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Asymmetric connectedness between China’s carbon and energy markets based on TVP-VAR model

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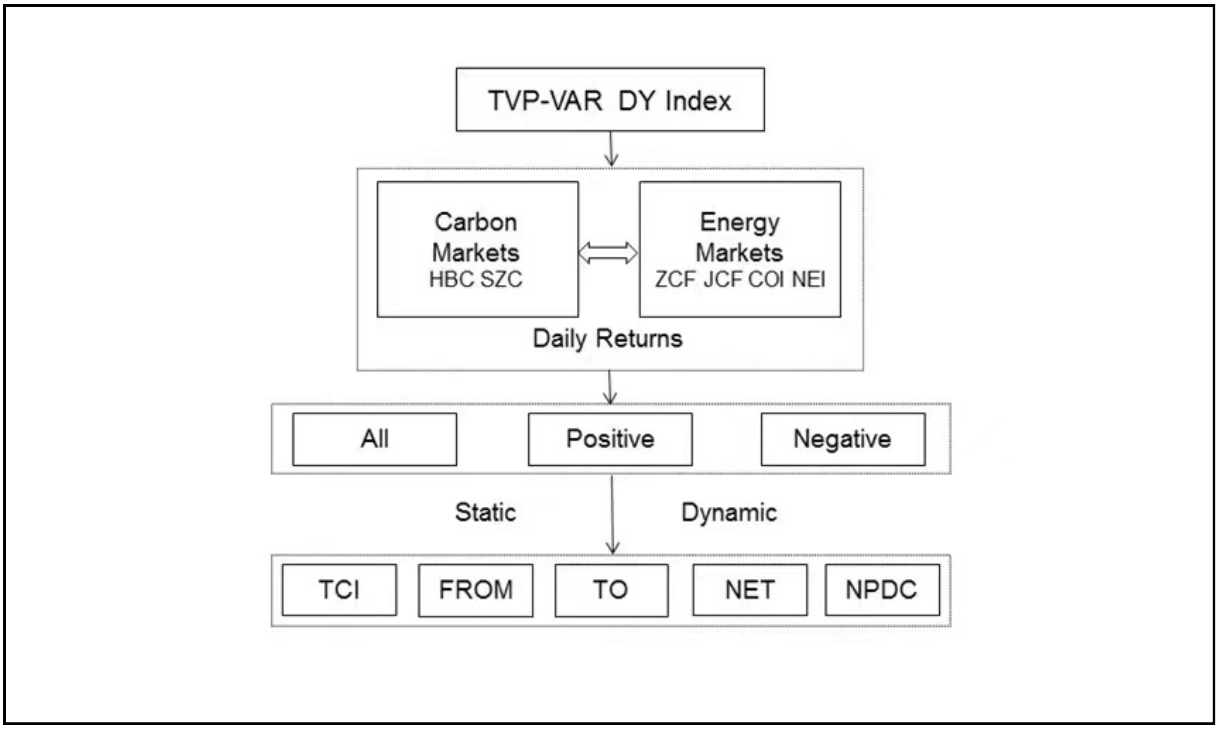
Graphical abstract



Public summary

■ This paper improves the Diebold-Yilmaz index model by time-varying parameter vector autoregressive (TVP-VAR) model.

■ This paper measures the static and dynamic spillovers between carbon trading markets, energy futures markets and energy stock markets.

■ This paper describes the asymmetric connectedness structure between carbon markets.

■ Compared with the Hubei pilot, Shenzhen pilot is more tightly connected to the energy markets, and the carbon markets have more substantial impacts on the energy markets when the prices of emission allowances rise.

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Asymmetric connectedness between China's carbon and energy markets based on TVP-VAR model

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Abstract: An intuitive portrayal of the correlation between the carbon and energy markets is essential for risk control and green financial investment management. In this paper, we examine the asymmetric propagation of return spillovers between carbon and energy markets at the sector level. To achieve that, we improve the Diebold-Yilmaz index by a time-varying vector autoregressive (TVP-VAR) model. In a unified network, our daily dataset includes the closing prices of the Hubei carbon market, Shenzhen carbon market, coal futures, and energy stock index. The findings reveal that both the Hubei and Shenzhen pilots typically generate net information spillovers on energy futures. In connection with energy stocks, the Hubei carbon market acts as a net receiver, while the Shenzhen carbon market is a net transmitter. Compared with the Hubei pilot, the Shenzhen pilot is more tightly connected to the energy markets. Furthermore, the spillovers of the carbon markets exhibit significant asymmetry. In most cases, they have more substantial impacts on the energy markets when the prices of emission allowances rise. The direction and magnitude of asymmetric spillovers across markets vary over time and can be influenced by certain economic or political events.

Keywords: carbon market; energy market; TVP-VAR; Diebold-Yilmaz model; asymmetrical connectedness

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2020 Mathematics Subject Classification: Management

1 Introduction

With rapid economic growth and excessive energy consumption, large amounts of greenhouse gas emissions have caused climate and ecological anomalies in recent years. It has become a global consensus to take active measures to address climate change. At the 75th session of the United Nations General Assembly, China announced that it would strive to reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060. The low carbon transformation of high energy consumption and carbon emission industries plays a pivotal role in achieving the "double carbon" target, which requires a large amount of financial support and is far from sufficient to rely on government subsidies alone. Both the carbon emission allowance trading markets (carbon market for short) and energy markets are playing an important role in the process, which can generate more investment demand and opportunities. Energy is the cornerstone of corporate production activities and economic development, and the financial markets associated with it have a strong influence on the overall system. The use of fossil energy and the application of new energy sources are closely related to the growth and reduction of total carbon emissions. The carbon market has become a globally recognized and effective tool for emission reduction[1]. Since 2013, China has established nine regional pilot carbon markets and launched a national unified carbon market in the power generation sector on July 21. The carbon market has the financial attribute of optimizing resource allocation. The information it releases may affect corporate decision-making and investor judgment, accelerating capital flows and thus creating linkages with other markets. At the same time, China is vigorously reforming the traditional fossil energy industry and developing new energy industries to optimize the energy consumption structure to reduce carbon emissions, further strengthening the linkage and risk contagion between the carbon and energy markets. An in-depth analysis of the spillover characteristics between China's carbon and energy markets is of great practical significance to further promote the rational formation of the intrinsic price transmission mechanism between the two markets and prevent the drastic price fluctuations of products in each market. Moreover, in the current economic situation, a "black swan" type event will considerably impact the regional and global economy. Extreme risk may be transmitted among multiple markets, so it is crucial to study the correlation between different markets to reduce the negative impact of such events on the stable development and investment returns of each market.

