Volatility spillover and hedging strategies among Chinese carbon, energy, and electricity markets

Abstract:

There is an intricate relationship between the carbon, energy, and electricity markets, and it is essential to clarify the relationship between them to promote the sustainable development of the three markets. This paper focuses on Chinese carbon, energy, and electricity markets and uses the TVP-VAR model to explore the risk spillover effects among these markets. It also combines the QVAR model with the TVP-VAR model to assess the impact of COVID-19 on their connectedness. Additionally, an effective diversified portfolio is constructed to cope with inter-market risk spillover. The empirical testing is conducted using a sample of eight bellwether stocks from Chinese carbon, energy, and electricity markets, spanning from August 1, 2013, to December 30, 2022. Results show that: 1. Risk spillover among the three markets is particularly evident in the downside or upside market. 2. The carbon market and electricity market are the largest recipients and transmitters of net risk spillovers, respectively. 3. During COVID-19, the carbon market enhanced the spillovers on other markets under market downside periods. Our findings provide theoretical references for market participants and regulators to address inter-market volatility spillovers.

Keywords: carbon market; energy market; electricity market; spillover effects; investment hedge

1. Introduction

Currently, climate change has emerged as a central global concern, driving countries to take proactive measures to mitigate and adapt to the escalating environmental risks. Among them, the carbon market has garnered significant attention as a key tool in addressing climate change (Gregory, 2021). In the carbon market, participants trade carbon credits or allowances, representing the entitlement to release a specific quantity of CO2 or other greenhouse gases into the atmosphere. Carbon markets aim to reduce greenhouse gas emissions cost-effectively and transparently. Simultaneously generating income to support initiatives aimed at mitigating and adapting to climate change. Now the global carbon market is still in its early stages of development, with various initiatives and mechanisms developed and implemented by different countries and regions. Notably, the European Union Emissions Trading System (EU ETS) stands out as the global largest carbon market, experiencing continuous growth since its implementation. The fluctuation in EUAs prices is impacted by multiple factors, including uncertainty in allowance trading, volatility transmitted from the global financial crisis, fluctuations in energy prices, and speculative behavior (Chevallier, 2009; Chevallier, 2011). These fluctuations not only impact long-term trend of the carbon market but also highlight investors' concerns about short-term manipulation.

The energy market, serving as the lifeblood of the global economy, encompasses not only traditional sources like coal, oil, and natural gas but is progressively transitioning towards cleaner and sustainable energy sources, including solar, wind, and hydropower. The price fluctuations within this market are shaped by a myriad of complex factors on a global scale, including, but not limited to, geopolitical events, climate change, technological innovations, and alterations in energy policies implemented by different national governments. The evolution of the worldwide energy market is profoundly influenced by shifts in consumer behavior, technological advancements, and the overarching global climate agenda. Emerging trends are steering the energy market away from conventional fuels towards more sustainable forms of energy. This transformation will play a decisive role in shaping the future trajectory of the global energy landscape and will have far-reaching implications for the global economic framework.

The electricity market serves as a platform that brings together various participants for power transactions, including power generators, transmission system operators, distribution companies, and end-users such as households and businesses. Globally, driven by the imperative to reduce carbon emissions, promote renewable energy, and advance societal digitization and electrification, numerous countries and regions have set ambitious carbon reduction targets. The electricity sector is facing escalating pressure for decarbonization and emission reduction, with global renewable energy generation accounting for nearly 30% of the total electricity production in 2022[1]. Changes within the electricity market of a particular country or region have the potential to diffuse and impact other regions.

[insert figure 1 here]

Fig. 1 Map of the relationship between carbon, energy, and electricity markets

The carbon, energy, and electricity markets are intricately interconnected and mutually influential (see Fig. 1). On the one hand, electricity generation is an essential source of greenhouse gas emissions. Carbon markets reduce carbon emissions by providing economic incentives for electricity producers to switch from traditional fossil fuel-based power generation to renewable sources, such as wind, hydrogen, and solar power, thereby reducing carbon emissions with low-carbon technologies. On the other hand, energy market also significantly impacts carbon market. Both transportation and production sectors are primary sources of greenhouse gas emissions. As market demand for renewable energy grows, the gradual replacement of traditional fossil energy with renewable energy is a significant pathway for diminishing carbon emissions, thereby fostering a sustainable energy future.

[1] "Electricity Market Report2023",https://www.iea.org/reports/electricity-market-report-2023.

There are spillover effects between carbon market, traditional energy market, new energy market, and electricity market (Qiao et al., 2021; De Menezes et al., 2016). The electricity market is a significant participant in the carbon market, and fossil fuel-based electricity generation serving as the predominant mode of power generation. Theoretically, fluctuations in energy and electricity market prices impact the operational activities of enterprises, consequently impacting the carbon trading market by influencing carbon emissions. Conversely, the fluctuation of carbon prices also changes production technology and fuel choices of industrial enterprises and influences the price of energy market and electricity market with its final emission reduction outcomes (Qiao et al., 2023; Li et al., 2022). Under extreme events (e.g., the US-China trade war, Russia-Ukraine military conflict, COVID-19 epidemic), dynamic correlations between different markets change. Typically, this is attributed to the influence of these events on energy prices, subsequently impacting prices in the energy market. Indirectly, it affects the electricity market and carbon market prices, which are closely linked to the energy market (Apostolakis et al., 2021; Pengli et al., 2020; Tian & Li, 2022).

In achieving global carbon reduction goals and fostering the synergistic growth of carbon markets, the stability of Chinese carbon market is paramount. 2021 to date, Chinese carbon market has established itself as the largest globally in terms of covered emissions, encompassing over 2,100 companies and approximately 4.5 billion tons of carbon emissions[2]. As a major player in global renewable energy investments, China has made remarkable progress in the renewable energy sector, with renewables accounting for 17.5% of China's primary

[2]"INTERACTIONS BETWEEN CARBON MARKETS, GREEN CERTIFICATE TRADING AND GREEN POWER TRADING IN CHINA",https://climatecooperation.cn/climate/interactions-between-carbon-markets-green-certificate-trading-and-green-power-trading-in-china/.

energy consumption in 2022[3]. However, Chinese energy structure remains relatively traditional, relying heavily on coal, which dominates its energy consumption at 56.2%[4]. As the largest global electricity consumer, China constituted 31% of world's electricity demand in 2022[5]. With the reform of the electricity market, China, as the largest global producer of solar and wind energy, will drive the development of renewable energy technologies worldwide (Xu et al., 2019) and shed light on the energy policies of other countries.

To examine the risk spillovers between Chinese carbon, energy, and electricity markets, and provide investors with effective risk-reducing portfolio strategies. Firstly, this paper combines TVP-VAR and QVAR models to assess the volatility spillover effects across the three markets under different market conditions. Secondly, this paper uses the COVID-19 pandemic as the dividing point of the research period to compare and examine how extreme events influence the spillover effects between markets. Finally, it is proposed to hedge inter-market risk spillover through investment portfolios and identify the optimal portfolio among the three markets.

Compared with existing studies, the marginal contribution of this paper is reflected in the following four aspects: Initially, we contribute novel evidence by investigating the interconnections among carbon, energy, and electricity markets through the application of TVP-VAR and QVAR models. Second, to provide a comprehensive depiction of the energy market landscape, this paper incorporates clean energy markets, including solar, hydrogen, and wind, in addition to traditional fossil energy markets. Third, by comparing the correlations

[3] "China's Policies and Actions on Carbon Peaking and Carbon Neutrality (2023)", https://www.cemf.net.cn/storage/tinymce/images/b5621bb51be5186e941d3e03d42de13e6580054e1daac.pdf
[4] "China's Policies and Actions on Carbon Peaking and Carbon Neutrality (2023)", https://www.cemf.net.cn/storage/tinymce/images/b5621bb51be5186e941d3e03d42de13e6580054e1daac.pdf
[5] "Electricity Market Report2023",https://www.iea.org/reports/electricity-market-report-2023.

between markets before and after COVID-19, aims to elucidate the complexities of spillover effects between markets during crisis periods. Fourth, this paper uniquely centers its investigation on the Chinese context, providing a more precise theoretical basis for the process through which prices are conveyed within Chinese carbon market.

The remainder of the paper is organized as follows: Section II contains the literature review, Section III outlines the research methodology and data, Section IV provides the analysis of results, Section V discusses the findings, and Section VI concludes the conclusions and policy implications. The flow chart of this study is shown in Fig. 2.

[insert figure 2 here]

Fig. 2 Research flow chart of this study

2. Literature Review

2.1 Research status of volatility spillovers between the carbon market and energy market

The risk spillover effects and volatility between energy market and carbon market are significant (Zhou et al., 2022; Liu et al., 2023; Alkathery et al., 2021). Firstly, fuel prices such as natural gas and petroleum are influenced by the price of CO_2 emissions, with higher (lower) fuel prices driving higher (lower) carbon prices (Boersen et al., 2014). Secondly, the consumption of renewable and non-renewable energy in the energy market affects CO_2 emissions. The rise in the consumption of renewable energy has the potential to alleviate environmental degradation, while the rise in non-renewable energy consumption has led to CO_2 emissions increase. Highlighting the critical role of renewable energy in the fight against climate change (Dogan & Ozturk, 2017； Wang et al., 2022a). Moreover, amid the European debt crisis, the descent in international petroleum prices, and the advent of the COVID-19 pandemic, there was a substantial surge in the overall interconnection among climate change, crude petroleum, renewable energy stock markets, and carbon emissions trading. (Li et al., 2023; Zhou et al., 2022; Jiang et al., 2022a; Jiang et al., 2022b; Katusiime, 2023).

In the short-term frequency, the total connectedness between the energy market and the carbon market is stronger compared to the medium- and long-term frequencies (Zhou et al., 2022; Shihong et al., 2017; Jiang et al., 2022b). In contrast, under higher-order moment conditions, it is found that short-term bidirectional spillover effects between the carbon market and the energy market are weak, while long-term spillover effects are significant (Dai et al., 2021).

