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The Time-Varying Spillover Effects between China's Carbon Markets and Energy Market: Evidence Using the TVP-DY Index Model

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Abstract

This paper proposes an integrated TVP-VAR model to investigate the volatility spillover mechanisms among different financial markets as well as their respective roles in the global volatility transmission system, including China's carbon market, crude oil, new energy, new energy automobile, coal and natural gas markets, which is named energy market. Utilizing the time-varying volatility spillover indices (TVP-DY), we find that there are obvious dynamic spillover effects between China's carbon and energy markets, and the sensitivity of different regional carbon markets to different energy markets varies. In addition, China's carbon market is mainly affected by price fluctuations in the traditional fossil energy market, but the new energy market can play an effective role in hedging risks. Moreover, China's carbon market and energy market have a fragile Cycle Spillover Network style, thus it is necessary to demonstrate a complex risk spillover mechanism between them.

Keywords

Carbon Market, New Energy Market, TVP-VAR Model, TVP-DY Spillover Index

1. Introduction

The issue of global climate change triggered by greenhouse gas emissions (mainly carbon dioxide) has become increasingly serious due to the rapid development of the global economy, threatening human survival and development (Han et al., 2019; Martin et al., 2014). In order to effectively handle the problems of climate change problems, fulfill the Paris Agreement commitments, and further ensure the achievement of global carbon emission reduction targets, China proposed a

framework for a carbon emissions trading market in 2011 and officially launched its first pilot carbon emissions trading permit in 2013. On 16 July 2021, China's carbon emissions trading market was officially opened, but due to the complexity of the underlying, the time horizon, and the uncertainty of the outcome, the carbon market is far more volatile than the stock market and always carries significant risks. With the further development of China's carbon market, the link between the carbon and the energy markets will become increasingly strong, resulting in price fluctuations in the energy market or carbon market caused by extreme events that could easily spread across the market. The introduction of the "carbon peaking and carbon neutrality" goals has also accelerated the development of the new energy industry and the new energy vehicle market. The 14th Five-Year Plan for Energy Conservation and Emission Reduction clearly states that in 2060, the achievement of the carbon peak target means that new energy vehicles will make up more than 88% of sales, while the current sales of new energy vehicles account for less than 20%, which results in companies crossing the border to create new energy automobiles, leading to sharp price fluctuations in the new energy vehicle market, which can easily cause the spread of risk. A large number of studies have shown that there is a significant spillover effect between the carbon market and the traditional fossil energy market (Zhao et al., 2021), but few studies have included the new energy market as part of the energy market (Pu & Zhao, 2020; Wang, Qiao, & Chen, 2021). The establishment of the carbon trading market in a market economy will influence the volatility of new energy company share prices through the carbon prices, further affecting the overall price volatility of the new energy market (Wang, Qiao, & Chen, 2021). Furthermore, the intensity of the spillover effect between the carbon and energy markets is unlikely to be constant, as investors' subjective expectations and investment behavior change over time, resulting in distinct price fluctuations between markets, and therefore the intensity of the spillover effect should shift as well. As a result, a comprehensive review of the time-varying volatility spillover between China's carbon and energy markets is critical for improving the formation of an intrinsic price mechanism between them, avoiding price volatility in the carbon market, and ensuring the smooth operation of China's carbon trading system.

2. Literature Review

Currently, scholars both at home and abroad attach great importance to ecology and environmental issues (Su et al., 2021a, 2021b; Tao et al., 2021; Wang, Su, Lobonţ, & Umar, 2021) more specifically; considerable attention has also been devoted to the study of the dynamic spillover effect of the carbon emission permit trading market. Many studies have studied the EU Emissions Trading Scheme (EU ETS), which is the most representative carbon trading market in the World. For example, Zhang and Sun (2016) used the DCC-TGARCH and BEKK-GARCH models to study the volatility effect between EU ETS and the

energy market, which demonstrates that the EU ETS has strong volatility spillover effects with the coal and natural gas markets, but not with the crude oil market. Balcılar et al. (2016) used the MS-DCC-GARCH model for EU ETS and the energy market to demonstrate the extreme volatility and time-varying risk transmission from the energy market to the EU ETS. Hai & Yang (2014), on the other hand, calculated the dynamic conditional correlation coefficients between EU ETS and the energy market based on the DCC-GARCH model, finding that the carbon market is positively correlated with the volatility of coal, crude oil, and natural gas markets, and the impact of coal and natural gas prices on carbon prices is highly susceptible to macroeconomic fluctuations. With the gradual maturity of China's carbon trading market, scholars have started to focus on the volatility spillover effects between China's carbon market and the energy market. Lin & Chen (2019) constructed VAR-DCC-GARCH and VAR-BEKK-GARCH models to investigate the linkages and spillover effects between China's pilot carbon emission trading markets and coal, and new energy markets, respectively, and found that there is no significant volatility spillover effect between the Beijing carbon emission trading market and the coal market. Meanwhile, Liu, Liang, & Chen (2020) used the VAR and DCC-GARCH models to explore the risk of China's carbon emission trading market; the study indicates that the spillover effect between China's coking coal market and carbon market is the strongest among all energy markets. In addition, most of the literature on the spillover effect of the carbon market is based on one or more GARCH models, such as E-GARCH, MVGARCH, and STR-EGARCH (Basher & Sadorsky, 2016; Boubaker & Raza, 2017; Engle et al., 2013; Engle & Kroner, 1995; de Nicola et al., 2016; Tsuji, 2018).

While the above literature provides useful insights into the transmission mechanism of volatility between carbon and energy markets, it is based on several GARCH models that measure volatility spillovers between the two markets and focus on the significance of the correlation coefficients, ignoring the global, directional and time-varying nature of the spillovers. Diebold and Yilmaz (2009, 2012, 2014) proposed static and dynamic spillover indices based on the generalized forecast error variance decomposition of vector autoregression (VAR) models to effectively overcome the above shortcomings. Zhao et al. (2021) used a time-varying DYCI obtained from a rolling-window to measure the spillover effects between China's regional carbon market and energy market, which has a bidirectional spillover effect. Meanwhile, the study also found that there are differences in the time-varying net spillover effect between different pilot carbon emissions and energy markets. However, Korobilis & Yilmaz (2018) reported that the time-varying DYCI obtained from rolling-window is sensitive to the choice of the width of the window. Rolling estimation means that valuable information from the sample is discarded and it also results in "built-in-persistence" in the dynamic interpretation. Antonakakis et al. (2020) and Liu and Gong (2020) introduced the connectedness index (TVP-DY) from the TVP-VAR model and verified the accuracy of the time-varying parameter method by applying it to the US banking

system and comparing it with the rolling-window method. For example, Zhang et al. (2021) used it to analyze the time-varying synergy between the energy and stock markets before and after the outbreak of the novel coronavirus (COVID-19). On the other hand, Jiang et al. (2022) used the model to investigate volatility spillover mechanisms among Bitcoin and other financial markets.