1.1 Brief overview of the literature

The correlation between carbon markets and energy markets has received much attention from scholars at home and abroad. The research findings vary according to different research subjects and approaches. Conver et al.(2007) found that energy prices have a significant impact on carbon prices in the EU based on dummy variables and multiple regressions[2]. Cao Guangxi et al.(2015) found that the Granger causality between the EU carbon market and oil price is not significant[3]. Balcilar et al.(2016) found significant dynamic risk spillovers from the coal market to the EU ETS based on the MS-DCC-GARCH model[4]. Uddin (2018) combined C-Vine Copula and CoVaR models to find that energy price volatility has a profound impact on EU carbon prices and that carbon assets can provide risk diversification effects for other commodities[5]. With the construction and development of China's regional carbon market, domestic scholars have successively conducted research on it. Guo Wenjun (2015) used the multiple dimensions Lasso method to find that Shenzhen carbon market is most influenced by the Euro exchange rate, followed by domestic oil price[6]. Studies by Tao Chunhua (2015) and Zhu Dongshan et al.(2016) both concluded that domestic carbon prices have no significant impact on new energy stock prices[7][8]. Cui Jie et al.(2018) demonstrated a cointegration relationship between the Beijing carbon market and the fossil energy market[9]. Wei Qi and Jin Zhuoran (2018) found a positive correlation between fossil energy and the Beijing carbon market based on linear regression analysis[10]. Zou Shaohui et al.(2020) used MSVAR model to reveal the dynamic evolution pattern of the nonlinear relationship among energy futures, energy stocks and Shenzhen carbon market. It was found that there is a regional switching effect of prices and a stronger persistence of nonstationary market states among markets[11]. Liu Jianhe et al.(2020) used the DCC-GARCH model to find that the correlation between the Hubei carbon market and coal market is more persistent and that there is a significant asymmetric spillover effect between them[12]. Xu Yingying (2021) used GAS Copula-CoVaR and found that compared to the Hubei carbon market, the Shenzhen carbon market is more affected by energy market uncertainty[13]. Wang Xu et al.(2021) constructed Copula-GARCH and DCC-GARCH models to reveal that the Shenzhen carbon market and the new energy market are dynamically dependent and that dynamic dependence increases when the market information is favorable[14]. Zhao Lingdi et al.(2021) used the Diebold-Yilmaz index model to study the two-way spillover effects between carbon and energy markets. They found that there are time-varying characteristics and regional differences in the spillover effect[15]. Zhang Shaobin et al. (2022) used the ARMA-GARCH-vine Copula model to analyze the multidimensional correlation between the Guangdong carbon price and several factors from the perspective of the international carbon market, energy price, and China’s economic situation. The results showed that the crude oil market plays a major role in the vine structure and that the carbon market is not strongly correlated with other markets[16]. Yao Yi et al.(2022) explored the dynamic evolution of information spillovers using the connected network and rolling window method. They found low information spillovers among the carbon, energy, and stock markets in China. The carbon market is the information transmitter, and the coal market is the largest information receiver in the network [17]. Wang Xiping et al. (2022) use the spillover index model and complex network analysis to capture the intensity and direction of risk spillover between the Beijing carbon market and various stock segment markets. The results show that the carbon market is a net receiver of risk from the stock market and is most influenced by new energy stocks[18]. In summary, the correlation between energy and carbon markets has been widely recognized. However, a uniform conclusion has yet to be reached regarding spillover direction, time-varying characteristics, degree of contribution, and regional differences.

In terms of research methods, there are four main categories. The first category is linear correlation measures, including the Granger causality test, linear regression, and simple vector autoregression. The model is too simple to portray the complex nonlinear correlations between markets. The second category is multivariate generalized autoregressive conditional heteroskedasticity models, such as BEKK-GARCH, DCC-GARCH, and MS-DCC-GARCH models. This method can better fit the motor’s spike and thick tail characteristics. However, it can only prove the existence of spillovers between markets rather than the extent and direction of spillovers. The third category is the copula model, which portrays nonlinear correlation structure and tail dependence. It is often combined with CoVaR methods to measure risk spillovers between markets. However, the copula model still cannot identify the net spillover and receiver of information. The excessive focus on tail information may ignore the market’s overall performance. The fourth category is the Diebold-Yilmaz spillover index method. The method is able to capture both the direction and intensity of spillovers between markets. Therefore, we choose it to analyze the connectedness of carbon and energy markets.

The marginal contributions of this paper are as follows: first, when using the Diebold-Yilmaz index approach, the literature uses the rolling window method to measure time-varying spillovers between carbon markets and other markets. The window width can impact the analysis results and cause the loss of valuable observations. In this paper, the TVP-VAR model avoids the problems associated with the choice of window width and can make fuller use of the sample data information. Second, this paper measures the spillover effects between the carbon and energy markets in both positive and negative return series to capture the asymmetry of the connectedness in the opposite price movement direction. Third, considering the importance of coal in China’s energy consumption structure and the development of new energy industries in recent years, this paper focuses on coal futures, coal stocks, and new energy stocks. The variable network includes China’s two most representative regional carbon markets, i.e., the Hubei and Shenzhen pilots. We put all of them into a unified framework for comparative analysis. This paper is organized as follows: Section 1 presents the research background and literature review. Second 2 introduces the correlation mechanism and the Diebold-Yilmaz connectedness measures improved by the TVP-VAR model. Section 3 presents the empirical analysis results based on the sample data. Section 4

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shows the discussion of the analysis conclusions and suggestions from the perspective of government and investors.

2 Mechanism and Model

2.1 Mechanism analysis

Based on market equilibrium theory, both the price of carbon emission allowances and the price of energy depend on the supply and demand in the market[19]. Emission control companies play an essential role in the correlation between the carbon and energy markets. Enterprises emit large amounts of greenhouse gases in their production processes. When the government intensifies its efforts to control emissions, it will reduce the setting and free distribution of carbon quotas, making it difficult for enterprises to reduce their greenhouse gas emissions in the short term. This change in the carbon market will cause changes in the spot or futures prices of energy. In consideration of cost control and development, emission control enterprises have two options: the first is to buy carbon allowances at a high price, and the second is to seek new energy technologies and equipment to reduce carbon emissions. Suppose the cost of purchasing carbon allowances is too high. In that case, companies will choose the second option, and emission control companies' demand for fossil energy will decline. In turn, changes in the price of fossil and new energy will influence the amount of fossil energy demanded by firms. The variation in carbon emissions of the emission-controlling companies will impact the carbon market by changing demand.

In addition, according to Hirschman's theory[20], changes in private information from one market can trigger price variation in related markets, resulting in intermarket interactions and linkages. While traditional energy companies profit from the extraction and sale of fossil energy, new energy companies are mainly engaged in developing and selling new energy technologies and equipment. On the one hand, carbon markets directly affect the revenue performance of both companies by influencing the demand for different energy products. On the other hand, the price signals from the carbon market may change investors' expectations and investment decisions regarding the development of energy companies, leading to volatility in energy stock prices. In addition, considering exogenous factors, the prices of carbon emission allowances and energy markets are also affected by the level of industrial development, the degree of financial market development, climate change, and other factors[21]. In turn, their changes can also affect macroeconomic developments[22]. Thus, it is reasonable to assume that there is a significant link between the carbon and energy markets.

2.2 TV-VAR

In the aftermath of the 2008 global financial crisis, measuring the propagation of financial crises across economies and markets has become a hot topic of academic research. In general, crises are unpredictable, but the transmission mechanisms associated with financial risk share certain similarities. In recent years, researchers have proposed a variety of measures to capture and characterize the transmission mechanisms associated with such events. One notable empirical method is the spillover index method proposed by Diebold and Yılmaz (DY index model)[23–25]. They proposed a framework for measuring interdependence in a network of variables based on the estimation of the forecast error variance decomposition derived from a VAR model. These measures allow us to further classify interdependence and provide granulated information, considering the fact that results can be obtained for (i) aggregate, (ii) directional, and (iii) net interdependence. Specifically, in terms of net interdependence, the approach is able to distinguish between net shock transmitters and net shock receivers, which helps to better understand the underlying dynamics and facilitate the formulation of policy implications. In their 2009 study, Diebold and Yilmaz investigated the interdependence between variables of interest by using a Cholesky-type VAR framework in which the order of the variables would affect the results. Subsequently, in 2012, they used a generalized VAR approach, where the order of the variables was irrelevant. Finally, in the 2014 study, Diebold and Yilmaz emphasized the concept of connectedness and provided a method to measure it.