For Chinese market, depending on the different economic development levels, environmental policies, and energy structure, the direction and magnitude of spillover effects between the energy and carbon markets vary across the carbon trading pilot cities (Wang et al., 2022b; Song et al., 2022). Meanwhile, in contrast to the energy market, the carbon market is particularly vulnerable to severe external shocks or seasonal fluctuations (Liu et al., 2023; Jiang et al., 2022b； Zhou et al., 2022).

2.2 Research status of volatility spillovers between the carbon market and electricity market

The electricity industry is a crucial area for carbon emissions and reduction, and the stable development of the carbon market relies significantly on the pivotal role played by the electricity market (Zhao et al., 2023a). On the one hand, focusing on the European carbon and electricity markets, employing the CoVAR method based on two-dimensional empirical mode decomposition, the study reveals a positive risk spillover effect from the carbon market to the electricity market. Conversely, the electricity market exhibits a negative risk spillover effect on the carbon market. The magnitude of risk spillover from the carbon market to the electricity market is smaller compared to the spillover from the electricity market to the carbon market, indicating that the electricity market contributes to risk diversification for the carbon market (Zhu et al., 2020). On the other hand, when the Chinese carbon market and listed electricity companies are studied, using the DY and BK spillover index model, it is found that in the short term, the carbon market tends to be a net recipient of risk. In contrast, in the medium to long term, carbon market tends to be a net spiller of risk (Wang et al.,2022). Furthermore, during periods of market crisis with high volatility, there is an observed escalation in correlation between the carbon and electricity markets (Zhao et al., 2023；Tian et al.,2016).

2.3 Research status of volatility spillovers between energy and electricity markets

In general, there is a reciprocal flow of information between the natural gas and coal markets in the electricity and energy markets, with a notably robust information transfer from natural gas to the electricity market (Xia et al., 2020; Chau et al., 2015). Return and volatility spillovers among the three markets—clean energy, electricity, and energy metals—exhibit notable time-varying features. These spillovers experience a pronounced escalation during extreme events, particularly under conditions characterized by extreme quantile (Zhang et al., 2023; Khalfaoui et al., 2022; Bouteska et al., 2023). For example, amidst the global financial crisis and the period spanning 2014 to 2016, marked by the shale petroleum revolution, the overall correlation between clean energy, electricity and carbon markets was high (Naeem et al., 2020). There is a weak long-term relationship between coal and electricity prices in China (Liu et al., 2013). Due to the low connectivity between electricity and energy markets, electricity futures can be a safe haven asset for risk diversification and mitigating petroleum shocks (Naeem et al., 2020).

2.4 Research status of volatility spillovers between the carbon market, energy market, and electricity market

There are bidirectional spillovers between electricity and fossil fuel markets and between carbon market and carbon emissions (Wang et al., 2021; Liu et al., 2023). The dynamic spillovers between carbon, fossil energy, and electricity markets exhibit notable time lags and periodic patterns. Studies have found that the impact of the carbon market on electricity and fossil energy markets is particularly pronounced (Qiao et al., 2023). The volatility of carbon futures can be predicted based on GARCH models (Byun & Cho, 2013). Among them, carbon prices are predominantly influenced by fluctuations in the energy market, with petroleum prices being the primary contributing factor (Ji et al., 2018; Tan et al., 2020). The energy market plays a pivotal role in fostering the connection between the carbon and the electricity markets (Zhao et al., 2023; Chai et al., 2022). For example, the Russia-Ukraine conflict led to rapid fluctuations in European natural gas prices. Since 2022, electricity markets have been affected by natural gas prices, with some influence on the carbon trading market (Zhao et al., 2023b; Wang et al., 2022c；Goodell et al., 2023; Liu et al., 2023).

In different regions, volatility effects vary among markets (Tang et al., 2022). European Electricity Exchanges consistently exert a significant influence on carbon futures prices. However, the precise impact varies across different countries' electricity exchanges, with some European electricity exchanges assuming a crucial role in determining carbon futures pricing (Boersen & Scholtens, 2014；Li et al., 2017). Among the Chinese carbon trading markets, volatility spillover effects in the Shanghai and Beijing carbon markets are primarily driven by the crude petroleum futures market. In the Hubei carbon market, primary sources are the crude petroleum and electricity markets, while in the Guangdong carbon market, the predominant source is the new energy market. (Qiao et al., 2021; Zhong & Zhong, 2023).

2.5 Evolution of Research Models on Market Risk Spillovers

Throughout extensive research endeavors, the investigation of risk spillovers between markets has evolved significantly, employing a spectrum of sophisticated econometrics methodologies. Initially, Zipp (2017) and Cludius et al. (2014) applied nonlinear econometric methods to measure the mechanism of price impact between markets, followed by Mosquera-López & Nursimulu (2019), who introduced rolling windows to find that price drivers between markets are different and time-varying. Subsequently, many studies began employing Granger causality to investigate the transmission of extreme risks between financial markets. However, as the analysis of volatility spillovers across multiple markets requires a multivariate approach (Chevallier, J. 2012), models such as MGARCH and CoVAR have been utilized in examining the transmission of volatility between different markets (Bollerslev et al., 1988; Engle & Kroner, 1995; Bollerslev, 1990; Gyamerah et al., 2022; Li et al., 2022; Adrian & Brunnermeier, 2011). For volatility spillovers between extreme markets, Su (2020) used a QVAR model to reveal extreme risk spillovers between G7 and BRICS equity markets. Meanwhile, Antonakakis et al. (2020) investigate the connectivity of exchange rate dynamics of currencies in circulation worldwide through the application of the TVP-VAR model, proving the model's efficacy in accurately identifying the directionality and time-varying nature of inter-market spillovers.

2.6 Comments on Literature

Existing research has done good explorations to understand the relationship between the three markets. However, there are still the following shortcomings: First, the existing literature fails to discuss inter-market volatility spillovers from multiple dimensions, such as combining multiple models to simultaneously consider the directionality and time-varying nature of volatility spillovers between markets of different states or even volatility spillovers between extreme markets in the context of COVID-19. Second, in the research on carbon market spillover effects, the new energy market is not adequately taken into account. Concurrently, the electricity market has not been considered a separate market. Third, existing research seldom considers the comparison of spillover effects across the three markets both pre and post the outbreak of COVID-19. Fourth, existing research mainly examines the interconnection between the EU carbon, energy, and electricity markets, with little focus on China, which is not conducive to effective decision-making by Chinese market policymakers.

3. Research Methodology and data

3.1 Spillover effects between different markets under extreme market conditions —— The Quantile VAR model

This study utilizes a quantile regression model (Koenker & Bassett, 1978), which exhibits greater robustness and less sensitivity to outliers than OLS regression for market time series data characterized by peaked and thick-tailed distributions. In this study, quartiles 0.01 and 0.99 represent downside and upside market states, respectively (Bouri et al., 2021; Dai & Zhu, 2023; Tiwari et al., 2022). From there, it becomes feasible to determine the interdependence among carbon, energy, and electricity markets during extreme market conditions. Estimating the dependence of y_t on x_t for a given x_t vector value at $\tau(\tau \in [0,1])$ quantile. The equation can be expressed as:

$$Q_\tau(y_t|x_t) = x_t \times \beta(\tau) \tag{1}$$

In equation (1), $Q_\tau(y_t) = F^{-1}(\tau)$, where $F(y_t)$ represents the probability distribution of the random variable y_t. The quantile τ takes values between $[0,1]$. Under different quartiles, the unknown parameter vector $\beta(\tau)$ will then be different. $\beta(\tau)$ can be obtained by minimizing the subsequent expression concerning:

$$\hat{\beta}(\tau) = arg \min_{\beta(\tau)} \sum_{t=1}^{T} \left(\tau - 1_{\{y_t < x_t\beta(\tau)\}}\right) |y_t - x_t\beta(\tau)| \tag{2}$$

In equation (2), $1_{\{y_t < x_t\beta(\tau)\}}$ is the usual indicator function. If x_t changes by one unit, $\hat{\beta}(\tau)$ can capture the range of changes in the conditional distribution of y_t at τ quantile. It is convenient for researchers to select the desired quantile for studying the conditional distribution of y_t on variable x_t.

The *n*-variable quantile VAR(*p*) model is expressed as follows:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), \qquad t = 1, \cdots, T \tag{3}$$

where,

$$y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{nt} \end{pmatrix}, c(\tau) = \begin{pmatrix} c_1(\tau) \\ c_2(\tau) \\ \vdots \\ c_n(\tau) \end{pmatrix}, e_t(\tau) = \begin{pmatrix} e_{1t}(\tau) \\ e_{2t}(\tau) \\ \vdots \\ e_{nt}(\tau) \end{pmatrix} \tag{4}$$

$$B_i(\tau) = \begin{pmatrix} \beta'_{i,1}(\tau) \\ \beta'_{i,2}(\tau) \\ \vdots \\ \beta'_{i,n}(\tau) \end{pmatrix} = \begin{pmatrix} \beta_{i,11}(\tau) & \beta_{i,12}(\tau) & \dots & \beta_{i,1n}(\tau) \\ \beta_{i,21}(\tau) & \beta_{i,22}(\tau) & \cdots & \beta_{i,2n}(\tau) \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{i,n1}(\tau) & \beta_{i,n2}(\tau) & \cdots & \beta_{i,nn}(\tau) \end{pmatrix} \tag{5}$$

In equation (4), y_t stand as the *n*-vector of the endogenous variables. The *n*-vector of intercepts at quantile τ is represented by $c(\tau)$, and $e_t(\tau)$ denotes the residuals at quantile τ. In equation (5), $B_i(\tau)\ for\ i = 1, \cdots, p$ represents the lag coefficient matrix at quantile τ.