In conclusion, research on the spillover effects between carbon and energy markets has mostly focused on fossil fuels like coal, oil, and natural gas, the most notable ones are the absence of discussion of new energy and carbon market systems. The adoption of "carbon peaking and carbon neutrality" goals has aided the establishment of new energy markets, notably the new energy vehicle industry, which has played the most significant role. Is the carbon market influencing the new energy and new energy automotive markets, and if so, how will they interact? When examining the volatility spillover effects of carbon and energy markets, it is critical to incorporate new energy markets. Although the DY spillover index model under the rolling window approach effectively overcomes the shortcomings of the GARCH model, which cannot specifically characterize the direction and time-varying nature of spillover, it is prone to overestimating the spillover effect from a methodological standpoint. Thus, this paper aims to characterize the time-varying bidirectional spillover patterns of China's carbon emission trading and energy markets (the integration of traditional fossil energy markets and new energy markets) by utilizing the time-varying connectedness approach based TVP-VAR model. Adapting the time-varying connectivity status of each carbon market and the energy market is benefit to confirm the price discovery mechanism and identify its dynamic changes, and to clarify the spillover tendency of each market in order to comprehend the dynamic interaction of carbon emission trading markets in China.

3. Methodology

3.1. TVP-VAR Approach

We refer to Antonakakis et al. (2020) work while employing the TVP-VAR model to measure the return connectedness amongst the target variables. This methodology is built on Diebold and Yilmaz (2009, 2012, 2014), who initially proposed the framework for analyzing dynamic connectedness. The major advantage of the TVP-VAR approach to connectedness over the previous methods is that it no longer becomes a necessity to work with a certain window size, which on being subjectively selected, could lead to varying results. In addition, it would also be possible to use sample sizes that are relatively small because data points are not being lost due to the use of rolling windows. The framework of return connectedness using the TVP-VAR is further explained as follows. The following equations describe a TVP-VAR model:

$$y_t = B_{0,t} + B_{1,t} y_{t-1} + \cdots + B_{p,t} y_{t-p} + \mu_t = X_t' \Theta_t + \mu_t \qquad \mu_t \sim N(0, \Sigma_t), \qquad (1)$$

$$X_t' = \left[1, y_{t-1}', \cdots, y_{t-p}' \right], \qquad (2)$$

where is a $n \times 1$ vector of observed dependent variables and $B_{0,t,\cdots,p,t}$ are $n \times n$ time-varying coefficients matrices rewritten as Θ_t matrix. X_t is the $n \times k, k = p + 1$ matrix including intercepts and lags of the endogenous variables. The independent structural shock in the regression equation is by μ_t with $n \times 1$ dimension presumed to be normally distributed heteroskedastic disturbance term with zero mean and time-varying variance-covariance matrix Σ_t. The relationships among China's carbon market return and energy market return are modeled by Σ_t, the variance-covariance matrix of disturbances which can be decomposed as,

$$\Sigma_t = A_t^{-1} H_t \left(A_t^{-1} \right)', \tag{3}$$

where A_t is a lower triangular matrix measures the simultaneous relationships among the variables. H_t is a matrix where stochastic volatilities are located on the diagonals.

$$A_t = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ a_{21,t} & 1 & 0 & \cdots & 0 \\ a_{31,t} & a_{32,t} & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{81,t} & a_{82,t} & a_{83,t} & \cdots & 1 \end{bmatrix}, H_t = \begin{bmatrix} h_{1,t} & 0 & 0 & \cdots & 0 \\ 0 & h_{2,t} & 0 & \cdots & 0 \\ 0 & 0 & h_{3,t} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & \cdots & h_{8,t} \end{bmatrix}. \tag{4}$$

Based on the following transition Equations (5)-(7) Primiceri (2005) and Nakajima (2011) time-varying parameters are assumed to change in represented state-space model, as follows:

$$\Theta_t = \Theta_{t-1} + v_t \qquad v_t \sim N(0, Q), \tag{5}$$

$$a_t = a_{t-1} + \zeta_t \qquad \zeta_t \sim N(0, S), \tag{6}$$

$$\ln h_{i,t} = \ln h_{i,t-1} + \sigma_i \eta_{i,t} \qquad \eta_{i,t} \sim N(0, 1). \tag{7}$$

As indicated by Equations (5) and (6) time-varying parameters of Θ_t and a_t follow a random walk process, whereas Stochastic volatilities h_t defined by Equation (7) follow independent geometric random walk. In addition, following Primiceri (2005) it is presumed that the coefficients of contemporaneous relations among variables evolve independently in each equation in order to simplify the inference and increase the efficiency of estimation. This suggests that the error terms of the measurement equation and the relation equations which are the parameters of A_t matrix are assumed to be independent.

3.2. Volatility Spillovers

Following the work of Koop et al. (1996) and Pesaran and Shin (1998), the next step is to calculate the scaled generalized forecast error variance decomposition (GFEVD), considering an H-step ahead forecast. Unlike the necessity of considering the ordering of variables as required in the error decomposition variance technique of Diebold and Yilmaz (2009), the GFEVD is entirely invariant to the same. In line with the approach of Diebold and Yılmaz (2014), to obtain the

GFEVD, the TVP-VAR is transformed to its corresponding vector moving average representation, TVP-VMA using the Wold theorem, by considering the following transformation:

$$y_t = \sum_{i=1}^{p} B_{it} y_{t-i} + \mu_t = \sum_{j=1}^{\infty} \Phi_{jt} \mu_{t-j}. \tag{8}$$

$\varphi_{ij,t}^g (H)$, which represents the unscaled GFEVD, is normalized to the scaled version to ensure that the summation in each row is unity. We arrive at $\underline{\varphi}_{ij,t}^g (H)$ which implies the pairwise directional connectedness from variable j to variable i, where it is measured as the influence that variable j has on variable i concerning its share in the error forecast variance. To compute the above terms, the following is done:

$$\varphi_{ij,t}^g (H) = \frac{\sigma_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(e_i' B_t \Sigma_t e_j \right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(e_i' B_t \Sigma_t B_t' e_j \right)}, \tag{9}$$

$$\tilde{\phi}_{ij,t}^g (H) = \frac{\varphi_{ij,t}^g (H)}{\sum_{j=1}^{k} \varphi_{ij,t}^g (H)}, \tag{10}$$

where, the selection vector is given by e_i such that for the index i, its value is 1 and 0 elsewhere. The connectedness measures are subsequently derived following the work of Diebold and Yilmaz (2012, 2014), as follows,

$$TO_{jt} (H) = \sum_{i,j=1,i \neq j}^{k} \tilde{\phi}_{ij,t}^g (H), \tag{11}$$

$$FROM_{jt} (H) = \sum_{j=1,i \neq j}^{k} \tilde{\phi}_{ji,t}^g (H), \tag{12}$$

$$NET_{jt} (H) = TO_{jt} - FROM_{jt}, \tag{13}$$

$$TSI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} = k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{14}$$

Here, Equation (11) is a measure of total directional connectedness from variable j TO all other variables in the network, while Equation (12) is a measure of total directional connectedness to variable j FROM all other variables in the network. Equation (13) is obtained as the difference between (11) and (12) and implies the net total direction of connectedness associated with the variable j. For instance, if $NET_{jt} > 0$, this would mean that j is a net driver of the network as it is primarily involved in transmitting shocks. Equation (14) is an aggregate measure of the total connectedness amongst all the variables in the network and seeks to serve as a proxy to the overall interconnectedness and risk associated with the market. A higher TSI_t would imply that a shock in a particular variable greatly affects the networks, inadvertently making the risk related to the network high. On the other hand, a lower level TSI_t would imply lower associated market risk as other variables in a network would not be as majorly impacted by shocks in a given variable.