Based on the DY index model above, Antonakakis et al. (2020) used a time-varying parametric vector auto-regressive model (TVP-VAR) to capture possible changes in the underlying structure of the data in a more flexible and robust manner[26]. Compared to the original DY index model, the model has three main advantages: first, since the heteroskedasticity process usually outperforms the homoskedasticity process, the time-varying variance-covariance structure facilitates the model to produce regression results that are more consistent with economic reality. Second, since it does not involve rolling window analysis, the model overcomes the selection burden of rolling window sizes, which may lead to unstable or flattened parameters, and avoids the loss of valuable observations. Third, since the model is estimated using the Kalman filter, it is insensitive to outliers. Specifically, the TVP-VAR(p) model is constructed as follows:

$$\boldsymbol{y}_t = \boldsymbol{A}_t z_{t-1} + \boldsymbol{\epsilon}_t \quad \boldsymbol{\epsilon}_t \mid \Omega_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}_t), \tag{1}$$

$$\operatorname{vec}(\boldsymbol{A}_t) = \operatorname{vec}(\boldsymbol{A}_{t-1}) + \boldsymbol{\xi}_t \quad \boldsymbol{\xi}_t \mid \boldsymbol{\Omega}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{\Xi}_t), \tag{2}$$

with

$$z_{t-1} = \begin{pmatrix} \boldsymbol{y}_{t-1} \\ \boldsymbol{y}_{t-2} \\ \vdots \\ \boldsymbol{y}_{t-p} \end{pmatrix} \quad \boldsymbol{A}_t' = \begin{pmatrix} \boldsymbol{A}_{1t} \\ \boldsymbol{A}_{2t} \\ \vdots \\ \boldsymbol{A}_{pt} \end{pmatrix},$$

where $\boldsymbol{y}_t$ and z_t represent $m\times 1$ and $mp\times 1$ vectors, $\boldsymbol{A}_t$ and $\boldsymbol{A}_{it}$ represent $m\times mp$ and $m\times m$ dimensional matrices, $\operatorname{vec}(\boldsymbol{A}_t)$ is the vectorisation of $\boldsymbol{A}_t$ which is an $m^2p\times 1$ dimensional vector. Ω_{t-1} is the information set until $t-1$. $\boldsymbol{\epsilon}_t$ and $\boldsymbol{\xi}_t$ represent $m\times 1$ and $m^2p\times 1$ vector,respectively, whereas the time-varying variance-covariance matrices $\boldsymbol{\Sigma}_t$ and Ξ_t are $m\times m$ and $m^2p\times m^2p$ dimensional matrices. In our study, we set the VAR estimation results of the first 60 days as the initialization of the Kalman filter.

Considering the numerical stability, we apply decay factors in the Kalman filter algorithm. The choice of decay factors is similar to the choice of priors in general, and depends on the expected amount of time variation in the parameters. Al-

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though the estimation procedures allow the decay factors to vary over time, we still keep them constant at fixed values because Koop and Korobilis (2013) found that the forecasting performance added by time-varying decay factors may be doubtful and increase the computation burden significantly[27]. Drawing on Adekoya et al. (2022)[28], the benchmark values for κ_1 and κ_2 were set at 0.99 and 0.99, respectively. In turn, the Kalman filter can be calculated as follows:

$$
\begin{aligned}
\operatorname{vec}(\boldsymbol{A}_t) \mid z_{1:t-1} &\sim N\left(\operatorname{vec}(\boldsymbol{A}_{t|t-1}), \boldsymbol{\Sigma}^A_{t|t-1}\right)\\
\boldsymbol{A}_{t|t-1} &= \boldsymbol{A}_{t-1|t-1}\\
\boldsymbol{\epsilon}_t &= \boldsymbol{y}_t - \boldsymbol{A}_{t|t-1} z_{t-1}\\
\boldsymbol{\Sigma}_t &= \kappa_2 \boldsymbol{\Sigma}_{t-1|t-1} + (1-\kappa_2)\boldsymbol{\epsilon}_t' \boldsymbol{\epsilon}_t\\
\boldsymbol{\Xi}_t &= (1-\kappa_1^{-1})\boldsymbol{\Sigma}^A_{t-1|t-1}\\
\boldsymbol{\Sigma}^A_{t|t-1} &= \boldsymbol{\Sigma}^A_{t-1|t-1} + \boldsymbol{\Xi}_t\\
\boldsymbol{\Sigma}_{t|t-1} &= z_{t-1} \boldsymbol{\Sigma}^A_{t|t-1} z'_{t-1} + \boldsymbol{\Sigma}_t
\end{aligned}
$$

Given the information at time t, $\boldsymbol{A}_t$,$\boldsymbol{\Sigma}^A_t$ and $\boldsymbol{\Sigma}_t$ can be updated as follows:

$$
\begin{aligned}
\operatorname{vec}(\boldsymbol{A}_t) \mid z_{1:t} &\sim N\left(\operatorname{vec}(\boldsymbol{A}_{t|t}), \boldsymbol{\Sigma}^A_{t|t}\right)\\
\boldsymbol{K}_t &= \boldsymbol{\Sigma}^A_{t|t-1} z'_{t-1} \boldsymbol{\Sigma}^{-1}_{t|t-1}\\
\boldsymbol{A}_{t|t} &= \boldsymbol{A}_{t|t-1} + \boldsymbol{K}_t(\boldsymbol{y}_t - \boldsymbol{A}_{t|t-1} z_{t-1})\\
\boldsymbol{\Sigma}^A_{t|t} &= (\boldsymbol{I} - \boldsymbol{K}_t)\boldsymbol{\Sigma}^A_{t|t-1}\\
\boldsymbol{\epsilon}_{t|t} &= \boldsymbol{y}_t - \boldsymbol{A}_{t|t} z_{t-1}\\
\boldsymbol{\Sigma}_{t|t} &= \kappa_2 \boldsymbol{\Sigma}_{t-1|t-1} + (1-\kappa_2)\boldsymbol{\epsilon}_{t|t}' \boldsymbol{\epsilon}_{t|t}
\end{aligned}
$$

where $\boldsymbol{K}_t$ denotes the Kalman gain, which explains how much the parameters $\boldsymbol{A}_t$ should be changed in any given state. To determine the generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD), the TVP-VAR must be transformed to its vector moving average (VMA) representation by the Wold representation theorem:

$$
\boldsymbol{y}_t = \sum_{j=0}^{\infty} \boldsymbol{B}_{jt} \boldsymbol{\epsilon}_{t-j}, \quad \boldsymbol{B}_{jt} = \boldsymbol{J}' \boldsymbol{M}_t^j \boldsymbol{J}, \quad j = 0,1,\ldots \tag{3}
$$

with

$$
\boldsymbol{M}_t = \begin{pmatrix} \boldsymbol{A}_t & \\ \boldsymbol{I}_{m(p-1)} & \boldsymbol{0}_{m(p-1)\times m} \end{pmatrix} \quad \boldsymbol{J} = \begin{pmatrix} \boldsymbol{I} \\ \boldsymbol{0} \\ \vdots \\ \boldsymbol{0} \end{pmatrix} \tag{4}
$$

where $\boldsymbol{B}_{jt}$ is an $m \times m$ dimensional matrix.

