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Research article

How can carbon markets drive the development of renewable energy sector？Empirical evidence from China

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Abstract: The reduction of carbon emissions has attracted significant global attention. This paper empirically analyzes the dynamic nonlinear linkages among carbon markets, green bonds, clean energy, and electricity markets by constructing DCC-GARCH and TVP-VAR-SV models, and places the four markets under a unified framework to analyze the volatility risk from a time-varying perspective, thereby enriching the research on China's carbon market and renewable energy sector. We found that extreme events have a significant impact on the dynamic connectivity among the four markets. The analysis of the shock impact indicates that the carbon market has a positive effect on the power market in the short and medium terms, but has a mitigating impact in the long term. Especially, when the other markets are hit, the carbon market has evident fluctuation in 2020. The green bond market has a positive influence on the carbon market, whereas the power market demonstrates adverse effects in the short and medium terms. The New Energy Index negatively impacts the power market in the short and medium terms, but is expected to have a positive effect after 2020, highlighting the growing need for renewable energy in the power system transformation. According to the findings mentioned above, we put forward appropriate recommendations.

Keywords: carbon market; green bonds; clean energy; electricity market; TVP-VAR-SV

JEL Codes: C1, C12, C15, C16, G1, G18

1. Introduction

Sustainable economic development has led to increasingly serious environmental problems and the frequent occurrence of emergencies, and thus it is undoubtedly a continuing and serious challenge to the world. Due to being in the process of development, China has a strong need for energy consumption to support its economic growth, resulting in high levels of carbon emissions (Zhou et al., 2021). In 1970, China emitted approximately 748.51 megatons of CO_2, a similar amount to Japan and Germany, one-fifth of the emissions in the US, and one-fourth of those in the EU. In 2021, China's emissions reached 10,523.03 million tons, 2.23 times more than the US, 10 times more than Japan, and 16 times more than Germany. As a result, the global concern for reducing carbon emissions has led to China's efforts. The Kyoto Protocol entered into force in 2005, prompting the establishment of carbon trading markets in various countries around the world. Since 2013, China has launched eight CET pilot carbon markets in Shenzhen, Shanghai, Beijing, Guangdong, Tianjin, Hubei, Chongqing, and Fujian. This system allows companies to trade the gaps and surpluses between allowances and actual emissions, with those lacking allowances to purchase them from the exchange, and those with excess allowances to earn extra income. On September 22, 2020, a declaration was made that China aims to achieve "dual carbon". Establishing a carbon market is a significant advancement and a useful mechanism to help achieve this objective, as reducing carbon emissions greatly relies on market forces. In China, the most crucial research topic is how to efficiently decrease greenhouse gas emissions and advance the growth of a carbon market, given its status as the largest carbon emitter. In July 2021, China will combine the initial eight pilot carbon markets into a unified carbon market that encompasses 2,225 major emission companies in the power generation sector, making it the largest carbon market globally that addresses greenhouse gas emissions. This move is seen as a necessary step towards reaching the goals of "dual carbon".

China's electricity, heat, gas, and water production and supply industries account for over 40% of the country's total carbon dioxide emissions, with thermal power generation being the primary contributor. Therefore, it is critical to China's long-term sustainable development to control the carbon emissions of the power sector and to accelerate its low-carbon transition. China emphasized on October 26, 2021 the need to speed up the development of an innovative power system dominated by renewable energy sources. Although the development of an innovative power system is hindered by the lack of development and liquidity of the carbon market at the present stage, it is necessary for carbon market to play a positive role in promoting the development of a new power system by market force. Scholars have studied the linkage between the electricity market and the carbon market in (Li et al., 2021; Wen et al., 2022; Zhao et al., 2023), the first two of these scholars finding that the changes in electricity price and the return of the electricity index have a certain risk impact on the price of the carbon quota. Zhao et al. (2023) found that the impact between the carbon market and the electricity market is more of a pass-through of price fluctuations and not a direct effect of returns. The low-carbon transformation of the power system is inevitably inseparable from the fund support from green bonds and green credit which are typical green financial products. Yin (2021) predicted that China will need RMB 400–700 billion to make an orderly transition away from its current coal-fired generation capacity. China's green bond market is growing rapidly due to the high demand for green investments (Xiao et al., 2021). By the end of 2022, China ranked first in the world in domestic and foreign currency green loan balance at RMB 11.95 trillion, of which green loans in the electric power, heat, and transportation industries accounted for 59.67% of the green loan balance. With the expansion of China's green bond market and the introduction of relevant policies, a small number of power enterprises have also chosen the green bond financing method. Coal-fired power plants have access to more corporate finance through green bonds rather than project finance (Chan et al., 2022). At the same time, green bonds contribute to the low-carbon transition of the power system by facilitating the advancement of green technologies and expanding the share of new installed capacity from renewable energy sources (Lin et al., 2022). COP26 underscored the significance of financial instruments and markets associated with 'carbon', including the importance of carbon markets and green bond markets (Ren, 2021; Arif, 2021).

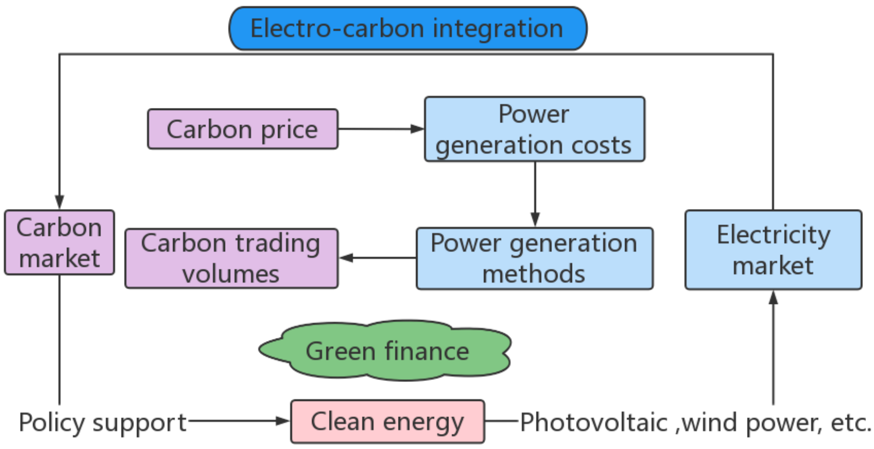

Figure 1. Linkage diagram between markets.