4. Empirical Study

In an empirical study, variational mode decomposition is first introduced to generate a stationary volatility dataset for TVP-VAR regression. Volatility spillover indicators, including overall spillovers, directional spillovers, and net spillovers, are computed by the variance decomposition matrices after TVP-VAR regression. Section 4.1 describes the sample data and volatility measurement. Section 4.2 presents the dynamic total connectedness between carbon and energy markets. Section 4.3 reports the dynamic directional connectedness of the carbon market and energy market. Net pairwise dynamic directional connectedness and directed weighted network analysis are discussed in Section 4.4 and Section 4.5. Finally, the robustness testing analysis is reported in Section 4.6.

4.1. Raw Data and Volatility Measurement

Although the national carbon emissions trading market launched on July 16, 2021, trading data is still few, thus this research will focus on pilot carbon trading market data. As of now, China has developed nine pilot carbon trading markets, each of which was formed at a different period and with varying amounts of market activity and liquidity. In comparison to pilot carbon markets in other locations, the Chongqing and Tianjin pilot carbon markets have low total carbon quota turnover and limited market liquidity, which is not typical. As non-pilot regions in China, the Fujian and Sichuan carbon markets were established late, making data consistency with other carbon markets difficult, while the quota products in the Shenzhen carbon market differ significantly from those in other carbon pilots, stipulating that the implementation period of carbon quotas is a natural year, with corresponding carbon quota products available for each year's compliance period, and that the Shenzhen carbon market's quota products differ significantly from those in other carbon. Finally, the carbon markets in Shanghai and Guangdong, which are more representative of the carbon market, were chosen as the research objects of the carbon market, named SHEA and GDEA respectively. And four energy sources, namely coal, crude oil, natural gas, and liquefied gas, which account for a relatively large proportion of China's energy consumption structure, were chosen as the research objects of the carbon market, based on the consumption structure of China's traditional and new energy markets and the availability of data. The data used in this study are obtained from Wind, and there are a total of 790 observations. Subsequently, the first-order logarithmic difference of the closing data of each studied market is used to measure the price return, and we utilize the GARCH(1, 1) model to calculate the daily volatilities. Finally, each volatility spillover index will be obtained as follows:

Step 1. Calculate the total volatility spillover index, denoted by $\tilde{\varphi}^{g}_{\bullet,j,t}(H)$.

Step 2. Calculate the directional volatility spillover received by each market j, donated by $FROM_{jt}(H)$ as well as the directional volatility spillover transmitted by each market j, donated by $TO_{jt}(H)$.

Step 3. Obtain the net volatility spillover from each market j, denoted

$NET_{jt}(H)$, meanwhile we can also obtain the aggregate measure of the total connectedness TSI_t.

Figure 1 presents the integrated daily volatility data and Table 1 reports the descriptive statistics for the integrated daily volatility data, Jarque-Bear test (JB) and augmented Dickey-Fuller test (ADF) are also introduced. All the null hypothesizes are rejected in the ADF test, which indicates that the volatility data of all studied markets are significantly stationary. The stationary time-series data will be utilized as volatility dataset in TVP-VAR regression. However, the results of skewness, kurtosis, and JB test illustrate that the volatility data are still leptokurtosis, which is commonly seen in carbon and energy markets for the so-called volatility aggregation phenomenon. As shown in Figure 1 and Table 1, natural gas market is the most volatile market among all the studied markets, especially in the period November 2017 to February 2018. The rising trends of volatility can also be found in other markets, such as the oil market which because of the
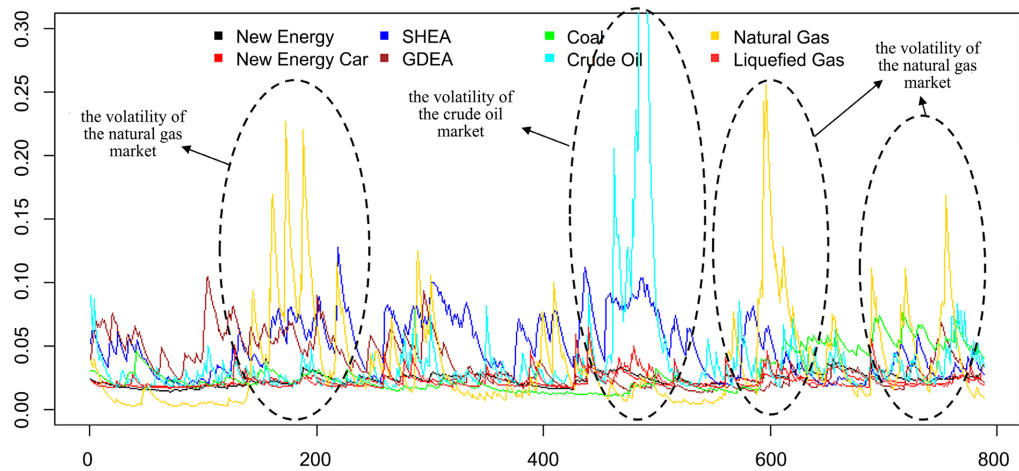

Figure 1. Daily volatility data. Source: Plottted by R.

Table 1. Descriptive statistics.

Market	Mean	Std.Dev.	Skewness	Kurtosis	JB Test	ADF Test
SHEA	0.049	0.023	0.557	−0.625	53.635***	−4.458***
GDEA	0.036	0.018	0.882	0.054	102.982***	−4.682**
LOF	0.024	0.005	0.251	−0.473	15.482***	−4.003***
GCA	0.022	0.004	0.903	0.810	129.895***	−5.067***
COM	0.028	0.016	1.091	0.021	157.352**	−2.702***
OIM	0.043	0.085	10.489	126.517	544162.447**	−8.083***
TRQ	0.036	0.039	2.179	6.051	1841.650***	−5.104***
YHQ	0.023	0.007	2.165	5.380	1579.561**	−7.768***

Note: ***, ** separately denotes the statistical significance level of 1% and 5%. And SHEA represents the Shanghai carbon market; GDEA represents the Guangdong carbon market; LOF represents the new energy market; GCA represents the new-energy-vehicle market; COM, OIM, TRQ and YHQ represent the coal, crude oil, natural gas and liquefied gas markets respectively. In addition, the number of observations is 790.

negative oil price event in 2021, during the period of carbon emission trading which price also extreme fluctuation, which indicates that carbon emission trading market may act as a volatility communicator.