2.3 Connectedness measurement

The GIRFs ($\boldsymbol{\Psi}_{ij,t}(H)$) measure the responses of all variables j following a shock in variable i. We compute the differences between an H-step-ahead forecast once where i is shocked and once where i is not shocked. The difference can be attributed to the shock in variable i, which can be calculated by:

$$
\begin{aligned}
\mathrm{GIRF}_t(H, \boldsymbol{\delta}_{j,t}, \boldsymbol{\Omega}_{t-1}) &= E(\boldsymbol{y}_{t+H} \mid \boldsymbol{e}_j = \boldsymbol{\delta}_{j,t} \boldsymbol{\Omega}_{t-1}) - E(\boldsymbol{y}_{t+J} \mid \boldsymbol{\Omega}_{t-1})\\
\boldsymbol{\Psi}_{j,t}(H) &= \frac{\boldsymbol{B}_{H,t} \boldsymbol{\Sigma}_t e_j}{\sqrt{\Sigma_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}} \quad \delta_{j,t} = \sqrt{\Sigma_{jj,t}}\\
\boldsymbol{\Psi}_{j,t}(H) &= \Sigma_{jj,t}^{-\frac{1}{2}} \boldsymbol{B}_{H,t} \boldsymbol{\Sigma}_t \boldsymbol{e}_j,
\end{aligned} \tag{5}
$$

where e_j is an $m \times 1$ selection vector with unity in the $j-th$ position and zero otherwise. The GFEVD $\tilde{\phi}_{ij,t}(H)$ measures the pairwise directional connectedness from j to i and represents the influence variable j has on i with respect to its forecast error variance share. It can be calculated as follows:

$$
\tilde{\phi}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi^2_{ij,t}}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi^2_{ij,t}} \tag{6}
$$

with $\Sigma_{j=1}^m \tilde{\phi}_{ij,t}(H) = 1$ and $\Sigma_{i,j=1}^m \tilde{\phi}_{ij,t}(H) = m$. These variance shares are normalized so that each row sums up to 1, which means that all variables explain 100% of $i's$ forecast error variance. The numerator represents the cumulative effect of a shock in i and the denominator is the cumulative effect of all the shocks. Based on GFEVD, the *total connectedness index* (TCI) is constructed by

$$
C_t(H) = 100 \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i,j=1}^{m} \tilde{\phi}_{ij,t}(H)} = 100 \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{m}. \tag{7}
$$

$C_t(H)$ illustrates how a shock in one variable spills over to others. In addition, Gabauer (2021) has shown that TCI can be decomposed into the *pairwise connectedness index* (PCI) which measures the interconnectedness between two variable i and j [29]:

$$
C_{ij,t} = 2 \frac{\tilde{\phi}_{ij,t}(H) + \tilde{\phi}_{ji,t}(H)}{\tilde{\phi}_{ij,t}(H) + \tilde{\phi}_{ji,t}(H) + \tilde{\phi}_{ii,t}(H) + \tilde{\phi}_{jj,t}(H)} \tag{8}
$$

This index ranges between [0, 1], representing the degree of bilateral interconnectedness across i and j. First, considering the case where i transmits its shock to all other variables, we construct the index called *total directional connectedness to others* and defined it as

$$
C_{i\to others,t}(H) = 100 \frac{\sum_{j=1, i\neq j}^{m} \tilde{\phi}_{ji,t}(H)}{\sum_{j=1}^{m} \tilde{\phi}_{ji,t}(H)}. \tag{9}
$$

Second, we measure the directional connectedness variable i receives from other variables, called *total directional connectedness from others* as

$$
C_{i\leftarrow others,t}(H) = 100 \frac{\sum_{j=1, i\neq j}^{m} \tilde{\phi}_{ij,t}(H)}{\sum_{i=1}^{m} \tilde{\phi}_{ij,t}(H)}. \tag{10}
$$

Third, the *net total directional connectedness* can be ob-

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tained by

$$C_{i,t} = C_{i\rightarrow others,t}(H) - C_{i\leftarrow others,t}(H). \tag{11}$$

$C_{i,t} > 0$ means that variable i influences the network more than the influences it receives from others. In contrast, $C_{i,t} < 0$ means that i is driven by the network. Finally, we measure the bidirectional relationships by computing the *net pairwise directional connectedness*,

$$NPDC_{i\rightarrow j}(H) = 100\left(\tilde{\phi}_{ji,t}(H) - \tilde{\phi}_{ij,t}(H)\right). \tag{12}$$

$NPDC_{i\rightarrow j}(H) > 0$ means that variable i dominates j and $NPDC_{i\rightarrow j}(H) < 0$ means that i is dominated by j.

3 Results and Discussion

3.1 Data and preliminary analysis

Currently, nine regional carbon emission allowance trading markets have been established in China. They have distinctive mechanism and rule design, showing significant differences in trading volume and activity. Up to now, the Hubei pilot has the largest volume and highest turnover, while the Shenzhen pilot was established the earliest and has the highest liquidity, and both markets have high maturity and good representativeness. Therefore, we choose the Hubei and Shenzhen carbon markets as the subjects of our study, which are denoted by HBC and SZC, respectively. For the energy futures market, the white paper "China's Energy Development in the New Era" released by the State Council in 2021 shows that coal accounts for up to 57.7% of total energy consumption, and it remains the mainstay of China's current energy use. In addition, oil consumption is predominantly dependent on imports, while natural gas prices are mainly controlled by the government. Considering the financial attributes and price discovery function of the futures market, we choose power coal futures and coke futures as energy market representatives, denoted by JCF and ZCF, respectively. Thermal coal is used in power generation and locomotive propulsion, and coke is used in the coking and steel industry. For the energy stock market, the Shenwan Coal Industry Index (Code: 000820) and CSI New Energy Index (Code: 399808) are selected in this paper and represented by COI and NEI, respectively. The CSI New Energy Index selects securities of listed companies involved in renewable energy production, application, storage and interactive equipment as the sample to reflect the overall performance of the new energy industry. The sample interval is from July 1, 2014 to June 30, 2021. The number of observation data for each variable is 1706, and the formula for return series is:

$$r_{i,t} = 100\ln\frac{P_{i,t}}{P_{i,t-1}} \tag{13}$$

Where $P_{i,t}$ and $P_{i,t-1}$ are the closing prices at time t and $t-1$. Figure 1 shows the closing prices of each market during the sample period. Energy futures and stock markets show similar trend changes, while the trajectories of the Hubei and