$\hat{B}_i(\tau)$ and $\hat{c}(\tau)$ are two coefficient matrices, which are assumed to conform to the population quantile restrictions for errors $e_t(\tau)$, $Q_\tau\left(e_t(\tau)\middle|y_{t-1}, \cdots, y_{t-p}\right) = 0$. These constraints suggest that the population responses at quantiles τ for y are delineated by:

$$Q_\tau\left(y_t\middle|y_{t-1}, \cdots, y_{t-p}\right) = \hat{c}(\tau) + \sum_{i=1}^{p} \hat{B}_i(\tau) \times y_{t-i} \tag{6}$$

3.2 Spillover effects between different markets under normal market conditions —— TVP-VAR model

To explore the time-varying linkages between the carbon, energy and electricity markets, this study combines the TVP-VAR model (Antonakakis et al., 2018) with quantile regression and analyzes the spillover effects among markets with the mean value representing the market normal state. The TVP-VAR model effectively avoids the issue of incomplete observations in spillover index measurement results affected by the size of the rolling window. Based on the Bayesian Information Criterion (BIC), the TVP-VAR (1) model can be mathematically formulated as：

$$Y_t = B_t Y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim N(0, \Sigma_t) \tag{7}$$

$$vec(B_t) = vec(B_{t-1}) + \nu_t \qquad \nu_t \sim N(0, S_t) \tag{8}$$

$$Y_t = \Phi_t \varepsilon_{t-1} + \varepsilon_t \tag{9}$$

In equations (7), (8) and (9), the vectors Y_t ,Y_{t-1} and ε_t are $K \times 1$ dimensional and B_t ,$\sum_t$ and $\Phi_t(\tau)$ are the $K \times K$ dimensional matrices. $vec(B_t)$ and ν_t are $K^2 \times 1$ dimensional， while S_t is a $K^2 \times K^2$ dimensional matrix. The dynamic connectedness approach by Diebold & Yilmaz (2012, 2014) relies on the Generalized Forecast Error Variance Decomposition (GFEVD) by (Pesaran & Shin, 1998; Koop et al., 1996), it is necessary to convert the TVP-VAR to TVP-VMA representation using the Wold representation theorem: $Y_t = \sum_{h=0}^{\infty} A_{ht}\varepsilon_{t-i}$ where $A_0 = I_k$.

The H-steps ahead GFEVD models how a shock in market j affects market *i*. This can be expressed as follows,

$$\Phi_{ij,t}^{gen}(H) = \frac{S_{jj,t}^{-1}\sum_{h=0}^{H-1}(e_i' A_{ht}\Sigma_t e_j)^2}{\sum_{h=0}^{H-1}(e_i' A_{ht}\Sigma_t A_{ht}' e_i)} \tag{10}$$

In equation (10), e_i is a $K \times 1$ dimensional zero vector with a value of 1 in its *i*th position, and S_{jj} represents the standard deviation of the error term in the *j*th equation. Subsequently, we standardize the spillover index to ensure that the total of each row in the variance decomposition matrix equals one:

$$\tilde{\Phi}_{ij,t}^{gen}(H) = \frac{\Phi_{ij,t}^{gen}(H)}{\sum_{j=1}^{N}\Phi_{ij,t}^{gen}(H)} \tag{11}$$

In equation (11), $\sum_{j=1}^{N}\tilde{\Phi}_{ij,t}^{N}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\Phi}_{ij,t}^{N}(H) = N$, the normalized GFEVD plays a central role in the connectedness approach, enabling the calculation of the overall directional connectedness from market i to other markets or from other markets to market i.

$$\mathrm{TCI}_t^g(H) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\Phi}_{ij,t}^{g}(H)}{\sum_{i,j=1}^{N}\Phi_{ij,t}^{g}(H)} \times 100 \tag{12}$$

In equation (12), TCI represents the total connectedness index measuring endogenous systemic spillovers from the three markets. It mainly highlights network interconnectivity, which also reflects the degree of risk between markets.

$$\mathrm{TO}_{i,t}^{g}(H) = \sum_{j=1,i\neq j}^{N}\tilde{\Phi}_{ji,t}^{g}(H) \times 100 \tag{13}$$

$$\mathrm{FROM}_{i,t}^{g}(H) = \sum_{j=1,i\neq j}^{N} \widetilde{\Phi}_{ij,t}^{g}(H) \times 100 \tag{14}$$

In equations (13) and (14), TO and FROM denote the volatility spillover that market i transmits and receives from all other markets, respectively.

$$\mathrm{NET}_{i,t}^{g}(H) = \mathrm{TO}_{i,t}^{g}(H) - \mathrm{FROM}_{i,t}^{g}(H) \tag{15}$$

In equation (15), NET calculates the disparity between the total directional connectedness derived from the TO and FROM aspects, resulting in the net total directional connectedness for market i. If NET > 0 (NET < 0), market i is identified as a net transmitter (receiver) of risk, signifying that market *i* is exerting influence (being influenced) within the network.

3.3 Investment strategy for managing market risk spillovers ——portfolio back-testing model

3.3.1 Bilateral hedge ratios and portfolio weights

The formula of the dynamic hedging ratio, as proposed by Kroner and Sultan (1993), is articulated as follows:

$$\beta_{ij,t} = \frac{\theta_{ij,t}}{\theta_{jj,t}} \tag{16}$$

In equation (16), at time t, $\theta_{ij,t}$ represents the conditional covariance between markets i and j, while $\theta_{jj,t}$ denotes the conditional variance of market j.

Kroner and Ng (1998) propose optimal portfolio weights for the bilateral relationship between markets *i* and *j* are computed as,

$$w_{ij,t} = \frac{\theta_{ii,t} - \theta_{ij,t}}{\theta_{ii,t} - 2\theta_{ij,t} + \theta_{jj,t}} \tag{17}$$

with

$$w_{ij,t} = \begin{cases} 0, & if w_{ij,t} < 0 \\ w_{ij,t}, & if 0 \leq w_{ij,t} \leq 1 \\ 1, & if w_{ij,t} > 1 \end{cases} \tag{18}$$

In equation (17), $w_{ij,t}$ represents the weight of market *i* in each 1RMB portfolio between markets *i* and *j* at time *t*. Further, the weight of market *j* in the same portfolio is given by $1 - w_{ij,t}$.

3.3.2 Minimum variance portfolio (MVP)

The MVP method is a commonly used method in portfolio analysis which aims to construct a portfolio with the lowest volatility founded on multiple markets as documented by Miller, M. H. (1960). The specific formula can be expressed as follows:

$$w_{\theta_t} = \frac{\theta_t^{-1} I}{I \theta_t^{-1} I} \tag{19}$$

In equation (19), the portfolio weight vector w_{θ_t} is a $K \times 1$ dimensional representation, where I denotes the *K*-dimensional vector of ones, and θ_t is the $K \times K$ conditional variance-covariance matrix for period *t*.

3.3.3 Minimum correlation portfolio (MCP)

The MCP was introduced by Christoffersen et al. (2014). This method resembles the MVP, but in this instance, the portfolio weights are derived by minimizing the conditional correlation rather than conditional covariance. Expressed as:

$$R_t = diag(\theta_t)^{-0.5} H_t diag(\theta_t)^{-0.5} \tag{20}$$

$$w_{R_t} = \frac{R_t^{-1} I}{I R_t^{-1} I} \tag{21}$$

3.3.4 Minimum connectedness portfolio (MCoP)

The MCoP method as outlined in Broadstock et al. (2022) through the pairwise connectedness index. Minimizing bilateral interconnections results in a portfolio approach that is less impacted by network shocks. Therefore, greater weight is assigned to markets that operate independently, exerting no influence on others and being unaffected by external forces. This is shown below:

$$w_{C_t} = \frac{PCI_t^{-1}I}{IPCI_t^{-1}I} \tag{22}$$

In equation (22), PCI_t is the matrix of pairwise connectedness index, and the identity matrix is symbolized as I.

3.3.5 Portfolio evaluation

To evaluate portfolios performance, we rely on two metrics: the Sharpe ratio and hedging effectiveness (Sharp, 1994; Ederington, 1979). The Sharpe ratio is the ratio of reward to volatility. The hedging effectiveness (*HE*) represents the percentage reduction in portfolio risk compared to investing in a single market, denoted as i. To assess the significance of this reduction, the paper employs the *HE* tests statistics by Antonakakis et al. (2020), calculated as follows:

$$SR = \frac{\bar{r}_p}{\sqrt{var(r_p)}} \tag{23}$$

In equation (23), r_p signifies the portfolio returns under the assumption that the risk-free rate is zero. *SR* provides insights into identifying the portfolio with the maximum return given the same level of volatility. As elevated SR values indicate greater returns relative to the portfolio's risk level.

$$HE_i = 1 - \frac{var(r_p)}{var(r_i)} \tag{24}$$

In equation (24), The portfolio variance is represented by $var(r_p)$, and $var(r_i)$ denotes the variance of market *i* without considering the portfolio. The HE_i represents the percentage decrease in variance of market *i*'s the unhedged position. A high (low) *HE* indexes indicates a substantial (minimal) reduction in risk.

3.4 Data

This study uses the daily highest and lowest prices of the Shenzhen carbon emission trading market from August 1, 2013 to December 30, 2022 as carbon market data. As China's carbon market is currently in the initial phase of pilot implementation, the data needs to be processed as follows: i) remove trading days with no trading volume. ii) remove trading days with no price changes. In the end, 1357 valid trading days are obtained.

This paper collects the highest and lowest prices of 1357 trading days in the energy and electricity markets corresponding to the carbon market. Among them, we select representative leading stocks in China's energy market, including the traditional energy market (petroleum, natural gas, coal) and the clean energy market (solar, hydrogen, wind). For China's electricity market, Guodian Power is used for the research. See Appendix Table A1 for a detailed data description.

The daily returns for the three markets are calculated as follows:

$$I_{it} = ln\left(P_{it,max}\right) - ln\left(P_{it,min}\right) \tag{25}$$

In equation (25), $P_{it,max}$ represents the highest price and $P_{it,min}$ denotes the lowest price of market *i* on day *t*, respectively.I_{it} is return on day *t*.

In this paper, the daily variance is estimated using each market's highest and lowest prices. The calculation of the variance for market i on day t is expressed as：:

$$\sigma_{it}^2 = \frac{I_{it}^2}{N-1} \tag{26}$$

$$\hat{\sigma}_{it}^2 = \sigma_{it}^2 \times 1000 \tag{27}$$

In equation (27), $\hat{\sigma}_{it}^2$ serves as an estimator for daily variance, so the derived estimate for the annualized daily percent standard deviation (volatility) is

$$\tilde{\sigma}_{it} = 100 \times \sqrt{365 \times \hat{\sigma}_{it}^2} \tag{28}$$

Since the objective of this paper includes the influence of the COVID-19 on risk spillovers between the three markets, we take January 1, 2020 as the onset of the pandemic and divide the daily data into two phases: pre- and post- the COVID-19 periods:

Pre-COVID-19 period (Phase 1): 936 valid trading days from August 1, 2013 to December 31, 2019.