With the continuous development of green bonds, carbon markets, electricity markets, and clean energy markets, the linkages among them are becoming more and more complex. How carbon markets as well as green bonds can contribute to the development of a clean-energy-led power system is the central question we want to examine. From a measurement perspective, we ask: Is there a dynamic linkage among the four markets? And, if so, is the impact unidirectional or bidirectional? Do the magnitude and direction of the linkage effects among markets change with different lags and under major event shocks? In response to the above questions, we first study the theoretical transmission mechanism between several markets to provide a certain theoretical basis for the empirical study of this paper. From linkage mechanism between the carbon market and the electricity market (Figure 1), power generation companies that are included in the carbon market will be influenced by the constraints of carbon emission in their power generation decisions and investment behavior when trading. As a result, fluctuations of carbon price will affect the cost of electricity generation by power companies and the price of shares, while changes in the power generation mode will also affect the supply and demand for carbon credits and therefore carbon price. The energy supply system of China has been transformed from coal-based to diversified, and renewable energy has gradually become the main source of new power supply installed capacity. When the renewable energy sector is stimulated by factors such as policy support and market share expansion, investors will generate expectations of increased profits in the new energy sector, leading to higher share prices for companies. At the same time, as the favorable policies for the new energy sector tend to be negative factors for carbon-intensive firms, resulting in the carbon-intensive sectors reducing their production capacity for anticipation of a relatively smaller market share, reducing the demand for fossil fuels and carbon credits and the carbon trading market tends to experience an oversupply situation, which ultimately leads to a fall in carbon trading prices.

Through the above background description and theoretical analysis of inter-market linkages, we find that the non-linear linkage effects among the carbon market, green bond market, and clean energy and electricity market in China can be studied from the perspective of dynamic time-varying effects, where traditional methods cannot capture the dynamic changes of relationships. If the non-linear relationship between the variables is ignored, some important features between the variables may be overlooked (Piotr & Witold, 2018). Therefore, this paper constructs equal interval, different time points, and three-dimensional impulse response functions through the internationally recognized frontier statistical TVP-VAR-SV model, this method can capture different economic conditions (Esmaeili & Rafei, 2021), while the introduction of time-varying parameters improves the accuracy of the model fit as well as the explanatory power of the model (Gong et al., 2021). The linkage effect between the indicators can be observed in detail through the impulse response results so as to analyze the risk transmission mechanism between markets.

The study as is structured as follows. Section 2 reviews existing studies on each market and model selection. We find that many scholars have studied one or two markets accordingly, but few articles have examined four markets under a unified framework under the background of renewable energy power system transformation. Section 3 discusses the theory of the model. In Section 4, the relationship between the variables is first tested for non-linearity, followed by an analysis of the dynamic shock effects between markets by constructing DCC-GARCH and TVP-VAR-SV models. The DCC-GARCH results indicate that the CSI New Energy Index shows a strong correlation with the electricity index, suggesting that the construction of the electricity system dominated by renewable energy will necessarily require the complementarity of the two markets. The results of the impulse response analysis of TVP-VAR-SV indicate that the connectivity between different markets is time-varying. The carbon market has a clear fluctuation in 2020 when the other three markets are affected, which indicates that China's renewable energy transformation and development is a big turning point. The electricity market reacts negatively to the carbon market in the short and medium terms, but converges directly to zero in the long term, fully demonstrating the demand for renewable energy in the transformation process of the power system. But, due to the uncertainty, volatility, and anti-peak regulation characteristics of the renewable power generation output, it will bring great challenges to the system power balance. In Section 5, the model is tested for robustness using short-term data of the unified carbon market in China. The study findings can offer valuable insights for policymakers crafting carbon trading strategies and for investors shaping their plans, as well as offering recommendations and guidance for the future growth of the domestic carbon market.

2. Literature review

In recent years, the EU carbon market has been the primary focus of numerous studies, with a particular emphasis on examining the factors that influence it and its connections to energy markets. Ji et al. (2018, 2019) analyzed connectivity networks, and rolling window techniques were employed to assess the information spillover between the carbon market and the electricity and energy markets. They discovered a feedback loop between the EU carbon market and the other markets, with Brent crude oil prices having a notable impact on carbon price volatility and playing a crucial role in risk transmission. Hanif (2021) used the Diebold and Yilmaz spillover index method and copula function to find that the connectivity spillover between the renewable energy stock index and EUA price is stronger in the short term than in the long term. In Li (2021), a deeper investigation was conducted into the variables that impact the pricing of EUA during various time periods through the use of TVP-VAR-SV. The correlation between the carbon market and other relative markets fluctuates significantly over time, with carbon prices showing greater responsiveness to short-term changes in electricity prices.

The majority of the literature mentioned above emphasizes coal, oil, natural gas, and so on, with limited study on the growing carbon market in China, particularly in the areas of clean energy and electricity markets. The power industry is a significant contributor to carbon emissions in the energy sector, responsible for approximately 40% of total emissions. The dominance of coal in China's energy sector is expected to persist for the foreseeable future, as power generation companies slowly transition from conventional energy sources to cleaner, more sustainable options over an extended period of time (Nong et al., 2022). In Yang's (2020) study, the DY spillover index was utilized to determine if the carbon market benefits from the 'carbon-electricity' system in the EU, particularly with significant involvement from German and Austrian utility companies. The study additionally highlights the importance of electricity demand in the transmission of risks. From a Chinese perspective, Li (2020) researched the spillover effects between the carbon pilot market and 10 listed Chinese power companies, and found that the carbon market is a net receiver of the power industry information, and the spillover effect between the CET market and China's power industry is weak. Nevertheless, there are constraints in the literature that could be explored in future research to analyze how the total capacity and percentage of renewable energy installations affect the relationship between power companies. Wen (2022) included the CSI300 power index and determined that it is the primary determinant of carbon price dynamics in Hubei.