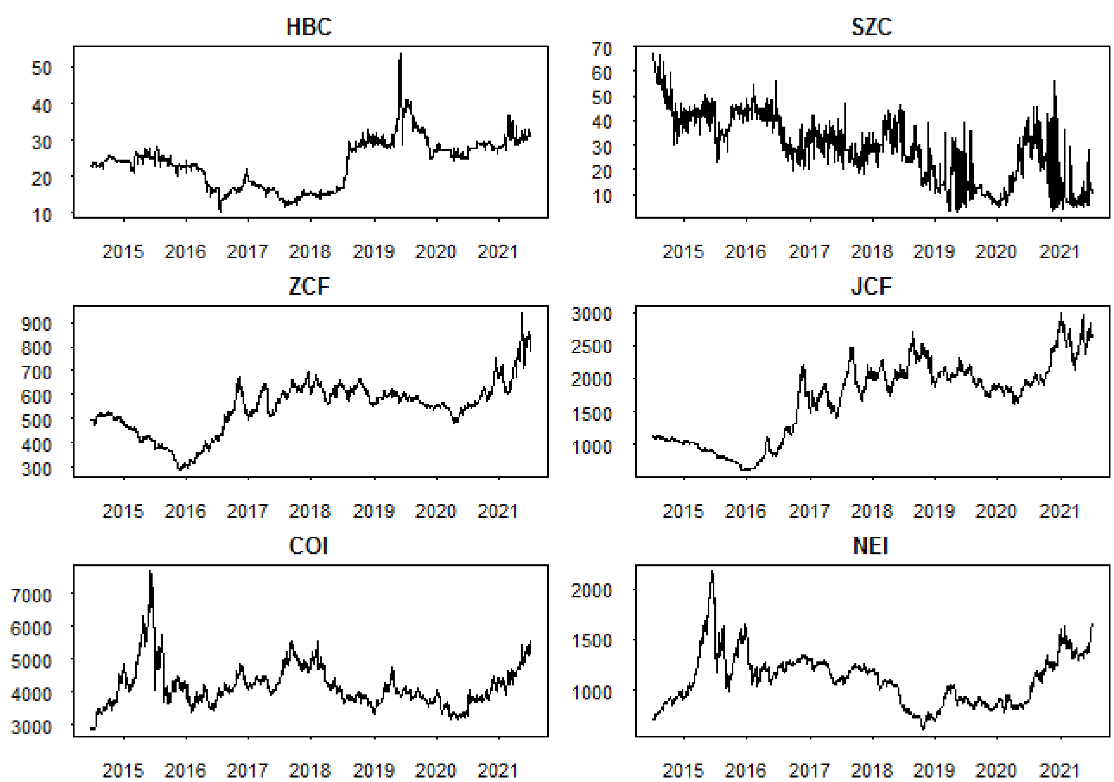

Fig. 1. Closing prices of each market

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Table 1. Descriptive statistics of the return series

	HBC	SZC	ZCF	JCF	COI	NEI
Mean	0.02	−0.11	0.03	0.05	0.04	0.05
Std.dev	2.95	33.99	1.57	2.14	2.16	2.05
Skewness	−0.31	0.23	−1.21	−1.03	−0.56	−0.90
Kurtosis	4.53	20.73	13.95	8.97	4.17	3.87
J-B	1488.60	30633.00	14283.00	6040.40	1328.00	1301.00
(Prob.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ADF	−14.13	−16.95	−11.63	−9.77	−12.69	−11.90
(Prob.)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Shenzhen carbon markets are very distinct, indicating a strong heterogeneity between them.

Table 1 reports the descriptive statistics of the return series. The carbon market has higher volatility than the energy futures and stock markets, and the volatility of the Shenzhen carbon market is much stronger than that of the Hubei carbon market. The values of kurtosis and J-B statistic indicate that all return series do not satisfy the normal distribution and are characterized by sharp peaks and thick tails. The larger the value of kurtosis is, the higher the frequency of extreme events. The results of the ADF test prove that the return series are all stable at the 1% significance level, so it is reasonable to apply the TVP-VAR model.

In addition, to investigate the asymmetry of market connectedness, we divide the return series into positive and negative groups. The process is as follows:

$$S_t = \begin{cases} 0, & \text{if } r_{i,t} < 0 \\ 1, & \text{if } r_{i,t} \geqslant 0 \end{cases}$$
$$r_{i,t}^{+} = S_t \cdot r_{i,t}$$
$$r_{i,t}^{-} = (1 - S_t) \cdot r_{i,t}$$

where $r_{i,t}^{-}$ and $r_{i,t}^{+}$ stand for the negative and positive return series. The overall, negative and positive returns are analyzed separately using TVP-VAR and Diebold-Yilmaz models.

3.2 Average connectedness measures

Based on the AIC, the lag order of the VAR model is fifth. According to previous research results, we set the number of periods for forecast variance decomposition to 10[15]. We first analyze the average connectedness measures. From top to bottom, Table 2 presents the results of overall, negative returns, and positive returns connectedness calculations in order. FROM denotes the sum of shocks to a market from other markets.TO denotes the sum of spillover effects of a market on other markets. The nondiagonal elements are the interactions between the variables in the network, while the elements in the main diagonal correspond to idiosyncratic shocks, i.e., own innovations. Taking the HBC as an example, we note that the value on the main diagonal is 86.70, which implies that 86.7% of the forecast error variance of the Hubei carbon market returns can be attributed to own innovations. In contrast, the remaining error is driven by changes in other markets within the network. Notably, 4.05% and 4.22% of the error variance comes from the futures and stock markets, respectively. In turn, the total spillover index of the Hubei carbon market to others is 9.43, giving it a net spillover index of -3.87, indicating that it is a net information receiver in the overall network. Similarly, we find that the Shenzhen carbon market is less impacted by other markets than the Hubei carbon market, generates more spillover effects and is the largest net information transmitter in the network. In addition, the returns of energy futures and stock indices are more susceptible to other markets than the carbon market, and the connectedness between the two variables of the same market type is more vital. According to the upper part of Table 3, the value of the total connectedness index (TCI) is 26.46%, which means that, on average, the interdependence of variables in the network is not very substantial.

The middle and lower parts of Table 2 present the connectedness measures of negative and positive returns, respectively. Qualitatively, these findings are similar to the above results in terms of the role played by each market (i.e., network information transmitter and network receiver). Nevertheless, it should be noted that both the carbon and futures markets are significantly more exposed to shocks from other markets when based on positive returns. At the same time, they create more significant spillover effects. In contrast, stock indices are more closely connected to other variables when prices decline. The above results suggest an asymmetry of the connectedness between the different variables when the market rises and falls. However, the average analysis is inherently static, making it challenging to capture the evolution of these measures over time. Considering that some economic or political events occurred throughout the sample period, these events may have led to positive or negative developments in the factors affecting the variables. In this regard, we turn to analyzing the dynamic connectedness measures.

3.3 Dynamic connectedness measures

3.3.1 Total connectedness

We first check the total dynamic connectedness. The results are shown in Figure 2. Note that the black shaded area illustrates the evolution of the overall TCI considering both positive and negative returns. The red line represents the dynamic TCI when only negative returns are considered. In contrast, the blue line refers to the evolution of the TCI based on positive returns. We note that the total connectedness index fluctuated between 17.82% and 62.90%, reaching its highest level in August 2014. Since then, the TCI has fluctuated by approximately 20-30%. Moreover, qualitatively, the results of the three different dynamic connectedness measures are similar, considering that they all exhibited substantial peaks and

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Table 2. Averaged connectedness results