Post-COVID-19 period (Phase 2): 421 valid trading days from January 1, 2020 to December 30, 2022.

4. Results analysis

4.1 Volatility spillover effects and correlation between two markets

From two perspectives, static and dynamic, respectively, this paper empirically investigates the volatility spillovers between carbon, energy, and electricity markets.

From a static perspective on volatility spillover, this study investigates the transmission of risk among the three markets in scenarios of market downturn, normalcy, and upswing, using the lower quantile (0.01), mean, middle quantile (0.5), and upper quantile (0.99), to complement the research on tail volatility spillovers. Fig. 3 shows spillover effects among carbon, electricity, and energy markets under different market conditions. Fig. 3(I) and Fig. 3(II) represent the spillover effects received and transmitted by carbon market to energy and electricity markets under each market condition. Fig. 3(III) and Fig. 3(IV) show total spillover effects received and passed by each market to other markets, respectively. Fig. 3(V) shows the net spillover effects of each market, and Fig. 3(VI) shows the shock effect of each market on itself.

[insert figure 3 here]

Fig. 3 Spillover Effects among three markets in China under different market conditions

Firstly, compared to a normal market state, spillover effects across the carbon market and energy, as well as electricity markets increase sharply during a downside or upside market state. Fig. 3(I) and Fig. 3(II) show that in the normal market state, the carbon market has the strongest shock reception (6.66%) and transmission (3.91%) of the natural gas market. However, during a market downturn, the volatility spillover between the carbon market and the wind market is particularly pronounced, with the carbon market receiving 3.6 times more shocks from the wind market than in the normal market state. At the same time, carbon market's transmission of shocks to wind market jumped from 1.68% to 9.3%. Especially in an upside market state, the total connectedness between the three markets significantly increases from 40.68% to 87.42%. The risk spillovers from carbon market to coal and petroleum markets increase significantly, with the carbon market receiving 5.46 times and 5 times more shocks from the coal and petroleum markets, respectively.

Secondly, carbon market exhibits weak connections to other markets in a normal market state, while the shock of the carbon market on others is extremely strong under an upside or downside market state. Fig. 3(III) and Fig. 3(IV) show that compared to a normal market state, the total spillover effect from the carbon market to other markets (15.45%) increases to 59.51% (85.12%) in a downside (upside) market state. It is worth noting that in a normal market condition, the fossil energy market (petroleum, coal, natural gas) and the electricity market exhibit significant spillover effects on other markets, with the electricity market having a 56.72% risk impact on other markets, followed by the petroleum (52.35%), natural gas (44%) and coal (39.07%) markets. For the new energy market, the solar market has prominent spillover effects among markets, with both the reception and transmission of shocks exceeding 40%. In addition, the results show that in a downside or upside market state, careful attention should be paid to the spillover effects of the carbon and new energy markets between markets.

Thirdly, each market's role and intensity change with different market states. Fig. 3 (V) shows carbon market is always a net receiver of market shocks, while petroleum and electricity markets are always net transmitters. However, during a downside or upside market state, the roles of wind, solar, coal, hydrogen, and natural gas markets in the intermarket spillover effects change.

Fourthly, each market's internal shocks vary across market conditions. Fig. 3(VI) shows that the effect of each market's own shocks decreases significantly in either downside or upside market state, i.e., each market spills risk into other markets.

[insert figure 4 here]

Fig. 4 Dynamic net directional connectedness between pairs of markets

From the dynamic volatility spillover perspective, the exact role between the three market pairs is determined through net pairwise connectedness graphs (Fig. 4). The carbon market has significant spillovers with both the energy and electricity markets, and the interactions between each pair of markets change over time. First, from the perspective of the carbon and energy markets, dynamic spillover effects between the carbon market and both the hydrogen and wind markets are similar. Before 2019, carbon market was a net recipient of shocks. However, after 2019, roles between the two markets are no longer stable, and the correlation between them weakens. Second, the transfer of volatility between the carbon and natural gas markets is manifested upfront as a large number of shocks originating in the natural gas market and affecting the carbon market. However, in 2019, the two sides started to shift their roles, with the carbon market becoming a transmitter of shocks to the natural gas market. Especially since 2021, with the shock effect strengthening. Third, over the study duration, carbon market is mainly in a position to receive a high level of shocks from the electricity market, with only a small number of shocks transmitted to the electricity market in 2021 (during the COVID-19 pandemic).

Amid the COVID-19 pandemic, spillover levels between electricity market and natural gas, solar, coal, and petroleum markets change similarly. For solar, natural gas, petroleum and coal markets, electricity market becomes their shock transmitter around 2021. Also of note are the natural gas and wind markets, along with the coal and petroleum markets. The natural gas market was a net receipt of shocks from wind market before the COVID-19 outbreak and began to transmit small shocks to wind market in the post-COVID-19 outbreak. Between the coal and petroleum markets, coal market has been a net receipt of risk from petroleum market for a long time, but the risk transmission effect from petroleum market to coal market increased after the COVID-19 outbreak.

4.2 Dynamic connectedness between the three markets

4.2.1 Dynamic total connectedness

Throughout this paper, elevated values of the total connectedness index (TCI) signify robust interconnectedness within the scrutinized markets. To put it differently, strong connectedness implies that the risks tied to the carbon, energy, and electricity markets are progressively aligning, reflecting a parallel level of market confidence. As depicted in Fig. 5, the total connectedness index is presented, showcasing the progression of overall co-movement among the three markets using TVP-VAR. The left of the dashed line represents the period before COVID-19, while the right represents the period after COVID-19. The black area signifies dynamic total connectedness, red line shows interconnectedness between markets externally, and the green line (SZER), deep blue line (Energy) and light blue (Electric) represent the connectivity between the carbon, energy, and electricity markets with each other, respectively.

[insert figure 5 here]

Fig. 5 Dynamic total connectedness among three markets in China

Fig. 5 shows from 2020 to 2022, coinciding with the COVID-19 pandemic, there was a substantial decrease in the total interconnectedness between markets, falling to around 20% in 2021. Dynamic connectedness between markets exhibited time lag and coupling during the COVID-19 pandemic. Throughout the study period, the extent of shocks transmitted to the carbon market from the energy and electricity markets was weak. However, from mid-2021 to 2022 (which corresponds to the period of the COVID-19 pandemic), the connectedness between carbon market and energy/electricity markets increased sharply. In addition, the dynamic trend of interconnection between energy and electricity markets resembled the pre-COVID-19 period but diverged notably from the trend in the carbon market. Only after a sharp increase in connectedness between the carbon market and other markets (from 2021 to 2022), connectedness between the electricity market and the carbon/energy markets increases substantially, which is coupled with the trend in the carbon market during the COVID-19 pandemic.

4.2.2 Dynamic connectedness in each market

The dynamic directional connectedness index between markets indicates the extent to which a given market transmits shocks to or receives shocks from other markets. We can accurately determine whether the specified market predominantly acts as a net recipient or transmitter of shocks at different times, as shown in Fig. 6.

[insert figure 6 here]

Fig. 6 Net directional connectedness among three markets in China

Fig. 6 shows that the solar market is almost always a shock receiver, while the petroleum and electricity markets predominantly act as risk transmitters between markets, and the electricity market experiences a sharp increase in risk transmission to around 60% in the period of the COVID-19. Furthermore, carbon market, although a significant shock receiver for most of the period, a noticeable shift to being a net transmitter of risk observed during the period from 2021 to 2022 (which corresponds to the COVID-19 pandemic period), with risk transmission peaking at around 15%. Coal, natural gas, hydrogen, and wind energy markets change their roles in market risk shocks over the study period, but during the COVID-19 pandemic, they all become stable risk receivers, with the risk received by the coal and natural gas markets increasing to 20%.

4.3 Comparison of spillover effects before and during the COVID-19 outbreak

4.3.1 Analysis of directed spillover effects among markets before and during the COVID-19 outbreak

This paper divides the research timeframe into two phases: from August 1, 2013, to December 31, 2019, and from January 2, 2022, to December 30, 2022. To study the influence of the COVID-19 pandemic on the volatility spillover effect and correlation between the carbon, energy, and electricity markets, respectively. The outcomes are shown in Fig. 7.

[insert figure 7 here]

Fig. 7 Comparison of spillover effects among markets before and during the COVID-19 pandemic

First, during the market downside, inter-market spillovers changed significantly following the outbreak of COVID-19. In Fig. 7(I), carbon market, as a recipient of shocks (-13.26%) before the COVID-19 outbreak, saw an overall 3.7-fold increase in spillover effects to other markets after the COVID-19 outbreak. At the same time, the electricity and coal markets also transmit significantly more shocks to most markets. Conversely, the natural gas market experienced a significant 12.37% increase in shocks received. Moreover, the spillover effects of the hydrogen, wind energy, petroleum, and solar markets on other markets varied in degrees of increase or decrease.

Second, before and during the COVID-19, there were large fluctuations in the net spillovers from the markets themselves. Fig.7(II) compares each market's change in net spillovers under different market conditions. It is worth noting that the carbon market behaves completely opposite before and during the outbreak of COVID-19 under downside and upside market conditions. Under the downside market, shocks within the carbon market itself are reduced, while spillovers transmitted to other markets are enhanced by 12.68%. Under the upside market, the spillover of the carbon market to other markets is reduced by a total of 19.73%.

Third, under all market states, the electricity market enhanced shocks to other markets in the wake of the COVID-19 pandemic. The electricity market under the upside state is the most volatile, adding a total of 17.32% of risk shocks to other markets.

Fourth, the role of each market in the three markets changed following the COVID-19 outbreak. The hydrogen, wind energy, natural gas, and solar markets all transitioned from being net receivers of shocks to being net transmitters of shocks. The coal market transitions from being a net transmitter of shocks to becoming a net receiver of shocks. These results affirm the substantial influence of the COVID-19 pandemic on the interconnectedness among the studied markets.