Green bonds are financial tools that provide funding for environmentally friendly projects that promote energy efficiency and reduce carbon emissions. Compared to traditional financial instruments, green bonds are a recent addition to the financial market, but play a crucial role in funding eco-friendly initiatives (Samuel et al., 2024). It is projected that clean energy will make up 62% of the world's energy output by 2050, leading to a 31% decrease in fossil fuel usage (Bloomberg NEF, 2020). This shift in energy has significantly boosted the development of the green bond sector. As a result, numerous academic researchers have concentrated on the correlation between green bonds and financial markets, as well as energy assets. Chai (2021) examined the changing nonlinear relationships among green bonds, renewable energy, and stock prices in the worldwide markets amidst the COVID-19 pandemic using a TVP-VAR-SV model. The findings indicate that green bonds result in a temporary rise in renewable energy and had a growing beneficial effect after COVID-19. Reboredo and Ugolini (2020) researched how the price of green bonds are affected by different types of markets, such as government bonds, high-yield corporate bonds, energy markets, and so on. They used a VAR model to analyze the price transmission and found that green bonds are influenced by these markets, with stronger connections to government and investment-grade bonds compared to high-yield bonds and energy markets.

The focus on investing in and using clean energy is growing (Strantzali & Aravossis, 2016; Wu, Wang et al., 2020). Numerous nations globally are implementing diverse renewable energy strategies to support the advancement of sustainable energy and are making efforts to expedite the shift towards sustainable energy sources (Li et al., 2021). Consequently, an increasing amount of research has also concentrated on the correlation between green bonds and renewable energy sources (Chen et al., 2023). In a study conducted by Nguyen in 2021, a strong relationship was discovered between environmentally friendly bonds and renewable energy through the analysis of rolling window wavelet correlations. Hammoudeh (2021) also reported conflicting results in that the direct correlation between the clean energy index and green bonds is constrained, but there is a significant association between green bonds and clean energy in both typical and extreme market scenarios. In Pham's (2021) study, a cross-quantile graphical framework was utilized to explore the relationship between green bonds and clean energy, revealing a stronger connection between the two during challenging market conditions.

From the above literature review, each market has been studied accordingly by scholars, but there is less analysis of the linkage effects between multiple markets. Ren (2022) developed a novel framework that assesses the connection between the EU carbon futures and green bond markets by considering various time scales and market situations. Standard VAR models with constant parameters only allow the impulse responses of variables to be plotted under the assumption that the parameters do not change over different ranges of impulse response points. The TVP-VAR-SV model, developed by Esmaeili & Rafei in 2021, incorporates time-varying parameters, which enhances both the precision of the model fitting and the explanatory capacity of the model (Gong et al., 2021; Li et al.,2023). Zhao (2022) utilized the TVP-VAR technique to examine dynamic fluctuations in the relationships between Chinese stocks, commodities, and carbon markets, with a specific emphasis on how extreme event shocks affect these market interactions. This study introduced the TVP-VAR-SV model (Primiceri, 2005) to examine the dynamic nonlinear connections between the Chinese carbon market, green bond market, renewable energy market, and electricity market. It is the first time these four markets were analyzed together using a unified framework to build DCC-GARCH and TVP-VAR-SV models for volatility risk analysis from a time-varying viewpoint, enhancing the research on the carbon market.

3. Methodology introduction

This paper introduces Primiceri's (2005) non-linear time-varying analysis tool, the time-varying parametric vector autoregressive model (TVP-VAR-SV), to explain the time-varying and non-linear characteristics between economic phenomena. Referencing this study, it is assumed that all parameters obey first-order random walk processes and are time-varying, and without the homoskedasticity assumption. The TVP-VAR-SV model is used to empirically demonstrate the time-varying effects of four markets, and to flexibly capture the time-varying and gradual characteristics, while accurately observing the mechanisms of interaction between economic variables at different intervals and points in time. TVP-VAR-SV is evolved from the structural vector autoregressive model (SVAR), and the basic form of an SVAR model with s-order lags is given by

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_s y_{t-s} + \mu_t \, , t = s+1, \cdots n \tag{1}$$

where y_t is the $k \times 1$ dimensional vector containing k endogenous variables, A_t represents the $k \times k$ dimensional joint parameter matrix, $F_1, \cdots F_s$ is the pending coefficient matrix, $t-1, \cdots t-s$ represent different lag periods, μ_t represents the error or structural impact, $\mu_t \sim (0, \Sigma\Sigma)$and A_t and Σ_t are expressed as

$$A = \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \alpha_{k1} & \cdots & 1 \end{pmatrix}, \Sigma = \begin{pmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_k \end{pmatrix} \tag{2}$$

Now, we can shift the terms of equation (1) as

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + \cdots B_s y_{t-s} + A^{-1}\Sigma\varepsilon_t \quad (3)$$

where $B_i = A^{-1}F_i$, $\varepsilon_t \sim N(0, I_k)$ and we stack coefficient matrix B_i by row elements and define $X_t = I_k \otimes (y'_{t-1}, y'_{t-2}, \cdots y'_{t-s})$, where $\otimes$ denotes the Kronecker product, and (3) can be written as：

$$y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t \, , t = s+1, \cdots n \quad (4)$$

SVAR models usually assume that the parameters (β, A, Σ) are invariant, and this paper relaxes this assumption here by assuming that all parameters obey a time-varying first-order stochastic wandering process, enabling the gradual and time-varying characteristics of the underlying economic phenomenon to be captured. Ultimately, the TVP-VAR-SV model is as follows:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t \quad (5)$$

where A_t and Σ_t are time-varying, and α_t is the lower triangular element of A_t. The log stochastic volatility matrix is $h_t = (h_{1t}, \cdots h_{kt})'$, where $h_{jt} = ln\sigma_{jt}^2 \, , j = 1, \cdots k \, , t = s+1, \cdots n$; $\beta_{t+1} = \beta_t + \mu_{\beta t}$, $\alpha_{t+1} = \alpha_t + \mu_{\alpha t}$, $h_{t+1} = h_t + \mu_{ht}$.

To avoid bias in the estimated parameters due to ignoring changes in volatility in stochastic perturbations, the TVP-VAR-SV model assumes stochastic volatility, but the likelihood function becomes more complex and the model is more difficult to estimate. The estimation in this study utilizes the MCMC algorithm introduced by Nakajima (2011). It regards the time-varying parameters in the model as latent variables and generates a sample from a high-dimensional posterior distribution. Let $y = \{y_t\}_{t-1}^{n}, \omega = (\Sigma_\beta, \Sigma_\alpha, \Sigma_h)$, set $\pi(\omega)$ as ω the prior probability, and sample from the posterior distribution $\pi(\beta, a, h, \omega|y)$ on the basis of a given y.The specific steps of the algorithm are as follows: first, initialise the parameters ;second, draw from the conditional posterior distribution; third, draw from the conditional posterior distribution; fourth, draw from the conditional posterior distribution; fifth, drawfrom the conditional posterior distribution; sixth, draw from the conditional posterior distribution; seventh, draw from the conditional posterior distribution; eighth, return to the second sampling step.