ALL	HBC	SZC	ZCF	JCF	COI	NEI	FROM
HBC	86.70	5.04	2.04	2.01	2.28	1.94	13.30
SZC	1.59	90.90	1.63	1.89	1.75	2.25	9.10
ZCF	2.06	4.60	73.45	12.73	5.20	1.95	26.55
JCF	2.33	3.33	12.74	69.77	8.80	3.02	30.23
COI	1.70	3.90	4.38	7.08	57.58	25.35	42.42
NEI	1.76	3.41	1.70	3.17	27.12	62.83	37.17
TO	9.43	20.28	22.51	26.89	45.15	34.51	158.77
NET	-3.87	11.18	-4.04	-3.34	2.74	-2.66	-
NEGATIVE	HBC	SZC	ZCF	JCF	COI	NEI	FROM
HBC	87.44	5.03	1.85	2.02	1.79	1.87	12.56
SZC	1.65	92.32	1.37	1.52	1.20	1.94	7.68
ZCF	2.20	4.61	76.52	11.06	3.81	1.81	23.48
JCF	2.62	5.45	11.01	72.24	5.89	2.79	27.76
COI	1.23	4.29	3.32	4.97	57.17	29.02	42.83
NEI	1.27	4.61	2.04	2.51	29.92	59.65	40.35
TO	8.97	24.00	19.58	22.08	42.61	37.42	158.77
NET	-3.87	16.32	-3.90	-5.68	-0.22	-2.93	-
POSITIVE	HBC	SZC	ZCF	JCF	COI	NEI	FROM
HBC	85.75	5.70	1.91	1.88	2.70	2.06	14.25
SZC	1.59	91.19	1.70	1.61	1.86	2.06	8.81
ZCF	2.57	8.52	71.35	11.47	4.59	1.50	28.65
JCF	2.05	6.49	11.43	70.13	7.01	2.90	29.87
COI	2.31	4.06	4.81	6.41	64.77	17.63	35.23
NEI	1.82	5.30	1.60	2.69	18.54	70.06	29.94
TO	10.34	30.06	22.45	24.06	34.69	26.15	146.75
NET	-3.91	21.25	-7.20	-5.81	-0.54	-3.80	-

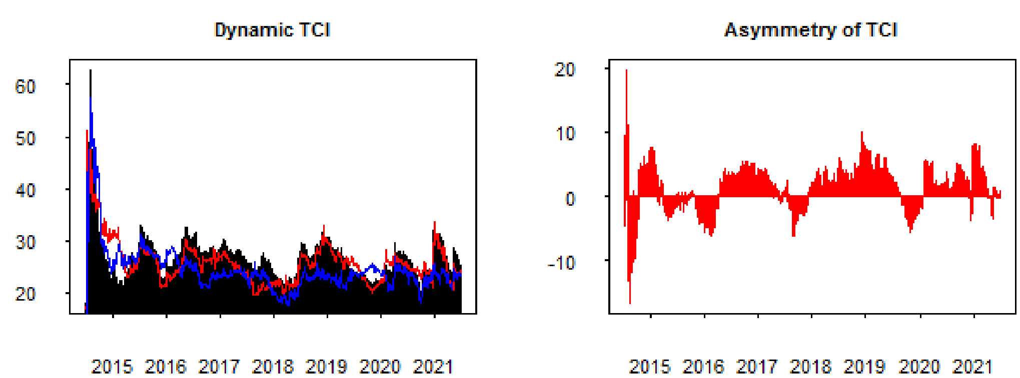

Fig. 2. Dynamic total connectedness

troughs around similar time intervals. Nevertheless, quantitatively, there is a clear difference between positive and negative returns. The right panel of Figure 2 exhibits the values of the TCI based on negative returns minus the TCI based on positive returns. The total connectedness of negative returns dominated during the study period. Total connectedness was dominated by positive returns for only 514 trading days, representing only 30% of all trading days.

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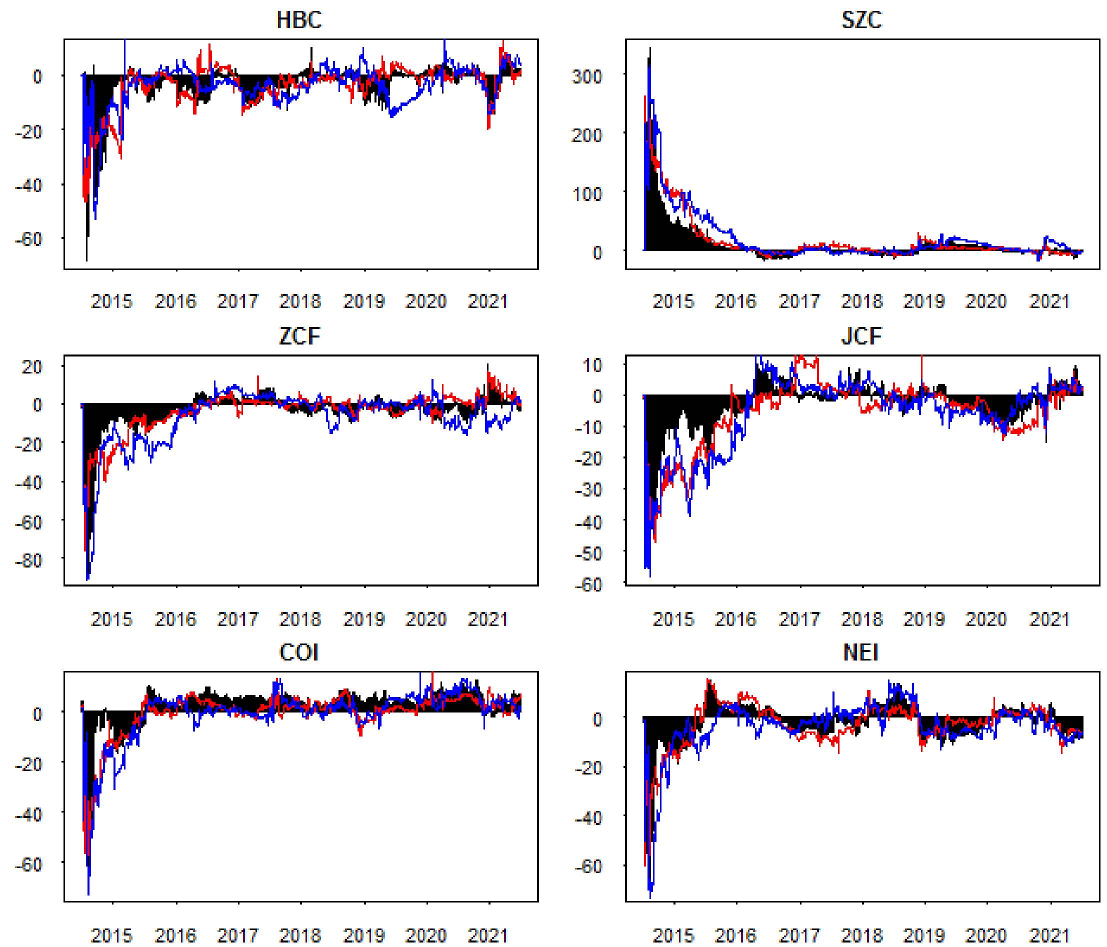

Fig. 3. Dynamic net total directional connectedness

3.3.2 Net directional connectedness

The results of the dynamic net total directional connectedness (NET CI) for each market are shown in Figure 3. The positive values in Figure 3 represent the net transmitters in the system, while the negative values represent the net receivers. The red line indicates the dynamic NET CI when only negative returns are considered, while the blue line refers to the NET CI based on positive returns. All variables in the system may shift between the two roles over time. Based on total returns, the share of the Hubei carbon market as a net receiver is 66.71% throughout the sample period, and its positive NET CI values were small, indicating that the Hubei carbon market gained more spillover effects from other markets during the sample period. The proportion of the Shenzhen carbon market as a net receiver is 42.37%. It is worth noting that the Shenzhen carbon market became a net information transmitter for the overall network from July 2014 to June 2016. Although the net spillovers gradually declined after reaching a peak in August 2014, they remained at a high level for some time after that, which may be related to the "Approval on Foreign Exchange Business related to Foreign Investors' Participation in Shenzhen Carbon Emissions Trading" issued by the State Administration of Foreign Exchange on August 8, 2014. This policy made the Shenzhen carbon market the first carbon market in China to be directly opened to foreign investors, which facilitated the use of foreign funds to promote the liquidity of the market and enhanced the freedom of trading. After March 24, 2016, the net spillovers of the Shenzhen carbon market significantly diminished but remained stronger than those of the Hubei carbon market. In most cases, coal futures played the role of a net information receiver. However, from 2016-early to 2017, they persistently became net information transmitters in the network, which may be related to the supply-side energy reform proposed by the state in November 2015. This policy proposed a structural adjustment for the entire coal industry starting in 2016, prompting dramatic price fluctuations of coal industry products and spillovers to other markets. After July 2015, the coal stock index continuously acted as a net transmitter, while the new energy stock market periodically switched between the two roles over time.