4.2. Dynamic Total Connectedness

The dynamic change of the total volatility spillover level in China's carbon and energy markets is shown in Figure 2. The entire spillover from the overall carbon and energy markets is vulnerable to the macroeconomic environment, as seen in Figure 1, with the total spillover index graph exhibiting three periods of dramatically increased volatility spillover. The first phase runs from Q3 2017 to Q2 2018 and is heavily impacted by the natural gas market. As the Chinese government has become more aware of the negative externality characteristics of burning large amounts of highly polluting fossil fuels such as coal, it has begun to give gas-based energy sources such as natural gas a high priority and has taken a series of measures to accelerate the use of natural gas, resulting in a significant increase in demand for low-polluting fossil energy sources such as gas, resulting in a sharp increase in the price of natural gas. The overall spillover index has risen. The crude oil market affects the second period, from 2020 to 2021, where the surprise US attack on Baghdad in early 2020 caused a sharp increase in crude oil prices, and the outbreak of the New Crown epidemic and the "negative oil price" event caused sharp price fluctuations in the short term, causing a spike in the spillover effect. Early in 2022, the global epidemic subsides, economic recovery accelerates, and China's "carbon peaking and carbon neutrality goals" target is formally implemented, resulting in a surge in natural gas demand in the country. Sharp price fluctuations in the domestic natural gas market create the third phase of volatile spillover growth, further driving the carbon
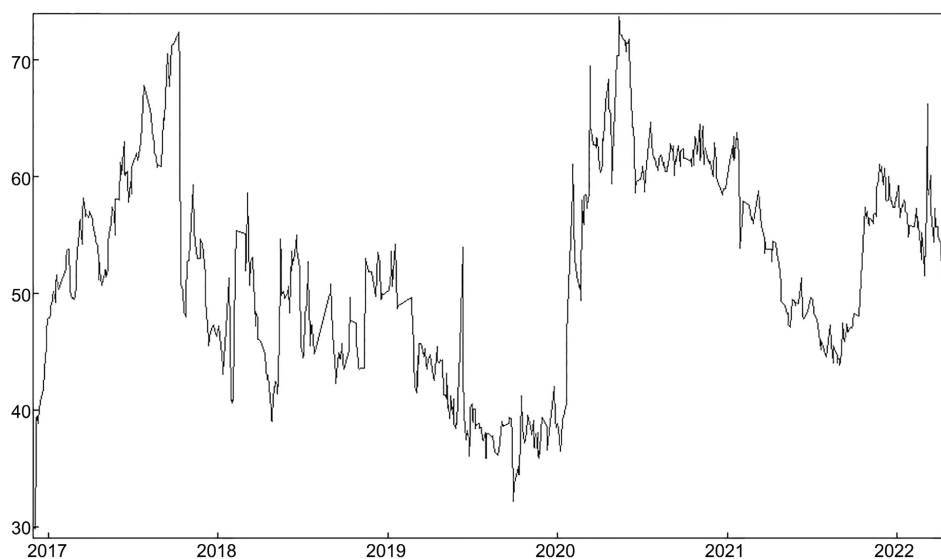

Figure 2. The total connectedness index of the carbon and energy market in China. The total connectedness index is calculated based on the estimation results from the TVP-VAR model. Source: Plotted by R.

market in 2022. The market and the energy markets have spillover effects. With their late emergence and relative lack of market information, new energy markets contribute relatively little to the total spillover intensity of the carbon and energy markets, so the next section of this paper will look at risk spillover and reception characteristics between markets, concerning individual markets.

4.3. From and to Connectedness Indexes

The total time-varying spillover index diagram only quantifies the magnitude of the overall volatility spillover effect between China's carbon and energy markets, but it cannot characterize changes in the directional and net spillover effects between the carbon market and various energy markets. As a result, the dynamic directional spillover impact, net spillover effect, and net pairwise spillover effect between each energy market and the carbon market are further investigated in this work.

The time-varying directional spillover effects between the carbon and energy markets are depicted in **Figure 3**. It's clear that the carbon market's volatility spillover effects from the energy market, as well as the degree of the carbon market's spillover impacts on each energy market, are both time-varying. The directional spillover index also reveals bidirectional and asymmetric time-varying spillover effects between China's carbon and energy markets.

Figure 4 plots the time-varying net spillover index between the carbon and energy markets. The time-varying net spillover relationship between the carbon market and the energy market in China is not always maintained at a specific
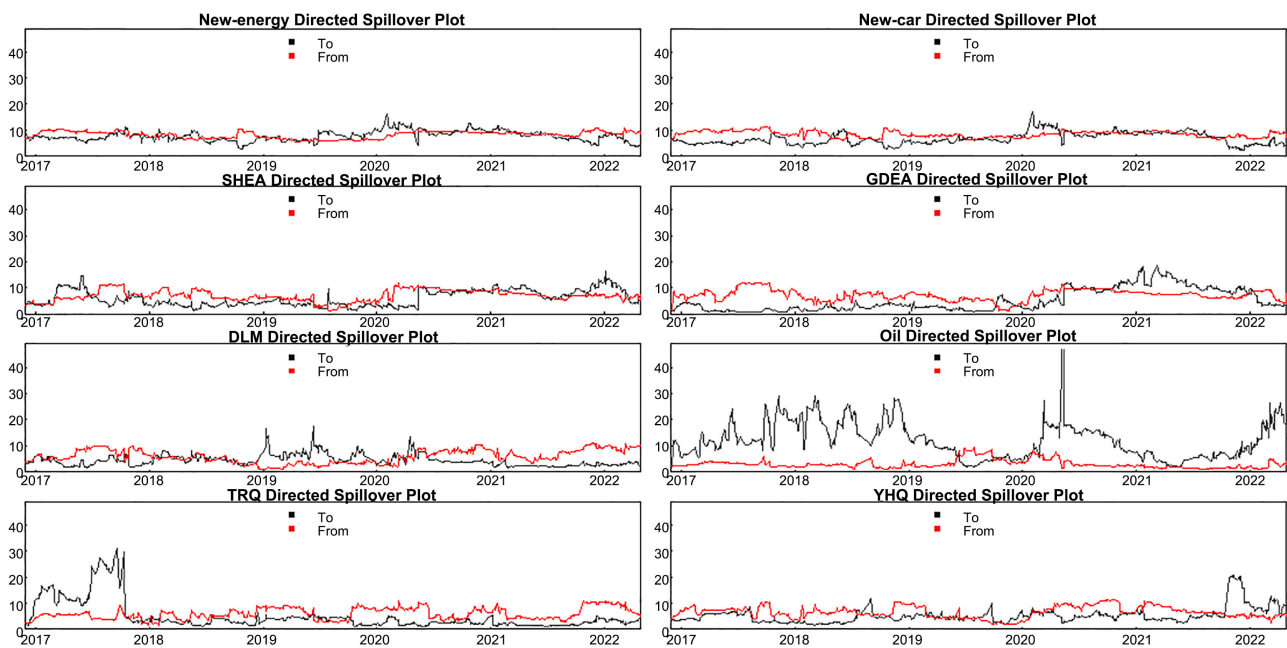