4. Empirical analysis

4.1. Data source and variable selection

This paper includes four variables of the Hubei carbon market, green bond market, clean energy market, and electricity market. The China Green Bond Index is the earliest published green bond index in China, which can better reflect China's green bond market. The economic focus in Hubei is primarily on the secondary industry, with power companies being the first to participate in the carbon market. The distribution of the Hubei carbon market primarily includes electric power and industrial companies (Chang et al., 2018; Zhou & Li, 2019). The CSI New Energy Index chooses 80 stocks from the CSI All-Share Index that are connected to renewable energy production, energy storage, and energy applications. The CSI 300 Electricity Index contains 93 listed electric power companies in China. All data are obtained from Wind (Table 1), with data dimensions from January 4, 2018 to September 30, 2022, and contain a total of 1098 observations after processing of missing values. The data treatment of log returns was adopted for all variables prior to modeling: $ln(x_{t+1}) - ln(x_t)$.

Table 1. Summary of the indicator data.

Market	Indicators	Variable name	Data sources
Carbon	Hubei carbon pilot	HBEA	Wind
Green bond	China Bond green bond index	CBGB	Wind
Clean energy	CS New Energy Index	CSXN	Wind
Electricity	CSI300 electricity Index	ELEC	Wind

4.2. Data test

4.2.1. Descriptive statistics, unit root test, and cointegration test

Table 2 shows that the skewness coefficients are both positive and negative, and that all of variables are asymmetrically distributed. The kurtosis coefficients of the data are all greater than 3, showing the characteristics of a spike distribution. The Jarque-Bera statistic test is passed at the 1% confidence level, meaning that the data does not follow a normal distribution. In summary, the data is mostly "spiky and backward tailed" and "asymmetric", reflecting the typical features of present market prices and stock information.

Table 2. Descriptive statistics of the variables.

	HBEA	CBGB	CSXN	ELEC
Mean	0.04	0.02	0.06	0.01
Median	0.00	0.02	0.14	0.06
Maximum	9.56	1.72	7.51	9.47
Minimum	−19.72	−0.82	−14.75	−17.70
Std. Dev.	3.09	0.10	2.12	1.76
Skewness	−0.29	2.89	−0.89	−1.30
Kurtosis	6.82	68.37	7.72	17.18
Jarque-Bera	1035.36	298796.30	1768.59	14412.97

Note: The Jarque-Bera statistic at the 1% confidence level passed the test "***"

As non-stationary time series are directly used to build the model, the results obtained are biased and there are pseudo-regressions. In this paper, the ADF test is used to test the stationarity of variables (Table 3). The results indicate that all variables are stationary at the 5% level and can be subsequently modeled.

Table 3. Stationary test.

yield data	T statistic	P value	stationarity
HBEA	−44.29	0.01	Stable
CBGB	−27.36	0.00	Stable
CSXN	−39.07	0.00	Stable
ELEC	−37.98	0.00	Stable

4.2.2. BDS non-linear test

Initially, the best VAR model for each pair of related market variables is determined by selecting the lag order using the Bare Pool Information Criterion and the Schwarz Criterion in order to generate a series of filtered residuals. The BDS technique, as described by Broock in 1996, is utilized to assess if the residuals adhere to the initial assumption of "independent identical distribution". If this assumption is disproved, it indicates the presence of a non-linear pattern within the residual data. Table 4 displays that the BDS test on the residual series from the bivariate VAR of the returns of correlated variables rejects the initial hypothesis at a 1% level of significance, indicating a notable non-linear relationship between the two series.

Table 4. Test of nonlinearity of BDS.

Bivariate VAR Residual sequence	Embedded Dimension	two	three	four	five	six
HBEA-CBGB	Residual 1	0.055***	0.098***	0.123***	0.133***	0.134***
	Residual 2	0.026***	0.045***	0.061***	0.067***	0.071***
HBEA-CSXN	Residual 1	0.055***	0.098***	0.123***	0.132***	0.133***
	Residual 2	0.001***	0.009***	0.018***	0.024***	0.028***
HBEA-ELEC	Residual 1	0.054***	0.097***	0.122***	0.132***	0.133***
	Residual 2	0.009***	0.012***	0.022***	0.028***	0.030***
CBGB-CSXN	Residual 1	0.027***	0.047***	0.063***	0.070***	0.073***
	Residual 2	0.001***	0.010***	0.018***	0.024***	0.030***
CBGB-ELEC	Residual 1	0.027***	0.046***	0.061***	0.068***	0.072***
	Residual 2	0.010***	0.014***	0.023***	0.028***	0.030***
CSXN-ELEC	Residual 1	0.011***	0.018***	0.027***	0.033***	0.036***
	Residual 2	0.001***	0.008***	0.017***	0.023***	0.027***

Notes: HBEA-CBGB refers to the bivariate VAR system of Hubei carbon price return and green bond return, with the same for the other related markets. "Residue 1" and "Residue 2" refer to the residual sequence obtained by VAR constructed with HBEA and CBGB as the dependent variable. The nested vector dimensions of BDS is 6.

4.3. Dynamic correlation analysis

This paper begins with a dynamic correlation analysis of the variables using a DCC-GARCH (1,1) model (Engle, 2002). Figure 2 intuitively shows that the conditional correlation coefficient between the variables has obvious time variation. It can be seen that there is no clear trend in the time-varying coefficient plots of the Hubei carbon market with the electricity index and the CSI New Energy Index, both fluctuating around a certain value, but showing an increase in correlation in early 2020 and early 2022. The green bond market is negatively correlated with the remaining three markets overall, which is consistent with Nguyen et al. (2021), where the clean energy sector of power companies is the main area of investment in green bonds. However, the funds raised from green bonds can be used for other green projects and the government and companies may place more emphasis on other green projects to rationalize the allocation of green resources, which leads to a decrease in financial support for the clean energy market. The clean energy market and the electricity market show a strong dynamic positive correlation, and the positive correlation gradually decreases with time. The developed power enterprises have already tried to reform green power before the official unification of the carbon market. After the unification of the carbon market in July 2021, these two markets may be more affected by the rest of the market factors. Not only power companies, but also the rest of the carbon-intensive industries are also gradually moving towards renewable energy. Overall, at the point in time when COVID-19 erupted, the dynamic correlation of volatility between the various markets was significantly strengthened, indicating that extreme events have a significant impact on the dynamic connectivity between the markets, which will be studied in depth later in this paper in the impulse response section.