Moreover, it is worth noting that the trajectory changes of the red and blue curves for each market in Figure 3 demonstrate significant variations, indicating the existence of asymmetry in the net spillovers. Some variables even played opposite roles based on the negative and positive returns at the

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same time. When the NET CI is positive, its more considerable absolute value indicates a more substantial net spillover from the variable. In contrast, its more considerable absolute value indicates a more intense net shock from others to the variable. Compared to negative returns, the Shenzhen carbon market's net spillovers based on positive returns were obviously more vital in most cases. In particular, from July 2014 to June 2016, the net shocks from the Shenzhen carbon market to each variable were dominated by positive returns.

3.3.3 Pairwise connectedness

We now turn to net pairwise directional dynamic connectedness. In this part, we focus on the pairwise linkages between carbon markets and other markets. Figure 4 illustrates the time-varying connectedness between pairs of variables within the network. Remember that the order in which each variable appears in the panel titles is critical to correctly explaining the results. For example, in the first panel titled "HBC-ZCF," a negative value in the panel means that the thermal coal futures transmit the return spillovers to the Hubei carbon market, and the Hubei carbon market is the net receiver in the same period. Figure 5 shows the time-varying PCI between the two variables, which reflects the degree of correlation between the pairs. Table 3 records the means of NET CI and PCI for the three return scenarios and the proportion of variables that act as net receivers.

Regarding the carbon and energy futures markets, the former acted as a net information transmitter in most cases. Energy futures have produced net spillovers on the carbon markets for a period of time after the supply-side reform. Compared to the Hubei carbon market, the Shenzhen carbon market has more substantial net spillover effects on energy futures. For the carbon and energy stock markets, the Hubei carbon market usually acted as a net information receiver, while the Shenzhen carbon market was a net information transmitter. Similar to the results in the previous section, the Shenzhen carbon market generated extremely high shocks to both futures and stocks in August 2014. Similarly, the Hubei carbon market played an information transmitter role in its relationship with energy futures and stocks in the early stage of establishment. When carbon markets acted as net transmitters, they generally had more substantial net spillovers driven by positive returns. According to Figure 6, the Shenzhen carbon market has been more connected to either of the other markets than the Hubei carbon market. Moreover, after September 2020, the connectedness between carbon and other mar-