4.3.2 Network analysis of spillover effects in the three markets

To further analyze the structural changes in spillover effects pre- and post-COVID-19 pandemic outbreak, this paper treats each market as a node. It calculates the average net spillover index, utilizing the TVP-VAR method. The color intensity and edge thickness representing the magnitude of the volatility spillover. Net spillover networks are constructed for the pre-COVID-19 period (August 1, 2013 to December 31, 2019) and for the post-COVID-19 period (January 2, 2022 to December 30, 2022). The results are shown in Fig. 8.

[insert figure 8 here]

Fig. 8 Net spillover network between markets before and during the COVID-19 pandemic

After the COVID-19 outbreak, the strength of spillovers between pairs of markets changed, but overall, spillovers between most markets increased during the COVID-19 outbreak. In Fig. 8(a), spillovers between the carbon and gas markets were most pronounced prior to the COVID-19 outbreak. However, after the COVID-19 outbreak (Fig. 8(b)), spillovers between the carbon market and the natural gas market weakened, whereas spillovers with the solar, coal, and petroleum markets increased. At the same time, spillovers between the electricity market and solar, coal and wind energy markets increase.

4.4 Investment strategies to address risk spillover in the three markets

4.4.1 Bilateral hedge ratios and portfolio weights

[insert figure 9 here]

Fig. 9 Bilateral hedge ratio between markets

Fig. 9 presents summary statistics on the hedge ratio between pairs of markets. In short, holding a long position of 1 RMB in the first market can be hedged by employing the average percentage of the hedge ratio from the short position in the second market. For instance, a hedge ratio of 51% between the coal and petroleum markets, indicates that 1RMB long position in coal can be hedged with 0.51RMB short position in petroleum, serving risk management purposes. It should be noted that the hedge ratios for natural gas market/carbon market, carbon market/natural gas market and hydrogen market/carbon market are negative, indicating an inverse correlation between the two markets, suggesting that the latter market can effectively hedge the former market.

In the case of hedging effectiveness of paired markets, a positive HE indicates that the investment will reduce market volatility. In Appendix Table A2, the coal/petroleum, petroleum/coal, and electricity/coal will effectively reduce the volatility of the markets, and the reduction in volatility is statistical significance at the 1% significance level. In other words, such portfolios effectively reduce financial risk. The dynamic investment hedge weights of the bilateral market can be observed in Appendix Fig.A2, which demonstrates the hedge weights among the three markets are changing over time, inferring that COVID-19 plays a role in determining the market bilateral investment weights to a certain extent over a short period.

4.4.2 Portfolio analysis to cope with volatility spillover among markets during the COVID-19 outbreak

Based on multiple approaches (MVP, MCP, MCoP), this paper constructs three multivariate portfolios, aiming to help investors optimize their investment strategies and mitigate risks effectively. The outcomes of the multivariate hedge effectiveness, portfolio weights and cumulative returns before and during the COVID-19 outbreak are shown in Appendix Table A4 and Fig. 10.

[insert figure 10 here]

Fig. 10 Equity line before and during the COVID-19 outbreak

Firstly, among the portfolio weights established by MCP and MCoP, the investment weight of the carbon market experienced substantial changes before and during the COVID-19 outbreak. The investment weight of the carbon market decreased from 0.29 to 0.19 in MCP, and from 0.26 to 0.15 in MCoP. Since COVID-19 emerged, although carbon market still had the highest investment weight in the entire portfolio based on MCP and MCoP, it also allocated investment weights relatively evenly to the energy and power markets, with the investment weights distributed more evenly across different markets.

Secondly, the investment effectiveness of the carbon market increased significantly amid the COVID-19 outbreak. Appendix Table A4 shows that regardless of which portfolio method is used to invest in the carbon market, investment effectiveness increases significantly to over 95% during the COVID-19 outbreak, and all exhibit statistical significance at the 1% confidence level. In view of this, investors could use the carbon market as part of their portfolio to hedge against the energy and power markets when conducting investments amid the COVID-19 outbreak.

Finally, MCP is the ideal portfolio method in an investment portfolio of three markets. The cumulative returns of portfolios crafted by MVP, MCP, and MCoP methods (Fig. 10) show that the configurations of portfolios created by MCP and MCoP are identical, and both approaches exhibit similar time-varying patterns across time. During the COVID-19 outbreak (Fig. 10 Panel B), there was a sustained upward development in investment returns after repeated flatness, indicating that MCP and MCoP methods outperform the MVP method. During the COVID-19 outbreak, the cumulative returns of the MCP method surpassed the other two portfolios.

In addition, repeated stagnation in investment returns amid the COVID-19 pandemic is temporary. Fig. 10 Panel B illustrates that in the period of the COVID-19 pandemic, portfolio returns as a whole show a consistent upward trajectory, although the portfolio returns repeatedly remained stagnant.

5. Discussion

5.1 Comparison with existing studies

In this research, the QVAR model and TVP-VAR model are employed to examine the spillover effects across the carbon, energy, and electricity markets. The study also aims to assess the changes in correlations between markets pre- and post-COVID-19 outbreak. Finally, this study establishes effective portfolio strategies to deal with the influence of risk spillovers among different markets. This study finds carbon market is more susceptible to shocks from extreme events during downturns, aligning with findings from previous studies (Liu & Man, 2023, Yuan et al., 2016, Jiang & Chen, 2022b). This paper finds the net direction of risk spillover is from the electricity market to the carbon market, i.e., the electricity market helps to diversify risks in the carbon market, which is the same as the observations made by Zhu et al (2020).

When studying energy market, this study considers both traditional and new energy. It is observed that the COVID-19 pandemic does not lead to an augmentation in the overall interconnectedness between markets. This differs from existing studies (Zhou & Wu, 2022, Jiang & Chen, 2022a) examining interconnectedness between the traditional energy market, metal market, and EU carbon market. For the carbon and energy markets, this study obtains that natural gas prices were the largest contributor to carbon prices before the COVID-19 pandemic, while petroleum prices became the largest contributor to carbon prices after the COVID-19 pandemic. This contradicts findings from prior research (Ji & Zhang, 2018;

Xueping et al., 2020), which consider petroleum prices in the energy market as the largest contributor to carbon prices. Existing studies mainly focused on the EU as the research object, omitting consideration of the COVID-19 pandemic, while this study divided the research period into two phases with the COVID-19 pandemic as a time node to specifically discuss the spillover effects between the carbon and energy markets.

Considering the increasing interconnections among global financial markets, it has become imperative for countries to correctly identify risk spillovers and network diffusion within the broader international financial landscape (Meng & Chen, 2023). China, being the globe's leading carbon emitter, frequently engages in interactions with other markets (Jiang W et al., 2022b). Regarding global carbon prices, fluctuations in the carbon market prices may influence global carbon pricing and trading. If Chinese carbon price is volatile, the EU, New Zealand, and South Korea may be affected by spillovers from carbon costs and carbon markets, further affecting global carbon emission reduction policies and carbon market stability. For emerging markets like Japan, India, and Brazil, which are preparing to implement carbon markets, this paper also provides an invaluable reference value in terms of inter-market risk spillovers.

Table 1 illustrates a comparison between this study and existing research.

[insert table 1 here]

5.2 Study Implications

This study examines the risk spillover effects between the carbon, energy, and electricity markets from multiple perspectives, which will be an important reference for policymakers and market participants. In particular, the paper highlights the influence of the COVID-19 outbreak on the spillover effects among markets, providing ideas for future market risk prediction in the face of emergencies. In addition, to actively address inter-market risk spillovers, this study constructs portfolio strategies that can serve as investment guidelines for investors.

5.3 Study Limitations

Due to data availability limitations, this study has some limitations. Significant differences exist in effective trading days among different carbon trading markets. This research opts for the Shenzhen carbon trading market due to its highest number of effective trading days. The uncertain repercussions of the study's findings could arise with the addition of carbon trading pilots from different regions of China.

6. Conclusions and Policy Implications

6.1 Conclusions

This study combines the QVAR model with the TVP-VAR model to investigate the risk spillover effects among the carbon, energy, and electricity markets under different market conditions. It aims to unveil the transmission paths and intensities of risks between markets. In addition, this research delves deeper into examining how inter-market spillovers are influenced by the COVID-19 pandemic and constructs investment portfolios to mitigate the risks associated with COVID-19. The primary conclusions are as:

Firstly, substantial spillovers exist among pairs of carbon, energy, and electricity markets. Under both extremely negative and positive market conditions, the connectedness between each pair of markets becomes stronger, and even stronger under an extremely positive market. Moreover, the carbon market consistently serves as the dominant net receipt of spillover effects among the three markets under all market conditions, while the electricity market serves as the primary net spillover transmitter. Second, during the COVID-19 pandemic outbreak, spillovers among carbon market and solar, coal and petroleum markets are increasing, and spillovers between electricity market and coal, solar and wind markets are also strengthened. Third, in a normal market, each market is dominated by its own internal shocks among itself. However, in an extremely downside market, internal shocks in the carbon market exhibit a diminishing influence, while the spillovers to the energy and electricity markets increase. Fourth, under the MCP and MCoP multiple portfolio methods, carbon market dominates the total investment allocation in the long run. Following the onset of the COVID-19 pandemic, the investment effectiveness in the carbon market has increased. Meanwhile, the carbon market also distributed investment weights relatively evenly to other markets, resulting in a more even distribution of investment weights across markets.

6.2 Policy Implications

This paper offers the following policy implications issues. Firstly, policymakers should keep a vigilant eye on the fluctuations in prices within the energy and electricity markets. This empirical study reveals a clearer and more detailed observation of the risk spillover relationships between markets in different periods, offering policymakers a more comprehensive perspective on inter-market risk spillovers. The experience of the inter-market risk spillover effect during the COVID-19 epidemic should be used as a lesson to prevent inter-market risk spillovers and strengthen the maintenance of carbon market stability. Specifically, efforts should be directed towards vigilant monitoring of natural gas, hydrogen, and electricity markets, as they represent the primary sources of risk for the carbon market. In addition, in the face of a prolonged period of economic recovery, wind, and coal markets may emerge as primary risk sources for the carbon market. In subsequent periods of economic growth, there should be an enhanced focus on monitoring traditional energy markets (natural gas, oil, coal).