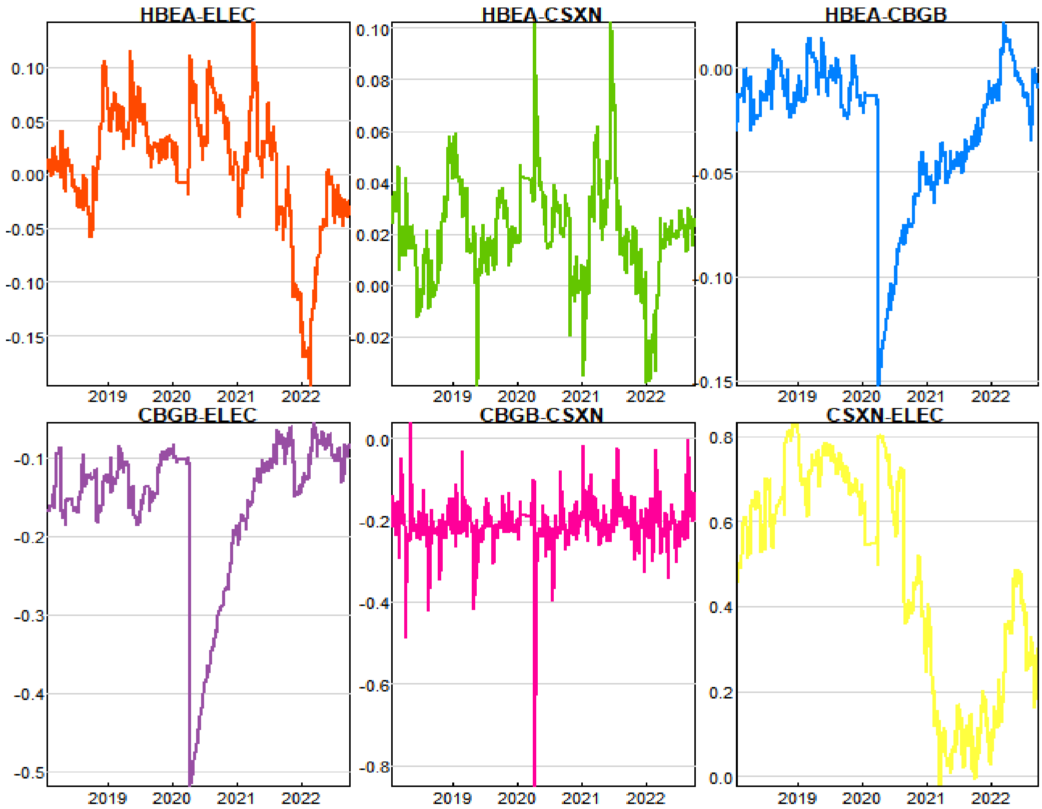

Figure 2. Dynamic conditional correlation coefficient plots.

4.4. Impact effect analysis

4.4.1. Estimation results of the TVP-SV-VAR model

In order to determine that the sampling is a stationary probability distribution, and to obtain the posterior distribution of the unknown parameters, a convergence diagnosis is required before estimation and inference of the samples. The MCMC algorithm is applied to carry out 20,000 samples and discard the initial 4,000 times to obtain a stable and valid sample. The Geweke test (Table 5) shows a convergence diagnostic value below the 5% threshold of 1.96, supporting the original hypothesis of convergence in the posterior distribution. With a maximum invalid factor of 199 in the table, we can extract approximately 100 uncorrelated samples from the 20,000 total, indicating an adequate number of samples for subsequent inference.

Table 5. Results of the MCMC estimates for the model parameters.

Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef
$(\Sigma_\beta)_1$	0.0023	0.0003	0.0019	0.0030	0.183	51.31
$(\Sigma_\beta)_2$	0.0023	0.0003	0.0019	0.0029	0.008	62.07
$(\Sigma_\alpha)_1$	0.0049	0.0011	0.0032	0.0075	0.617	175.25
$(\Sigma_\alpha)_2$	0.0050	0.0013	0.0032	0.0079	0.130	199.33
$(\Sigma_h)_1$	0.7716	0.0539	0.6730	0.8833	0.380	20.78
$(\Sigma_h)_2$	0.4800	0.0386	0.4079	0.5595	0.080	41.65

4.4.2. Time-varying impulse response analysis

Impulse response analysis was performed for two types of impulse response functions at equal time intervals and at different time points, respectively. Figure 3 shows the impulse response plots for equal time intervals, reflecting the impulse response of each variable after being subjected to a positive unit shock at different lead times, the lead times chosen here being periods 1, 2, and 3, respectively. In Figure 4, the impulse response outcomes for the three variables are displayed at various time intervals, enabling a comparison of the variations in reaction to shocks for each variable at different time intervals. This section compares the performance of the carbon market in 2018, the recovery from the epidemic in March 2020, and the launch of the national carbon market in July 2021 by analyzing three specific dates: December 3, 2018; March 3, 2020; and July 21, 2021.