Figure 3. The dynamic directional connectedness of the studied market. The black line represents the "To Spillover" of carbon market volatility i to other energy markets, and the red line represents the "From Spillover" of the carbon market volatility i from other energy markets; the directions of the "To Spillover" and "From Spillover" are indicated by plus and minus signs, respectively. Source: Plotted by R.
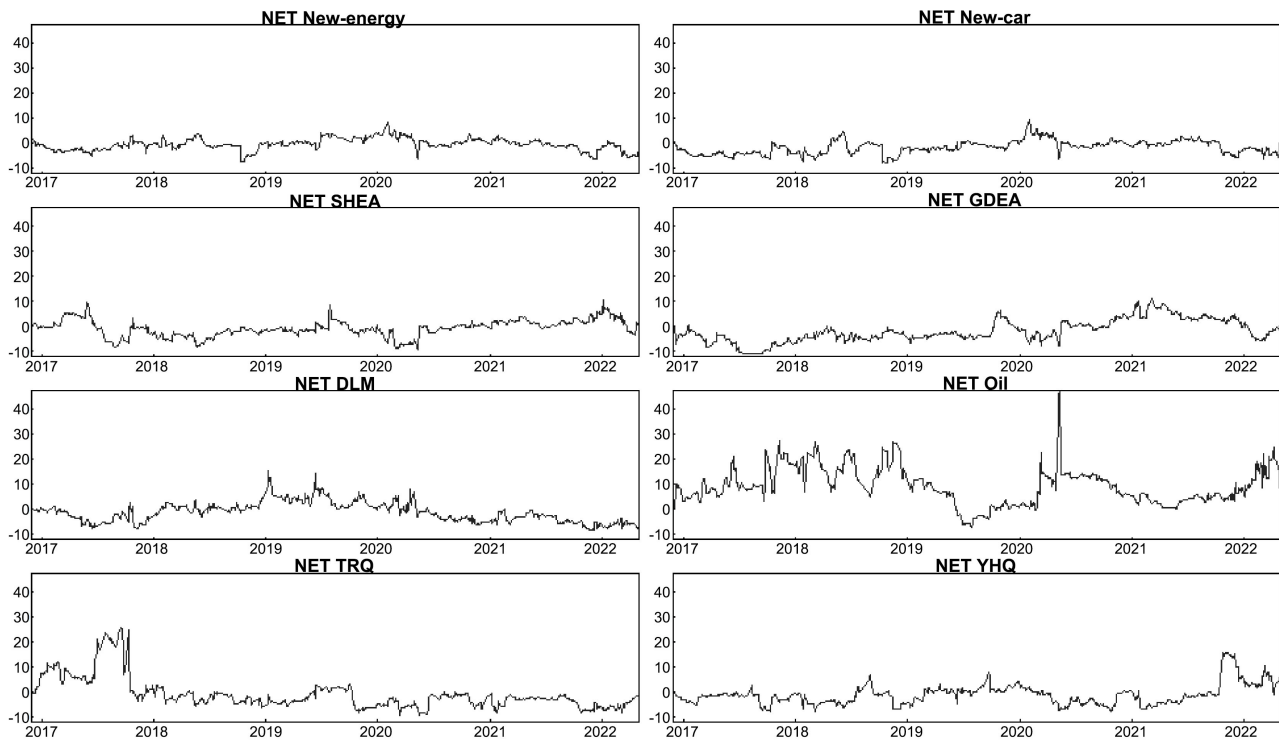
Figure 4. The dynamic net connectedness of carbon and energy market. Source: Plotted by R.

steady-state, but can change over time to produce positive (the degree of spillover from the carbon market to the volatility of the energy market is greater than the degree of spillover into the market) and negative (the degree of spillover from the carbon market to the volatility of the energy market is greater than the degree of spillover into the market) and negative (the degree of spillover (the degree of spillover from the carbon market to the volatility of the energy market is less than the degree of spillover into the market). The phenomena fluctuate between positive and negative (carbon market spillover to energy market volatility is larger than spillover), implying that there is not only a net spillover in one direction, but also a net spillover in both ways.

According to the time-varying spillover indices between the carbon and energy markets, both markets exhibit both a positive and a negative tendency during the corresponding period when one is experiencing strong price volatility. Sustained economic growth, sudden political events changes in external environmental factors can cause an increase in market uncertainty, leading to persistent price volatility, and with the existence of synergies between the carbon and energy markets, the volatility risk arising from price volatility can be transmitted within and between markets, resulting in a significant increase in the time-varying spillover index in the corresponding period.

Meanwhile, the results in **Figure 3** show that the new energy market, Guangdong carbon trading market and liquefied natural gas market play the role of risk receivers in the overall carbon and energy market system, while the crude oil market, Shanghai carbon trading market, coal market and natural gas market

mainly act as risk transmitters. In the case of the coal market, for example, the strong increase in power coal prices due to the oversupply in the coal market in early 2021 makes the coal market a major risk spiller, which is reflected in the high peaks of the spillover curve in the spillover diagram. The unbalanced state of the market due to the imbalance between supply and demand is often the main cause of risk spillovers, and also reflects the need for the government to implement price control policies on the coal market in China. The new energy market, which has been stimulated by China's "carbon peaking and carbon neutrality goals" target, also plays a major role as a risk transmitter in the system. As the new energy market is relatively new and lacks an effective regulatory mechanism, it is important to refer to the coal market, where the market is the main regulator, with government regulation, in order to maintain a balance between supply and demand in the new energy market, thereby stabilizing the economy and preventing risk. Further analysis from Figure 4 shows that, unlike the crude oil market as the main risk spillover expressed in previous studies, the propagation of risk from the crude oil market is highly directional and time-varying, but not persistent. Since the agreement between OPEC and non-OPEC producers to cut production in 2016, the crude oil market has been a major spillover of risk due to the prolonged and sustained turmoil, but when the 'negative oil price' event broke out, the crude oil market quickly spread the risk to other markets linked to it, but immediately thereafter returned to It is neither a spillover nor a recipient of risk.