Secondly, based on the comparative analysis before and after the COVID-19 pandemic, this paper proposes effective measures to address risk spillover between the carbon, energy, and electricity markets during international emergencies: (i) In the event of a sudden decline in economic activities, leveraging macroeconomic control measures by the government becomes crucial. Consideration should be given to temporarily adjusting the pricing mechanism of the carbon market, alleviating issues related to excessive cost burdens on enterprises. This approach aims to safeguard international economic and social stability, fostering sustainable development. (ii) Increasing investments in renewable energy projects including solar energy, hydrogen, and wind energy is recommended. Encouraging the growth of renewable energy sources helps decrease reliance on high-carbon energy, promoting a shift towards cleaner alternatives.

Thirdly, propels the marketization of carbon quota trading and strengthens market collaborative mechanisms. In the evolution of the national carbon trading market, government policymakers should enhance their involvement in macro-control. This will make the price of carbon emission allowances more marketable, thereby bolstering market liquidity, stabilizing carbon trading market prices, and effectively mitigating the impact of emergencies. Additionally, it is imperative to ensure policy coordination between the carbon market and energy market, preventing contradictions between policies and fostering organic integration of the two.

Fourthly, promotes international cooperation. Strengthen international collaboration in climate financing to support the efforts of developing countries in establishing carbon markets and facilitating the shift towards sustainable energy. This contributes to the equitable development of global carbon markets and reduces inequality among them. Facilitate information sharing, policy coordination, and exchange of best practices between carbon, energy, and power markets. This can be achieved by establishing international organizations, working groups, or platforms to enhance cooperation at the international level.

Fifthly, establish diversified portfolios incorporating both the carbon market and new energy markets. This may prove advantageous for hedging the elevated risks associated with investing in traditional energy markets, as optimized investment portfolios involving the carbon market can mitigate their volatility. Furthermore, to alleviate the adverse impacts of carbon market risk spillover, promoting international cooperation can be facilitated through the establishment of global standards and regulations. This collaboration may involve sharing carbon market experiences, promoting green finance, and encouraging sustainable investments, enabling nations to collectively address climate change and energy security challenges.

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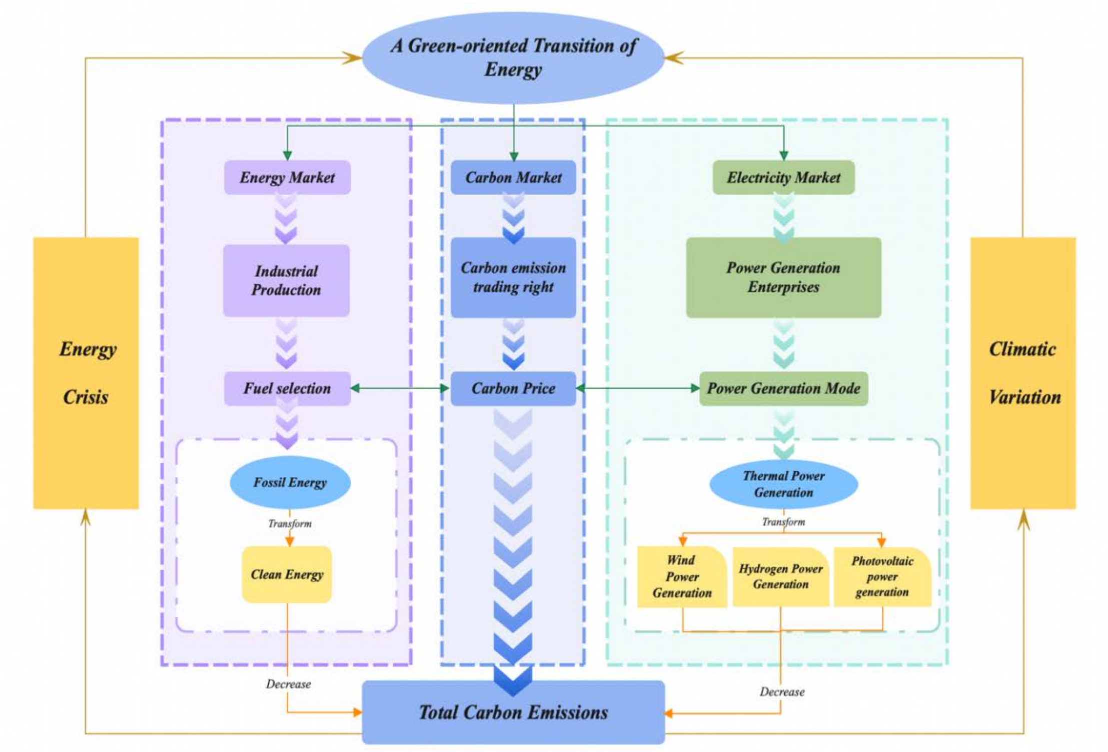


Fig. 1 Map of the relationship between carbon, energy, and electricity markets

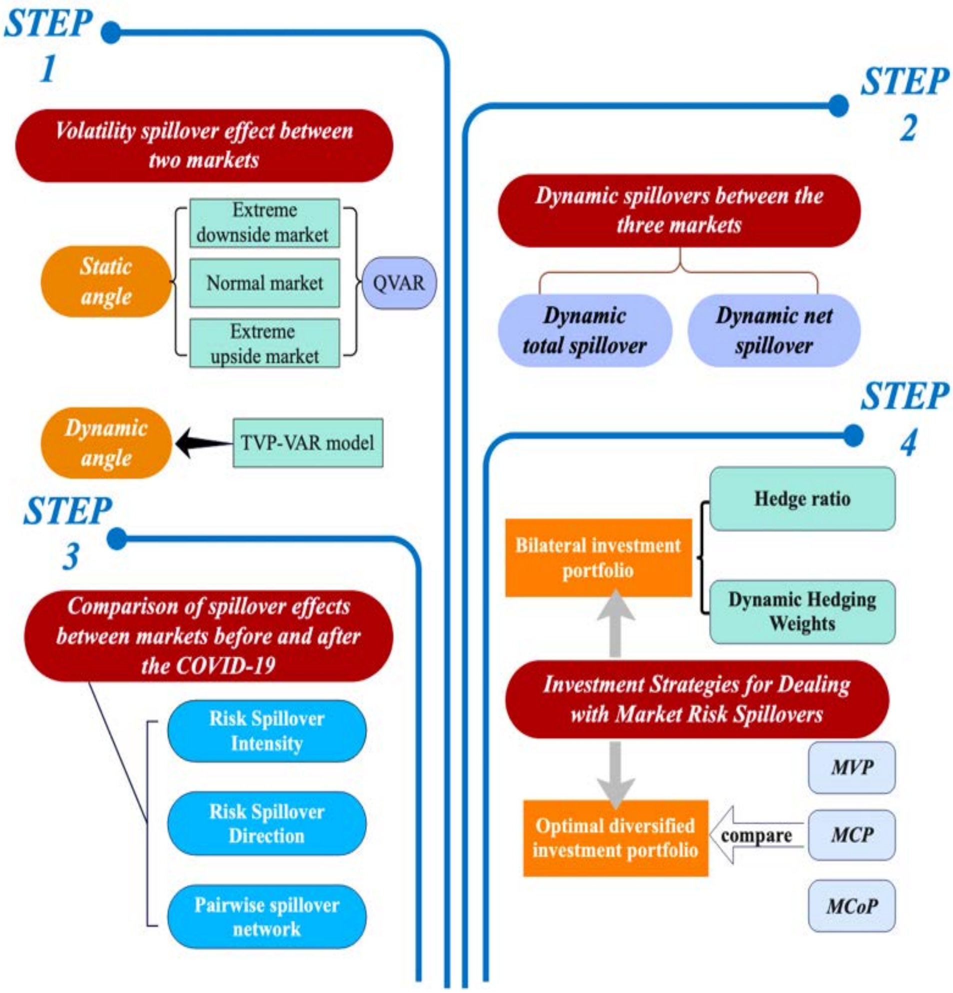
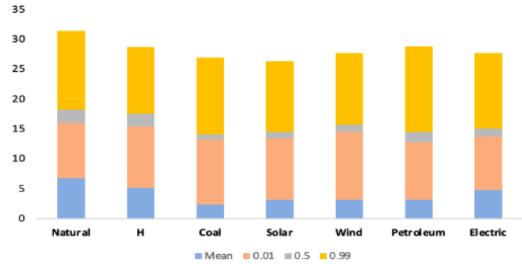
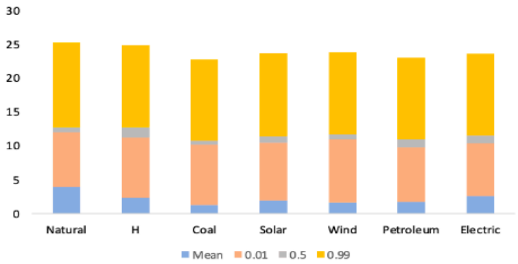


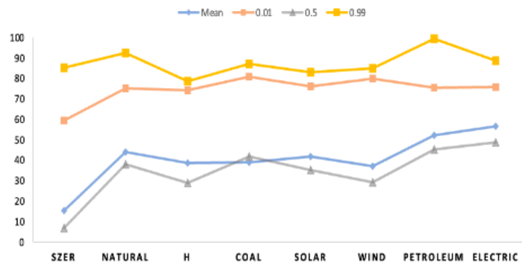
Fig. 2 Research flow chart of this study



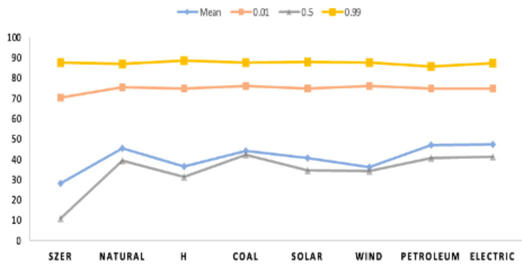
(I)Volatility spillover of carbon market from other markets under different market conditions