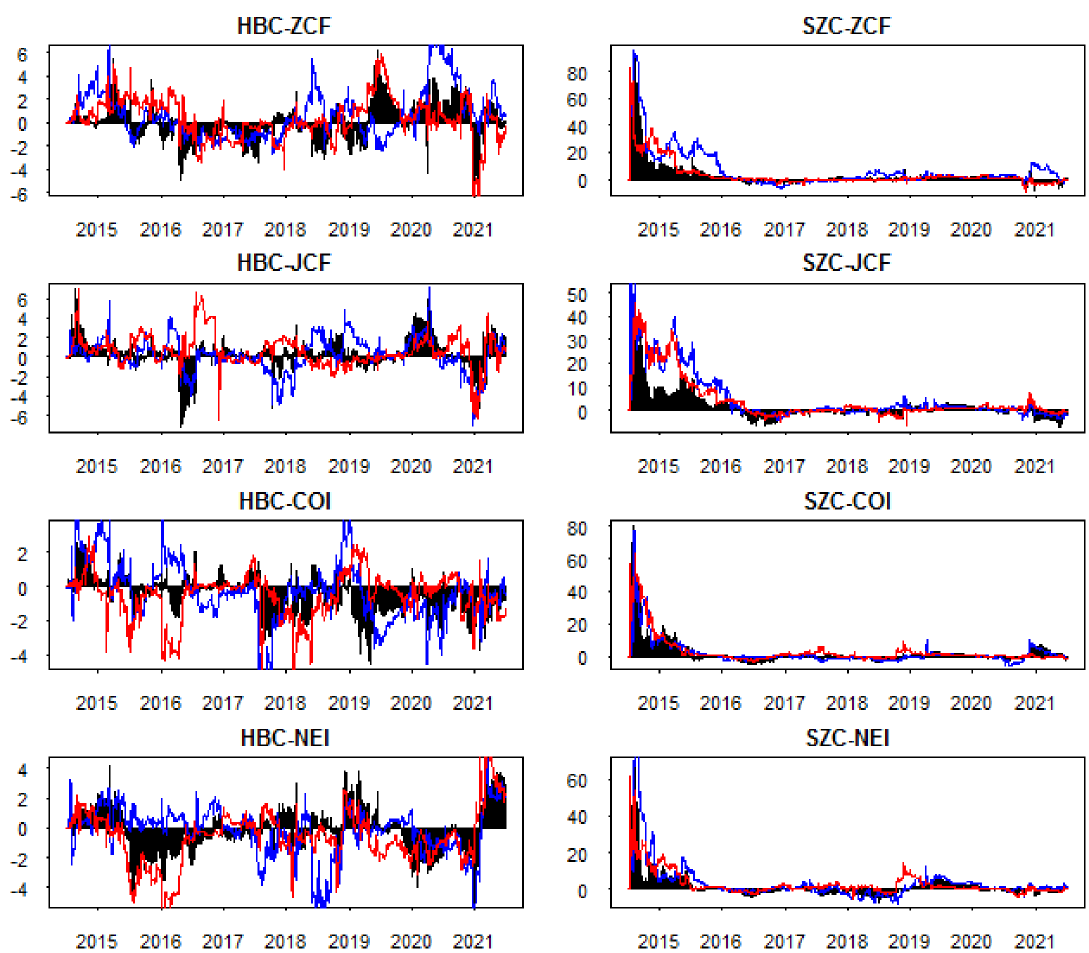

Fig. 4. Dynamic net pairwise directional connectedness

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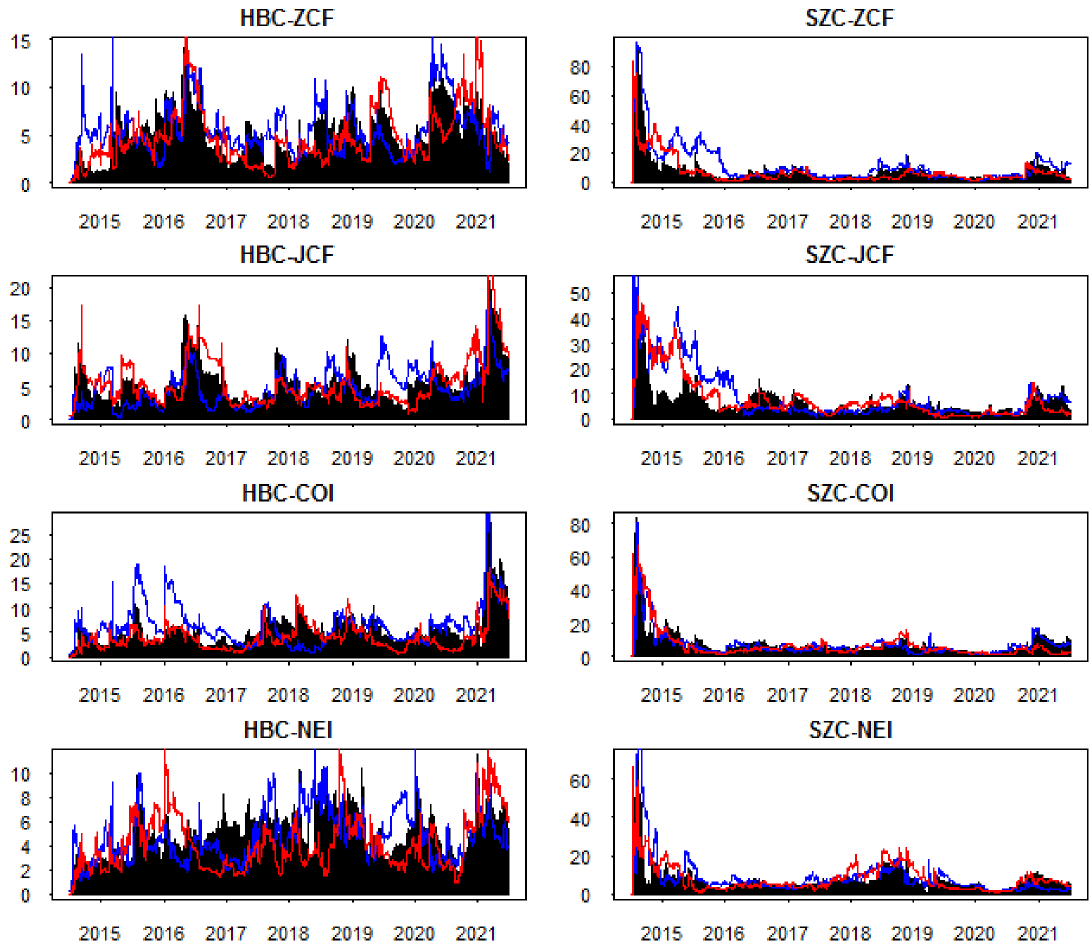

Fig. 5. Dynamic pairwise connectedness

Table 3. means of pairwise PCI,NET CI and ratio of net receivers

	H-ZCF	S-ZCF	H-JCF	S-JCF	H-COI	S-COI	H-NEI	S-NEI
PCI	4.93	7.08	5.45	6.23	5.31	7.07	4.77	6.95
PCI(-)	4.74	6.62	5.66	7.91	4.02	6.75	4.15	8.03
PCI(+)	5.51	11.38	4.89	9.19	6.40	7.07	4.80	8.41
NET	0.01	2.97	0.32	1.44	−0.58	2.15	−0.18	1.17
NET(-)	0.35	3.24	0.60	3.93	−0.55	3.09	−0.60	2.68
NET(+)	0.66	6.82	0.16	4.88	−0.39	2.21	−0.23	3.24
Ratio	49.71	34.41	37.34	48.53	67.53	48.46	57.27	54.87
Ratio(-)	41.01	43.61	35.23	38.45	65.18	30.30	66.30	31.01
Ratio(+)	44.26	29.31	44.49	37.22	65.71	49.82	49.00	33.29

kets showed an upward trend, which may be related to the proposed “Carbon Peak, Carbon Neutral” target. In addition, the time-varying pairwise connectedness also shows significant asymmetry. It is worth noting that, except for ”HBC-JCF”, all pairs showed higher correlations based on the positive returns, indicating that the carbon markets may have higher synergies with other markets in the rising price state.

The differences between the Hubei and Shenzhen carbon markets in the connection network may be attributed to the following characteristics of the two markets: in terms of the threshold for the inclusion of enterprises, the inclusion criteria of the Hubei carbon market are much higher than those of Shenzhen, and the number of enterprises included in the Shenzhen carbon market is more than twice the number of enterprises in the Hubei carbon market. In terms of the industries covered, all the enterprises in the Hubei carbon market

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are from secondary industry, while the enterprises in the Shenzhen carbon market cover both secondary and tertiary industries. For the auction of carbon emission allowances, the Hubei carbon market targets enterprises with a shortage of allowances, while the Shenzhen carbon market targets investors. Although the Hubei carbon market has a larger trading volume, the Shenzhen carbon market has a larger number and variety of participants and a more liberal and open trading environment. Of course, the regional disparities exhibited by the carbon market may be related to many factors. In this regard, this paper only makes preliminary inferences.

3.4 Robustness analysis

To verify the robustness of the above findings, we perform three treatments. First, the spillover level of the Shenzhen carbon market from July to December 2014 is much higher than in other periods, which may affect the comparative analysis between the two carbon markets. In this paper, we also conduct a computational analysis based on the sample data from 2015. We found that the Shenzhen carbon market is still more substantial than the Hubei carbon market in terms of the correlation with other markets. Second, the decay coefficient of the TVR-VAR model is reset, i.e.,$\kappa_2 = 0.96$. Third, the number of periods in the forecast variance decomposition is replaced with 15 and 20. The model results show differences in some details, but all the conclusions about both carbon markets remain unchanged.

4 Conclusions

This paper applied the TVP-VAR and Diebold-Yilmaz index models to measure the asymmetric dynamic connectedness and spillover effects between carbon and energy markets. The analysis results show that the Hubei and Shenzhen carbon markets significantly differ in their correlation with the energy markets. Specifically, we have obtained the following conclusions. First, the volatility of carbon market returns is greater than that of energy futures and stock indices. Second, in the overall network system, the Hubei carbon market acts as the net information receiver, and the Shenzhen carbon market acts as the information transmitter in most cases. Third, in the pairwise relationship, both carbon markets generate more net spillover effects on energy futures. In the relationship with stock indices, the Hubei carbon market is mainly a net receiver, while the Shenzhen carbon market is a net transmitter. Compared to the Hubei carbon market, Shenzhen is more closely correlated with the energy markets. In addition, both carbon markets show strong spillover effects in the early stage of establishing or opening to foreign investors, but this effect may gradually decline. Fourth, the connectedness between the carbon and energy markets has significant asymmetry, and the mutual impact between them is more substantial in the case of a rising market. It is worth noting that exogenous events such as the supply-side reform of the coal industry and the proposed “carbon peaking and carbon neutral” policy influence the connectedness between markets.

Based on the above findings, this paper proposes the following recommendations: government departments need to strengthen the dynamic monitoring of car- bon and energy markets, detect the characteristics of market risk contagion among industries in a timely manner and provide reasonable policy guidance to reduce the negative impact of structural tightness. The formation of an inherently stable price mechanism between the Chinese carbon markets and energy markets should be accelerated. While building the national unified carbon market trading system, regional differences should be taken into account and effectively coordinated to facilitate the stable operation of the carbon trading system. Investors, when involved in carbon and energy markets, should pay attention to the asymmetrical intercorrelation of different markets and fully consider the management of investment portfolios.

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Conflict of interest

The authors declare that they have no conflict of interest.

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