4.4. Net Pairwise Dynamic Directional Connectedness

To better explain the volatility characteristics of the time-varying spillovers between the carbon market and the various energy markets, the paper also plots the net pairwise spillover index between the carbon and energy markets, as shown in Figure 5. The net spillover index plot further demonstrates that the Guangdong carbon market is the main risk taker and the Shanghai carbon market and the traditional energy market are the main risk propagators.

Further analysis of the inter-market directional premium index and net pairing premium index plots reveals that energy markets also show some variability in the time-varying directional premium and net premium characteristics for different pilot carbon markets. From 2016 to early 2017 crude oil market shocks triggered by the OPEC production cut agreement had a greater impact on the Guangdong carbon market premium index, with the net premium index showing positive values, while the Shanghai carbon market did. The net pairing premium index did not change significantly, for the Shanghai carbon market, its net pairing premium index changed significantly in a negative direction during the LPG price shock period and in a positive direction during the natural gas price shock period. The alternating effects of low-polluting fossil energy price shocks cause the net spillover index for the Shanghai carbon market to remain above and below the zero value. The main sources of risk for the new energy market, the new energy vehicle market, are likewise the crude oil market and the natural
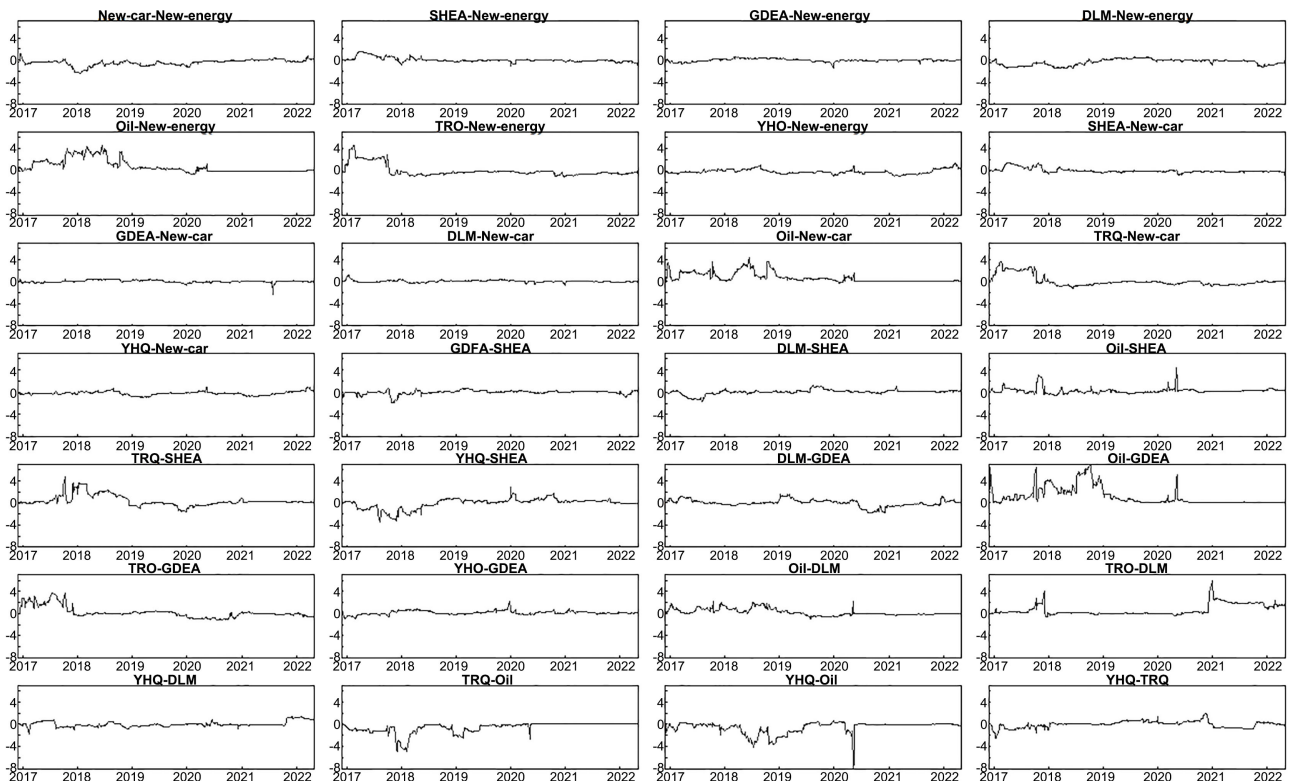
Figure 5. The dynamic net pairwise connectedness of carbon and energy market. The results are based on the time-varying connectedness approach based on the TVP-VAR model, and the solid line represents the changing trend of the net volatility spillover from one market to another. Source: Plotted by R.

gas market. The volatility of crude oil prices, as a substitute for fuel vehicles, causes increased volatility spillover to the fuel vehicle market, which further causes increased volatility in the new energy vehicle market.

However, according to the paired net spillover index chart of the carbon market, traditional energy market, and new energy market in Figure 5, we find that between 2021 and 2022, against the backdrop of repeated new crown epidemics and weakening economic fundamentals, the new energy market and new energy vehicle market are not affected by the shocks in crude oil prices and natural gas prices, and still maintain a net spillover index of zero. It is not difficult to conclude that the new energy market has a certain role in hedging the risk of commodity price fluctuations, thus providing a new perspective for investors' investment decision-making behavior.

The directional spillover index and net spillover index plots between the carbon and energy markets show that, firstly, the directional and net spillover between the carbon and energy markets also exhibit extreme time-variability. Secondly, the time-varying directional spillover indexes between the carbon and energy markets also show that their spillover of them are bidirectional and asymmetric. Overall, during periods of severe price shocks in traditional energy markets such as crude oil, coal, and natural gas, the carbon market suffers significantly higher spillover effects than in other periods. Moreover, new energy

markets can be used as an effective hedge against the risk of extreme volatility in commodities during the period examined.