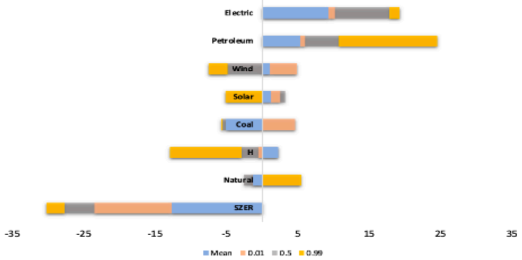
(II)Volatility spillovers from carbon market to other markets under different market conditions



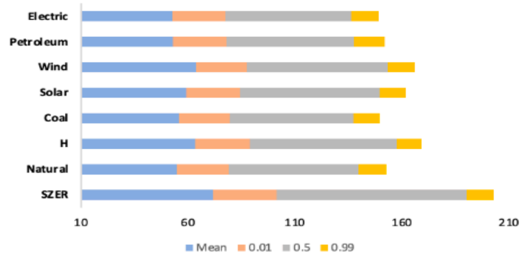
(III)Total volatility spillovers from each market to other markets under different market conditions



(IV)Each market receives the total volatility spillover of other markets under different market conditions



(V)Net volatility spillover of each market under different market conditions



(VI)Impact spillover effect of each market on itself under different market conditions

Fig. 3 Spillover Effects among three markets in China under different market conditions

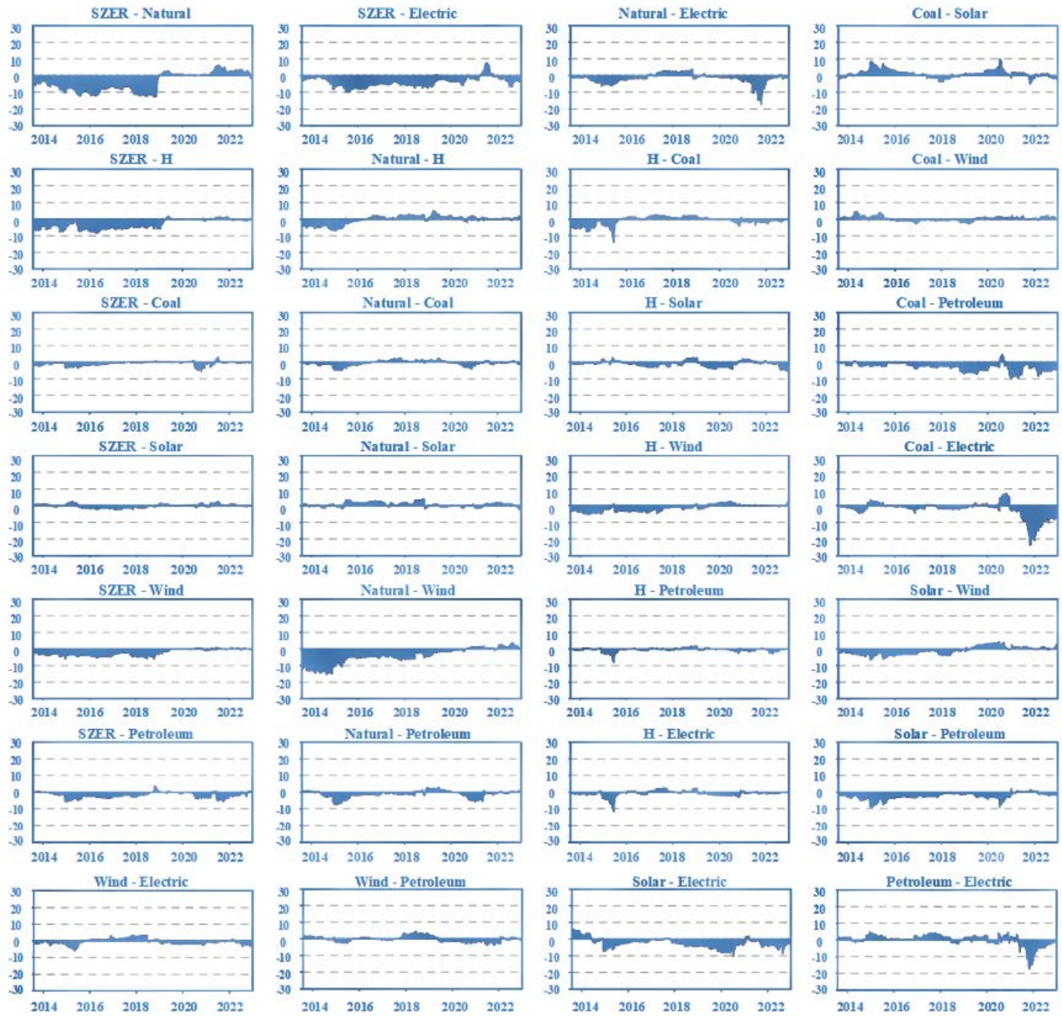


Fig. 4 Dynamic net directional connectedness between pairs of markets

Note: results are derived from a TVP-VAR model employing a lag length of order 1 (based on BIC) and a forecasting horizon of 20 steps ahead.

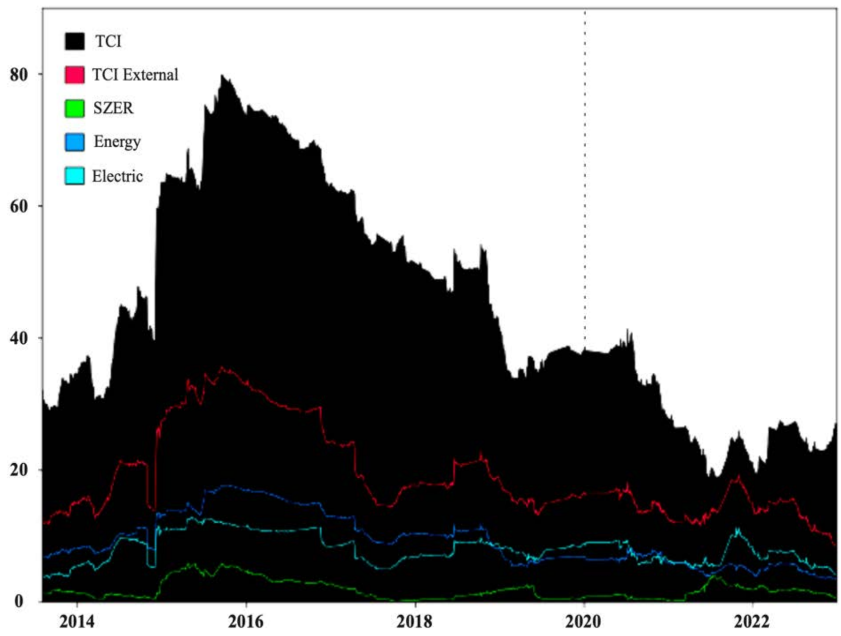


Fig. 5 Dynamic total connectedness among three markets in China

Note: results are derived from a TVP-VAR model employing a lag length of order 1 (based on BIC) and a forecasting horizon of 20 steps ahead.

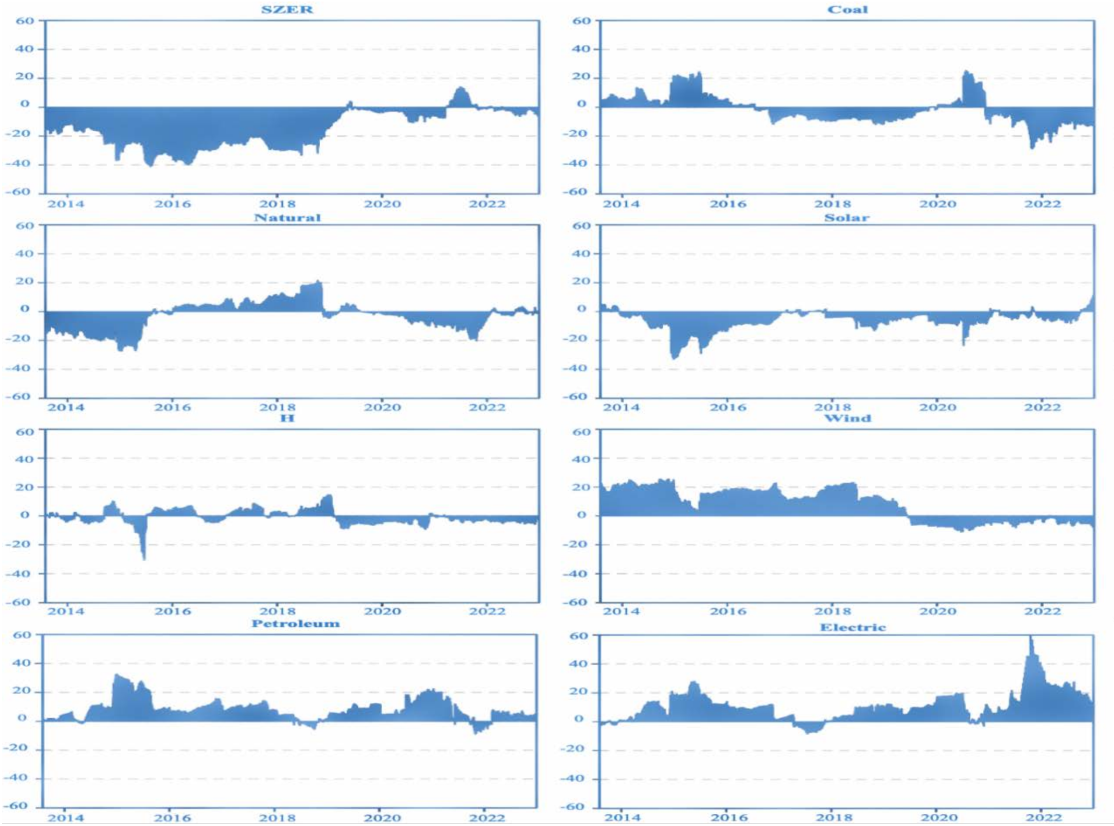


Fig. 6 Net directional connectedness among three markets in China

Note: results are derived from a TVP-VAR model employing a lag length of order 1 (based on BIC) and a forecasting horizon of 20 steps ahead.