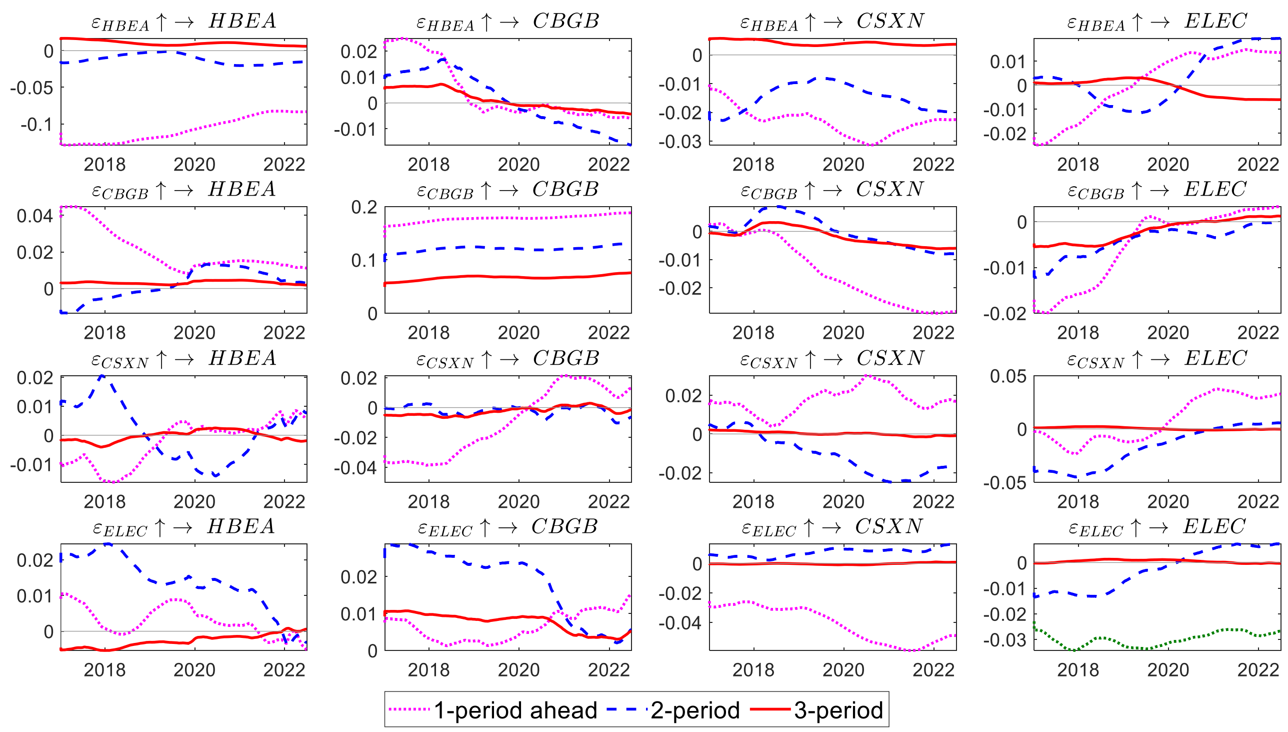

Figure 3. Equal time interval impulse response.

In the Hubei carbon market, a positive shock of 1 unit on the variable results in short- and medium-term negative impacts on the electricity index, which gradually turns positive over time within the same period. However, in the long term, this effect has shifted to negative in recent years, suggesting that China's electricity market has been increasingly influenced by the carbon market. Consequently, electricity companies will need to allocate more resources towards carbon emissions reduction and transformation in the long run. The clean energy index demonstrates a detrimental impact in the short and intermediate term, yet a beneficial impact in the distant future, suggesting that the boost from the carbon market on the clean energy sector is not immediate, but rather indirectly influenced by various markets. Specifically, when the other three markets are hit, the carbon market had a significant fluctuation in 2020, which foreshadowed that China's green transformation in 2020 will greatly affect the carbon market.

The green bond market is seen as an attractive market because the issuance or trading of green bonds can increase equity market prices. The green bond market is less exposed to risks or external shocks than the traditional bond market, but may be affected positively or negatively by macroeconomic factors. Therefore, the main focus of this paper is on the transmission of information from the green bond market to other markets. When it is subject to a positive shock, the carbon market shows a significant positive effect in three periods in recent years, indicating that the green bond market has a significant positive impact on the performance of the carbon market. Specifically, the increase in green bond issuance and the restriction of carbon emission allowances have caused higher carbon prices, which then increases the production costs of some high carbon energy companies, ultimately encouraging a low carbon transition for companies to help improve their competitive advantage in the future. The electricity market before 2021 showed a significant negative effect of green bond market, and after turned into a positive effect with a gradual increase, which is due to the traditional electric power enterprise is undergoing a green power reform transition period before 2021. When the law of power generation has not yet been mastered, and the fuel commodity demand increased, leading to higher cost.

Most power companies have been supported by green bond funding in recent years, and the transformation of their businesses has slowly smoothed out so that they can eventually achieve low-carbon development. It has been shown that recent reductions in the cost of remote wind power generation are not only due to technological advances, but also due in large part to green financing, which can provide investors and operators of offshore wind turbine farms with cheaper sources of capital and revenue (Zhao et al., 2022)

When the Power Index is subject to a shock, the Hubei carbon market shows a volatile positive effect in the short to medium term and a small negative effect in the long term because the carbon market, which acts as an information overflow, is more susceptible to policy and other factors. When the CSI New Energy Index receives a positive shock, the Hubei carbon market shows a negative effect in the short to medium term, but turns positive after July 2021 and remains positive in the long term, which is consistent with the results of Hanif (2021) in a study showing a positive dependence between carbon prices and renewable energy stocks. We also find that the degree of dependence between the two markets increases significantly during the 2020 pandemic, possibly due to the economic downturn during the COVID-19 pandemic, where companies reduced their demand for clean energy to reduce costs, slowing the transition process, but this in turn led to an increase in demand for carbon credits, which will test investors' decision skills, a finding that also informs subsequent point-in-time impulse response analysis. The electricity market responds negatively in the current period, but converges directly to zero in the medium to long term, demonstrating that the need for new energy sources in the transition process of a new energy-dominated power system. But, the uncertainty, volatility, and anti-peak characteristics of wind power generation will pose a significant challenge to the system power balance (Irena, 2019). In order to eliminate or weaken the impact of new energy uncertainty and volatility on system safety as well as economic operation, the power system needs to have sufficient response and regulation capabilities.