4.5. Directed Weighted Network Analysis

To further explore the changes of spillover effects between carbon and energy markets, we take each market as a node and construct spillover network diagrams of carbon markets with non-participating new energy markets and participating new energy markets respectively, using the dynamic average spillover matrix between markets as the adjacency matrix. From the fully connected spillover network diagram in Figure 6, we find that the spillover network between the carbon market and the energy market has a typical cycle-network characteristic, for example, the access and importance of each node in the network are the same. This reflects that the complex system of carbon and energy markets is extremely fragile and whatever a shock to either market would rapidly disrupt the whole complex system. Therefore, the government must improve the efficiency of the market to ensure the coordinated development of the carbon emissions trading market. Further by calculating the nodal importance indicators of the spillover network, it was found that after adding the new energy market to the energy market, the degree of importance of each market decreased from 0.167 to 0.125, but the degree of access increased from 5 to 7 in both cases, fully demonstrating the hedging effect of the new energy market mentioned in the previous section, and also providing a new perspective for the regulator's regulatory strategy formulation and risk prediction.
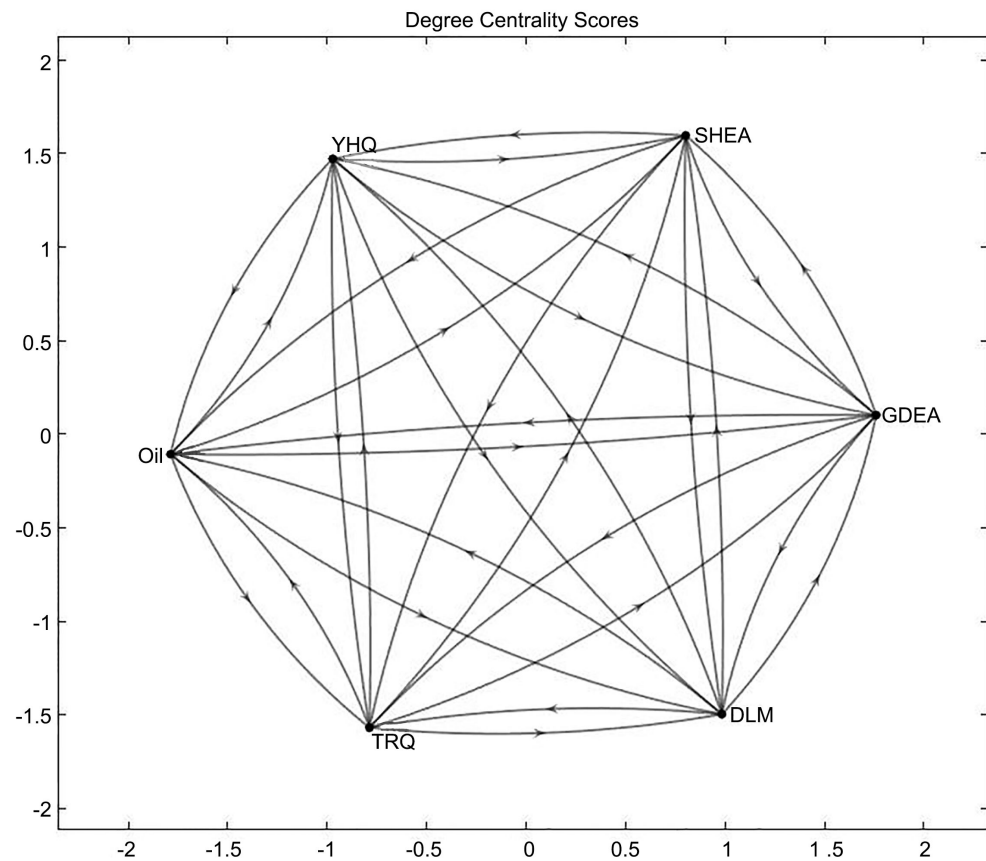

Degree Centrality Scores
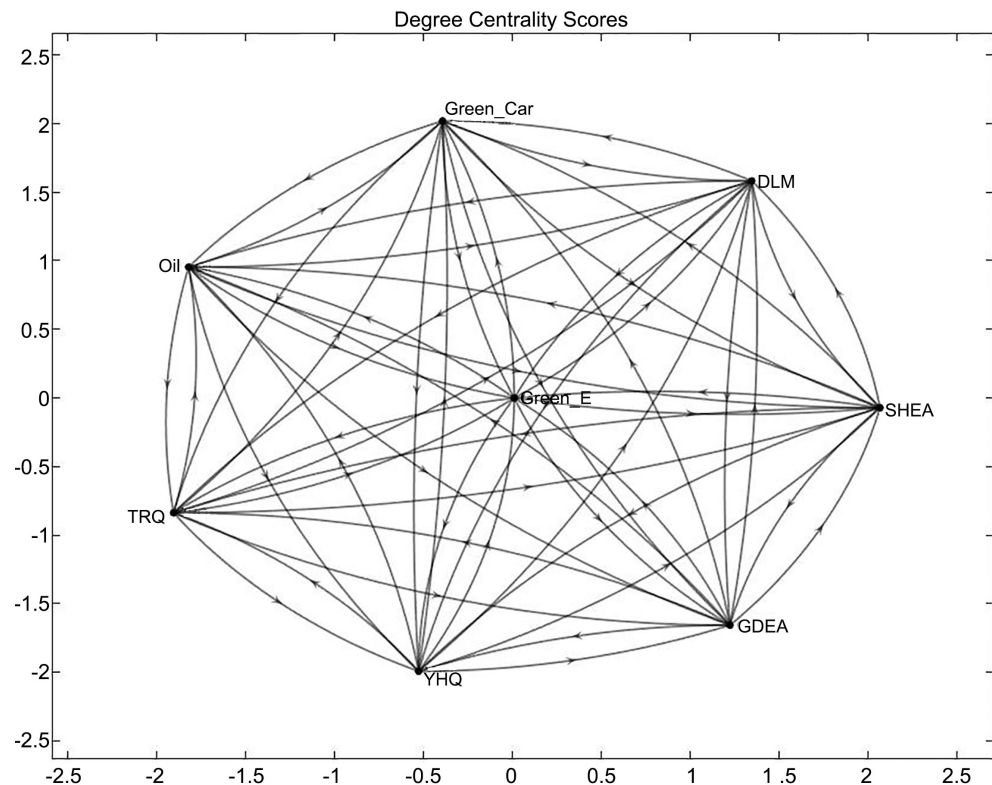
Figure 6. Directed weighted network for the volatility spillover of the carbon and energy markets. Each node illustrates the net transmitter of spillover. Vertices are weighted by averaged net pairwise directional connectedness measures. Meanwhile, the volatility spillover index between carbon and energy markets is expressed by the thickness of the edge. Source: Plotted by Matlab.

4.6. Robustness Testing

Based on the aforementioned, this paper uses the Kalman filter with the forgetting factor to estimate the unknown parameters, which overcomes the disadvantages of the Monte Carlo method that relies on the ranking of variables. Therefore, this paper uses the method of changing the prediction period to test the robustness of the empirical results and calculates the dynamic average spillover index table with prediction periods of 15 and 20 weeks respectively to compare with the dynamic average spillover index table with the initial prediction period of 10 weeks. The results are shown in Table 2 and Table 3. By comparing the results of the spillover indices in Table 3, it can be seen that when the forecast periods are 15 and 20 weeks respectively, the results are generally consistent with the results of the dynamic average spillover index with a forecast period of 10 weeks, and the dynamic average net spillover relationship between the carbon and energy markets based on the full sample remains stable, thus indicating that increasing the forecast period has almost no effect on the estimation results, which in turn indicates that the model used in this paper is the validity of the model used in this paper.