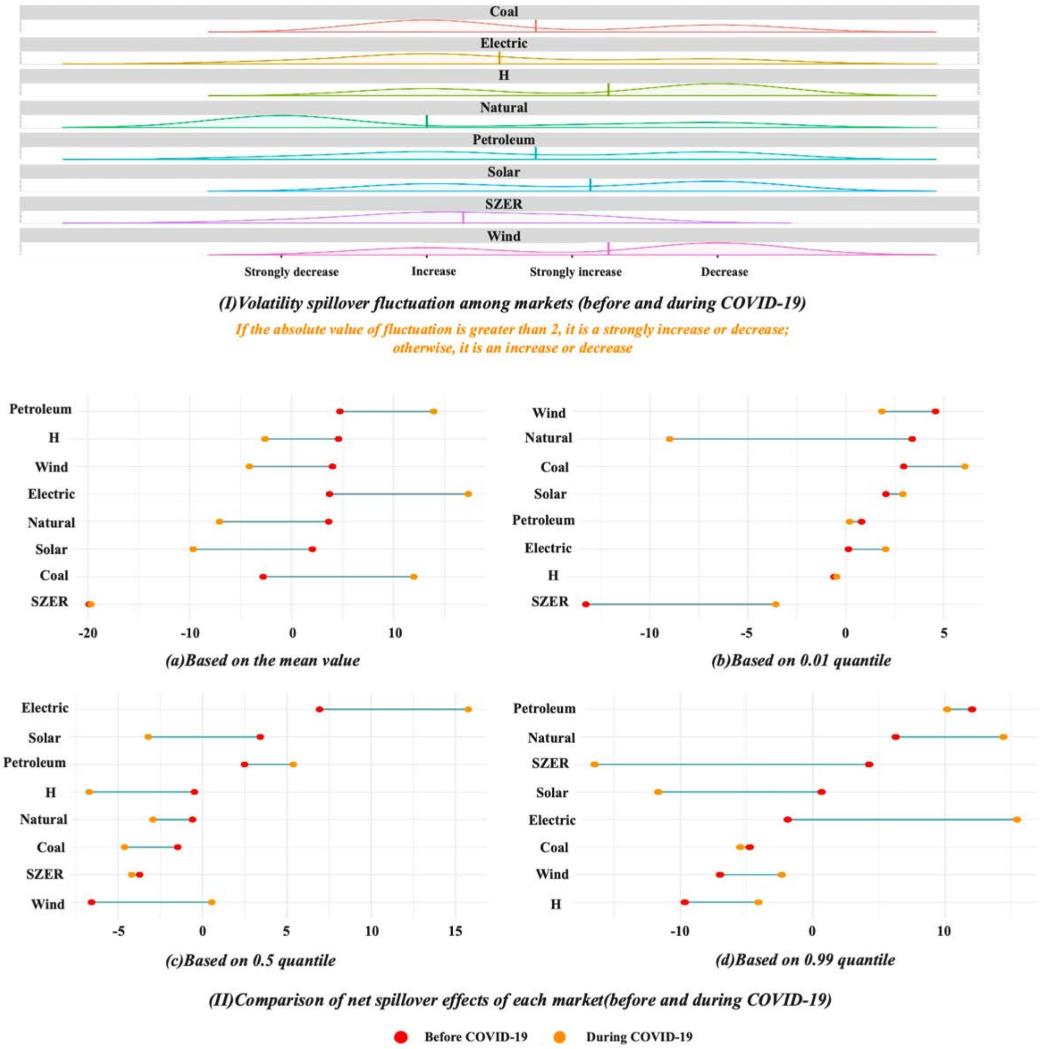
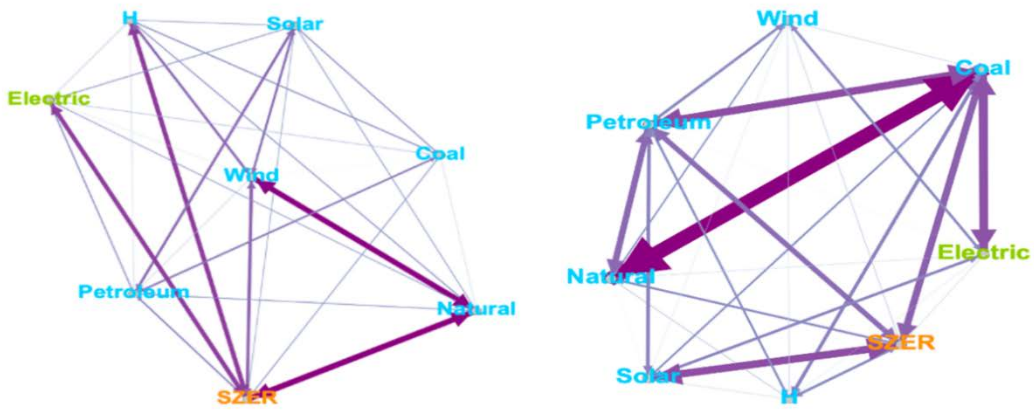


Fig. 7 Comparison of spillover effects among markets before and during the COVID-19 pandemic



(a) Before the outbreak of COVID-19

(b) During the outbreak of COVID-19

Fig. 8 Net spillover network between markets before and during the COVID-19 pandemic

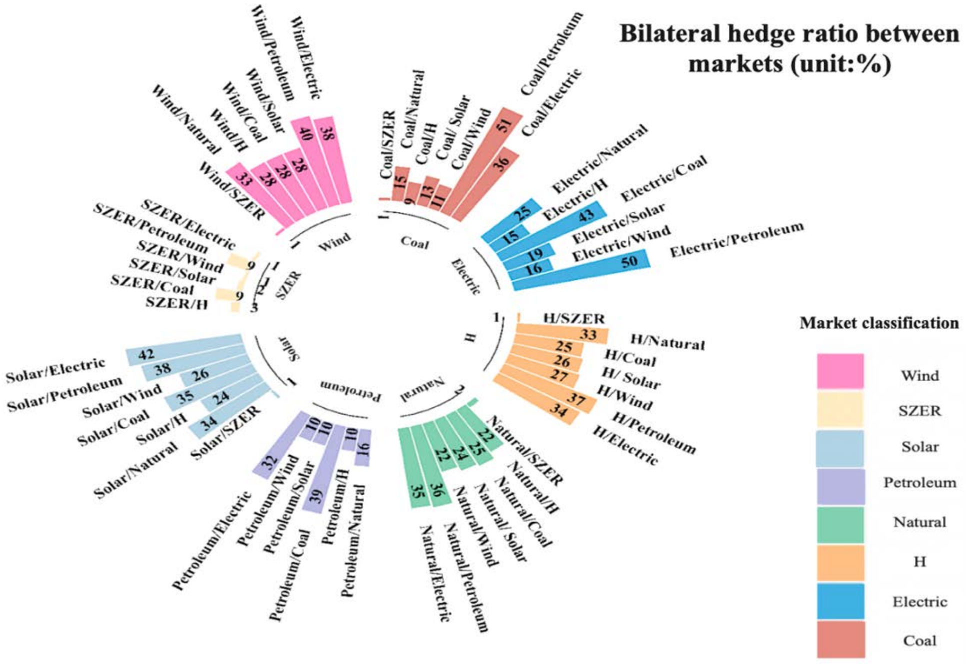


Fig. 9 Bilateral hedge ratio between markets

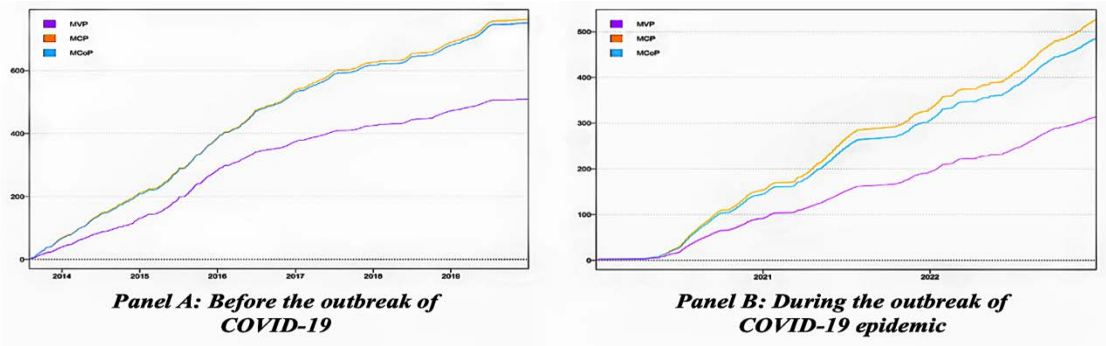


Fig. 10 Equity line before and during the COVID-19 outbreak

Note: This figure illustrates the accumulated total of portfolio returns. MVP denotes the Minimum Variance Portfolio, MCP signifies the Minimum Correlation Portfolio, and MCoP corresponds to the Minimum Connectedness Portfolio.

Table 1. Comparison with previous research.

Study	Method	Spillover effects Considerations	Investment portfolio Considerations	Results and findings
(Jiang&Chen, 2022b)	DY and Generalized Vector Autoregressive model	Yes	No	Spillovers in the carbon market after COVID-19 are approximately twice as pronounced as those observed in the pre-COVID-19 period.
(Chevallier, J. 2012)	CCC, DCC-MGARCH and BEKK models	No	No	Over time, the dynamic correlations among oil, gas, and CO2 prices are collectively modeled.
(Yuan Tian et al., 2016)	dynamic conditional correlation multivariate GARCH model	No	Yes	The stock market generally exhibits a positive response to changes in EUA prices, but there was an inverse relationship for carbon intensive producers.
(Zhang et al., 2023)	The quantile spillover index	Yes	No	The return and volatility spillovers within the clean energy, electricity, and energy metals markets have remarkable time-varying features.
(Nie et al., 2022)	DY and BK model	Yes	No	In the short run, the spillover effect of renewable energy stocks on carbon prices is notably impactful.
(Zhu et al., 2020)	BEMD-based CoVAR model	Yes	No	For modes with intermediate frequency, there exist reciprocal negative risk spillover effects between carbon market and electricity market.
This study	QVAR and TVP-VAR models	Yes	Yes	Amid the COVID-19 outbreak, there has been an escalation in the volatility spillover effect between the carbon market and other markets.