS	NEW
ARMA(0,0)	− 5823.36	− 7192.35	− 6431.72	− 10,545.28	− 7204.44	− 10,517.01	− 9018.47
ARMA(0,1)	− 5826.98	− 7268.56	− 6452.48	− 10,576.99	− 7204.68	− 10,820.13	− 9022.79
ARMA(0,2)	− 5824.98	− 7270.19	− 6453.25	**− 10,584.08**	− 7205.42	− 10,954.44	− 9022.05
ARMA(1,0)	− 5827.01	− 7271.07	− 6452.87	− 10,571.24	− 7204.49	− 10,951.58	− 9023.13
ARMA(1,1)	**− 5841.03**	− 7269.32	− 6452.94	− 10,581.42	− 7209.48	− 10,964.15	**− 9024.44**
ARMA(1,2)	− 5839.66	− 7270.33	− 6452.13	− 10,582.22	− 7207.96	− 10,979.81	− 9022.85
ARMA(2,0)	− 5825.02	− 7269.38	− 6454.18	− 10,582.96	− 7205.42	10,969.68	− 9022.28
ARMA(2,1)	− 5823.01	− 7267.48	− 6452.79	− 10,583.15	− 7207.97	**− 10,982.93**	− 9022.86
ARMA(2,2)	− 5840.92	**− 7273.63**	**− 6456.80**	− 10,581.68	**− 7246.97**	− 10,979.24	− 9020.65

The minimum AIC values are shown in bold.

Table 10 Summary statistics of VaR and CoVaR for carbon markets conditional on energy markets

	Mean	Median	Maximum	Minimum	Std. Dev	Skewness	Kurtosis
$VaR^{GD}(D)$	−0.0519	−0.0373	−0.0156	−0.4366	0.0404	−2.3860	15.0976
$VaR^{GD}(U)$	0.0533	0.0384	0.4089	0.0168	0.0412	2.1717	11.5758
$CoVaR^{GD|COAL}(D)$	−0.1022	−0.0732	−0.0314	−0.8053	0.0786	−2.2591	13.4229
$CoVaR^{GD|COAL}(U)$	0.1036	0.0752	0.7518	0.0326	0.0795	2.1492	11.6166
$CoVaR^{GD|OIL}(D)$	−0.0979	−0.0702	−0.0300	−0.7732	0.0753	−2.2640	13.4902
$CoVaR^{GD|OIL}(U)$	0.0993	0.0719	0.7220	0.0312	0.0761	2.1493	11.6039
$CoVaR^{GD|GAS}(D)$	−0.0743	−0.0533	−0.0227	−0.6009	0.0574	−2.3033	14.0200
$CoVaR^{GD|GAS}(U)$	0.0757	0.0546	0.5617	0.0238	0.0582	2.1528	11.5443
$CoVaR^{GD|NEW}(D)$	−0.1004	−0.0719	−0.0308	−0.7918	0.0772	−2.2611	13.4503
$CoVaR^{GD|NEW}(U)$	0.1018	0.0738	0.7393	0.0320	0.0781	2.1492	11.6113
$VaR_{HB}(D)$	−0.0321	−0.0252	0.0000	−0.3939	0.0284	−3.4413	28.5042
$VaR_{HB}(U)$	0.0321	0.0245	0.4391	0.0000	0.0288	3.9011	36.1878
$CoVaR^{HB|COAL}(D)$	−0.0583	−0.0461	0.0000	−0.6448	0.0506	−3.3775	26.9912
$CoVaR^{HB|COAL}(U)$	0.0583	0.0453	0.7305	0.0000	0.0510	3.6542	31.7024
$CoVaR^{HB|OIL}(D)$	−0.0508	−0.0400	0.0000	−0.5726	0.0442	−3.3821	27.1310
$CoVaR^{HB|OIL}(U)$	0.0507	0.0393	0.6467	0.0000	0.0445	3.6959	32.4600
$CoVaR^{HB|GAS}(D)$	−0.0706	−0.0560	0.0000	−0.7627	0.0611	−3.3766	26.9130
$CoVaR^{HB|GAS}(U)$	0.0706	0.0549	0.8674	0.0000	0.0615	3.6080	30.8629
$CoVaR^{HB|NEW}(D)$	−0.0489	−0.0384	0.0000	−0.5544	0.0426	−3.3841	27.1861
$CoVaR^{HB|NEW}(U)$	0.0488	0.0378	0.6255	0.0000	0.0429	3.7088	32.6956
$VaR^{SZ}(D)$	−0.0567	−0.0510	−0.0200	−0.1827	0.0265	−0.9960	3.9753
$VaR^{SZ}(U)$	0.0559	0.0506	0.1941	0.0191	0.0262	1.0355	4.3012
$CoVaR^{SZ|COAL}(D)$	−0.0725	−0.0656	−0.0257	−0.2358	0.0338	−0.9971	4.0063
$CoVaR^{SZ|COAL}(U)$	0.0717	0.0652	0.2472	0.0247	0.0335	1.0286	4.2662
$CoVaR^{SZ|OIL}(D)$	−0.0705	−0.0638	−0.0250	−0.2290	0.0329	−0.9969	4.0030
$CoVaR^{SZ|OIL}(U)$	0.0697	0.0633	0.2404	0.0240	0.0326	1.0293	4.2699
$CoVaR^{SZ|GAS}(D)$	−0.0783	−0.0709	−0.0277	−0.2550	0.0365	−0.9975	4.0148
$CoVaR^{SZ|GAS}(U)$	0.0775	0.0705	0.2664	0.0267	0.0362	1.0268	4.2568
$CoVaR^{SZ|NEW}(D)$	−0.0763	−0.0690	−0.0270	−0.2483	0.0356	−0.9974	4.0120
$CoVaR^{SZ|NEW}(U)$	0.0804	0.0732	0.2761	0.0277	0.0375	1.0261	4.2525

Fig. 3 The changes in daily prices for three carbon pilots (unit: Yuan)
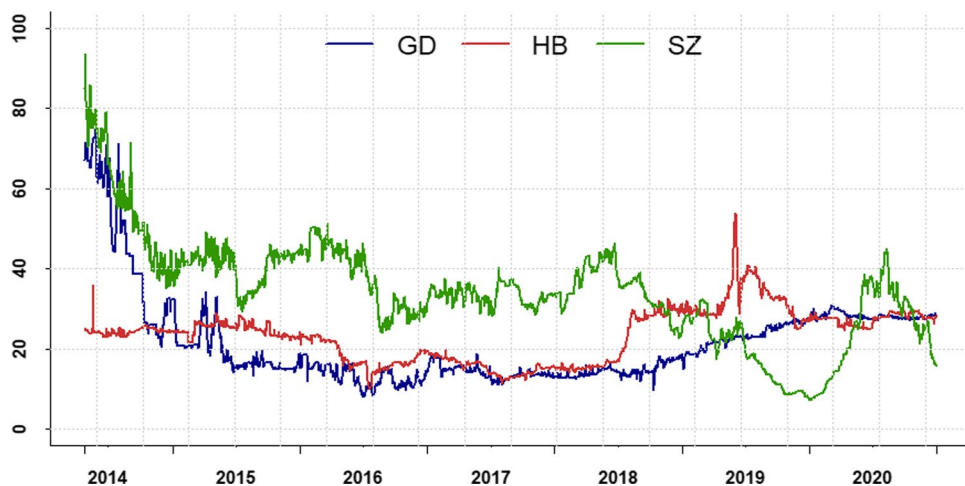
Declarations

Ethics approval Not applicable.

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