Table 2. Average dynamic spillover index ($H = 10$).

Spillover Index	LOF	GCA	SHEA	GDEA	COM	OIM	TRQ	YHQ	From
$H = 10$									
LOF	38.7	29.6	2.8	1.6	2.6	8.5	7.7	8.4	61.3
GCA	33.0	41.9	2.6	1.5	1.1	6.9	6.6	6.5	58.1
SHEA	2.2	2.0	73.3	1.6	3.5	5.2	6.2	6.0	26.7
GDEA	1.9	1.3	1.9	75.1	2.5	8.7	5.6	2.9	24.9
COM	5.7	0.8	3.3	2.8	75.8	2.5	6.8	2.4	24.2
OIM	2.1	1.4	3.1	1.0	1.0	86.4	1.2	3.8	13.6
TRQ	7.3	5.6	3.7	4.1	2.0	5.4	66.3	5.6	33.7
YHQ	9.3	7.9	6.6	1.9	1.9	8.0	5.8	58.6	41.4
To	61.5	48.7	24.1	14.4	14.5	45.3	36.9	35.6	283.8
NSI	0.2	−9.4	−2.6	−10.4	−9.7	31.7	6.2	−5.8	
NPSI	3.0	6.0	3.0	5.0	5.0	0.0	1.0	5.0	35.5

Table 3. Average dynamic spillover index ($H = 15, 20$).

Spillover Index	LOF	GCA	SHEA	GDEA	COM	OIM	TRQ	YHQ	From
$H = 15$									
LOF	37.8	29.0	3.3	1.9	2.9	8.6	8.0	8.4	62.2
GCA	32.5	40.9	3.0	1.7	1.3	7.0	7.0	6.6	59.1
SHEA	2.9	2.5	68.3	2.1	4.3	6.2	6.9	6.7	31.7
GDEA	2.4	1.6	2.4	69.0	3.8	10.0	7.2	3.7	31.0
COM	6.0	1.1	3.5	3.1	72.2	3.5	7.8	2.8	27.8
OIM	2.2	1.4	3.4	1.2	1.5	85.0	1.5	3.8	15.0
TRQ	7.5	6.0	4.1	5.3	2.3	5.8	62.9	6.2	37.1
YHQ	9.2	7.7	6.8	2.0	2.3	9.3	6.3	56.4	43.6
To	62.7	49.4	26.5	17.3	18.4	50.3	44.7	38.2	307.5
NSI	0.6	−9.7	−5.2	−13.7	−9.4	35.3	7.5	−5.4	
NPSI	3.0	6.0	3.0	6.0	4.0	0.0	1.0	5.0	38.4
$H = 20$									
LOF	37.2	28.5	3.7	2.1	3.3	8.6	8.3	8.4	62.8
GCA	32.2	40.1	3.4	1.8	1.6	7.1	7.2	6.6	59.9
SHEA	3.6	2.9	64.8	2.4	5.3	6.6	7.4	7.0	35.2
GDEA	2.9	2.0	2.6	64.9	4.9	10.6	7.9	4.2	35.1
COM	6.3	1.3	3.7	3.5	69.5	4.3	8.3	3.1	30.5
OIM	2.3	1.5	3.6	1.4	1.9	83.9	1.7	3.8	16.1
TRQ	7.6	6.3	4.3	5.8	2.6	6.0	60.9	6.4	39.1
YHQ	9.2	7.7	6.9	2.1	2.5	10.0	6.5	55.2	44.8
To	64.0	50.1	28.1	19.2	22.1	53.2	47.3	39.5	323.4
NSI	1.2	−9.8	−7.1	−15.9	−8.4	37.1	8.2	−5.3	
NPSI	3.0	5.0	4.0	7.0	4.0	0.0	1.0	4.0	40.4

5. Conclusion and Policy Implications

This paper constructs a time-varying DY spillover index model based on a generalized forecast error decomposition by using a time-varying vector autoregressive model (TVP-VAR) to systematically analyze the spillover effects between China's carbon and energy markets in a quantitative manner. Unlike previous studies, this paper includes the new energy market when considering the energy market, based on the current economic development in China, to enrich the study of the linkage between the carbon market and the energy market. The main conclusions of this paper are as follows:

1) The volatility spillover between China's carbon and energy markets has significant time-varying characteristics, and the total spillover and directional spillover between markets exhibit strong time-variability in both size and direction, thus showing that the risk transmission between carbon and energy markets has strong uncertainty. Further analysis of the various types of inter-market spillover indices reveals that when price shocks occur in energy markets, the level of total spillover between carbon and energy markets tends to rise significantly, but the extent to which different pilot carbon markets respond to shocks from different markets varies, with the Shanghai carbon market being influenced mainly by the natural gas market and the Guangdong carbon market being influenced mainly by the crude oil market.

2) The carbon market is very closely linked to the energy market, with risk propagation showing a circular pattern centered on the new energy market, spreading to the carbon market, the crude oil market, the coal market, and the natural gas market respectively. New energy investments can be used as an effective hedge against commodity risk during a new epidemic.

In general, there is an obvious dynamic linkage between China's carbon and energy markets, and the level of spillover between markets is also highly time-varying, which is not conducive to preventing the risk of price fluctuations between carbon and new energy markets. In this regard, some policy implications can be drawn from the above conclusions. First, improving the construction of the carbon emission trading and energy markets to form an inherently stable price mechanism between the markets. The results of the study found that the degree of volatility transmission between China's carbon market and the traditional fossil energy market is much greater than that between China's carbon market and the new energy market. To effectively prevent the impact of fossil energy price volatility on China's carbon market, the price of carbon emission rights should be integrated into China's energy price system for a comprehensive examination, to form a stable price mechanism between China's carbon market and the fossil energy market. Second, improving China's carbon market's risk monitoring and early warning mechanisms. As the main risk spillover party, the carbon market absorbs the vast majority of risks from the energy market. On the one hand, carbon market regulators should pay close attention to price fluctuations in the energy market and be alert to the risk fluctuations they may generate,

and on the other hand, in the context of a national carbon market, fully consider the risks of different regional energy markets and carbon markets, formulate proven risk regulation strategies and improve the carbon market's risk Monitoring. In addition, the design of the national unified carbon market system and the process of managing rules should also take into account the characteristics of each regional carbon market, to reduce the adverse effects of different shocks with a diversified trading system, and comprehensively analyze the impact of external shocks such as energy price fluctuations on different regional carbon markets, effectively reducing regional heterogeneity and promoting fair competition in the carbon market. Third, the risk-oriented role of the new energy market should be fully exploited. The results of the study show that the new energy market has a better role in hedging against major risk shocks, and it is important for investors to appropriately favor new energy investments and choose diversified investment strategies in their investment decisions, to effectively reduce the adverse effects of major unexpected shocks and maintain a balanced level of returns.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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