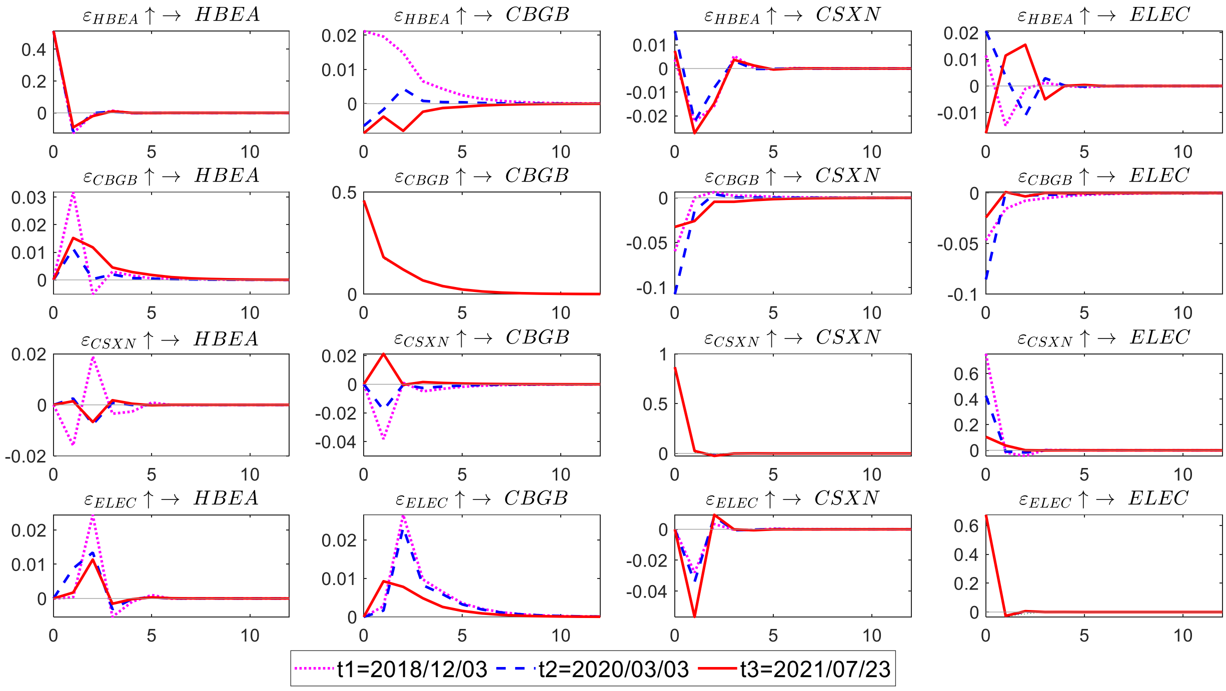

Figure 4. Impulse response plot of different points.

Figure 4 demonstrates that the impulse response of the Green Bond Index at each point in time converges over time when the Hubei carbon market is hit. The carbon market had minimal influence on the green bond market up to the seventh period. In December 2018, there was a favorable reaction, while the other two time periods of the Green Bond Index saw unfavorable responses, suggesting that the carbon market in Hubei briefly hindered the green bond market due to the pandemic. The CSI New Energy Index gradually converged to zero after a negative response in the current period at all three time points. The electricity index responded differently at three time points with both positive and negative responses, indicating that the carbon market had a different impact on the electricity market. The unified carbon market in China has a notable influence on the electricity market in the medium term, showcasing the efficacy of this policy. The Hubei carbon market showed a positive effect at all three points in time when the green bond index was hit, indicating the unique role of green finance in the development of the carbon market. The CSI New Energy Index and the CSI300 electricity index showed a negative effect and gradually decreased to zero at three points in time with the increase of the lag period. The new energy market and power companies were hit hard by the pandemic, and financing is urgently needed, but there are limits to what green bonds can do. When the CSI New Energy Index was hit, the Hubei carbon market showed greater volatility at all three points in time, indicating that China's carbon market has been gradually influenced by the development of the new energy market in recent years. The green bond index experienced a downturn until the Chinese national carbon market was unified, with the negative volatility of clean energy on green bonds being linked to the high risk associated with the clean energy sector. This risk could potentially harm the green bond market (He et al., 2019). However, the establishment of the national carbon market has significantly aided in the steady growth of the clean energy market, leading to a gradual decrease in risk that will ultimately benefit the positive development of the green bond market. The electricity index shows a positive effect at all three points in time, and it is clear that the important influence of new energy to accelerate electricity market reform will not change significantly regardless of the period.

4.4.3. Three-dimensional time-varying impulse response analysis

In order to globally measure the time-varying dynamic connectivity effects between different markets, Figure 5 shows a three-dimensional time-varying impulse response diagram. The results show that when the Hubei carbon market was hit, the power market as well as the new energy market had either positive or negative dynamics at different lead times as well as time periods. Such an apparent change in form deserves our attention, and we cannot absolutely define the inter-market impact as positive or negative. The electricity market reacts more slowly to the green bond shock, while the new energy market reacts more quickly and sensitively, and both markets have reached their maximum negative effect under the shock of the 2020 epidemic, which was not found in the previous analysis. When the electricity market is hit, the rest of the markets have a maximum effect at the medium term, reflecting the fact that the electricity market, as a pillar industry, does not directly affect other markets, but indirectly affects related markets. At the same time, we can see more intuitively that the effects of the carbon market have all shown signs of slowing down in recent years when the other three markets have been hit, suggesting that it will be affected by more major events and drivers as the development of carbon markets and the expansion of its influence, so we need to look at the carbon market in more depth.

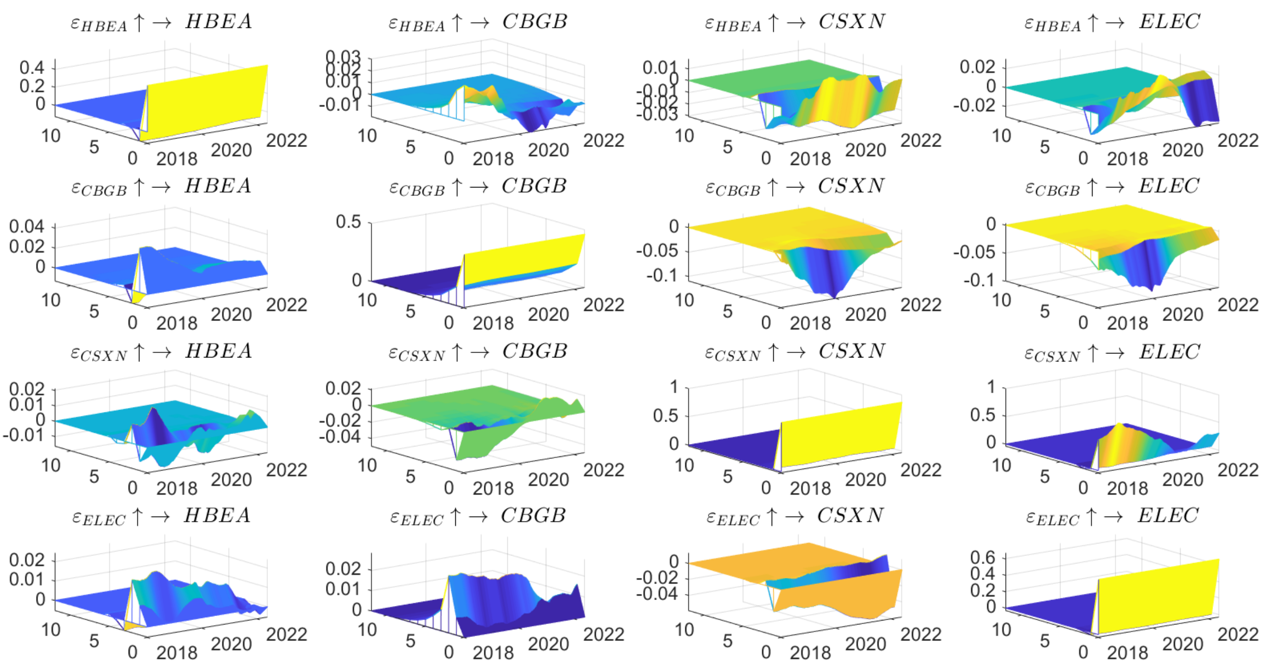

Figure 5. Three-dimensional time-varying impulse response.

4.5. Robustness test

The results of the robustness is verified through further analysis, and robustness can be achieved with smaller samples (Avkiran & Cai, 2014; He, 2020). Therefore, we use data from the daily opening of the national (Chinese) carbon marketfrom 16 July 2021 to 30 September 2022 for modeling, and compare the results with the impulse responses of the Hubei carbon market for the same time period to test its robustness. Table 6 shows that the invalidation factor is less than 100, indicating that the model has a high efficiency of posterior extraction and can be used for further analysis.

Table 6. The MCMC estimation results for the national carbon market model parameters.

Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef
$(\Sigma_\beta)_1$	0.0022	0.0002	0.0018	0.0027	0.513	14.23
$(\Sigma_\beta)_2$	0.0023	0.0003	0.0018	0.0028	0.002	15.63
$(\Sigma_\alpha)_1$	0.0051	0.0011	0.0033	0.0077	0.296	61.16
$(\Sigma_\alpha)_2$	0.0055	0.0015	0.0033	0.0090	0.339	95.52
$(\Sigma_h)_1$	1.2027	0.1267	0.9771	1.4721	0.557	16.28
$(\Sigma_h)_2$	0.3470	0.0640	0.2405	0.4863	0.755	42.99

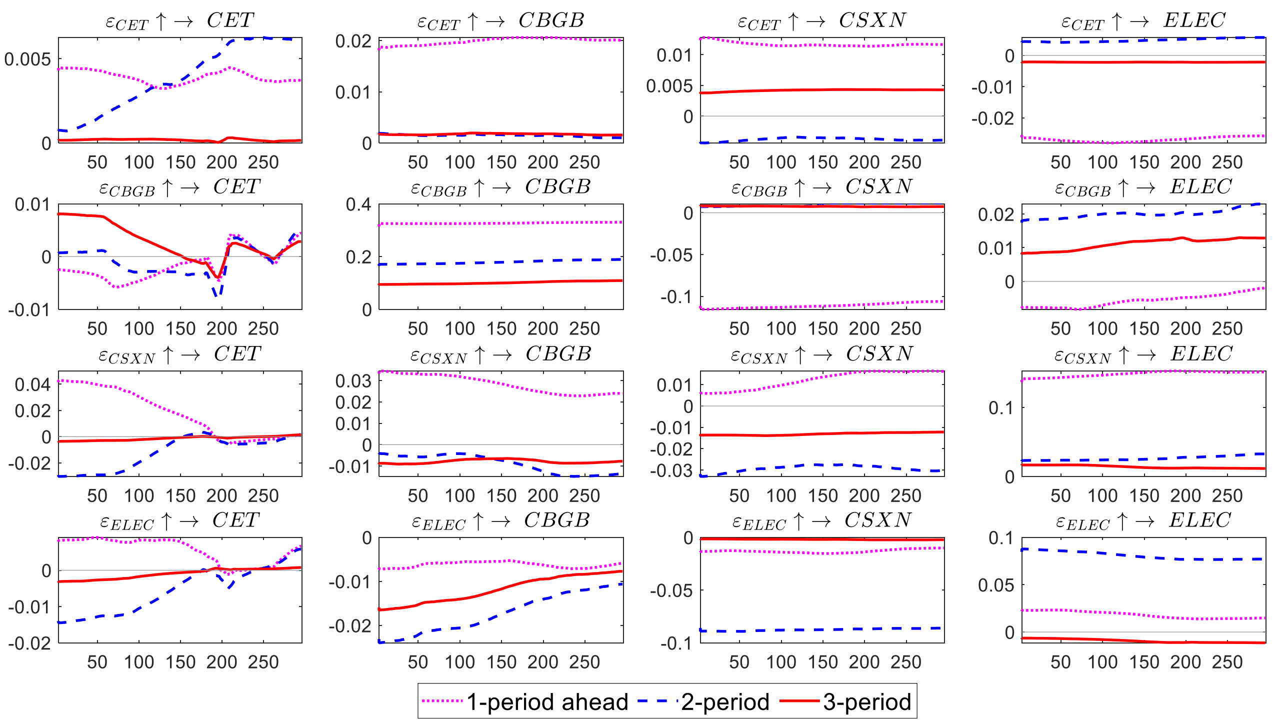

Figure 6. Equal interval impulse response diagram of the national carbon market.

Figure 6 and Figure 7 display the impulse response outcomes, specifically highlighting the carbon market's response compared to the other three markets (top row and left column). While the impulse responses of the national carbon market and the Hubei carbon market differ, they share numerous similarities. The impact on the new energy market from changes in the carbon market varies over time, with a short-term positive response followed by a negative trend in the medium term and a smaller positive effect in the long term. Conversely, the power market initially experiences a negative effect, which shifts to a positive response in the medium term and eventually stabilizes close to zero in the long term. During shocks, the three remaining markets show similar performance in all areas except for electricity, likely due to the Hubei carbon pilot market being less influenced by policy and external factors compared to the national pilot market. In general, the connections among markets change over time, and our findings are fairly stable when incorporating data from the Hubei carbon trading market for analysis in situations where there is not enough data from the Chinese carbon market.

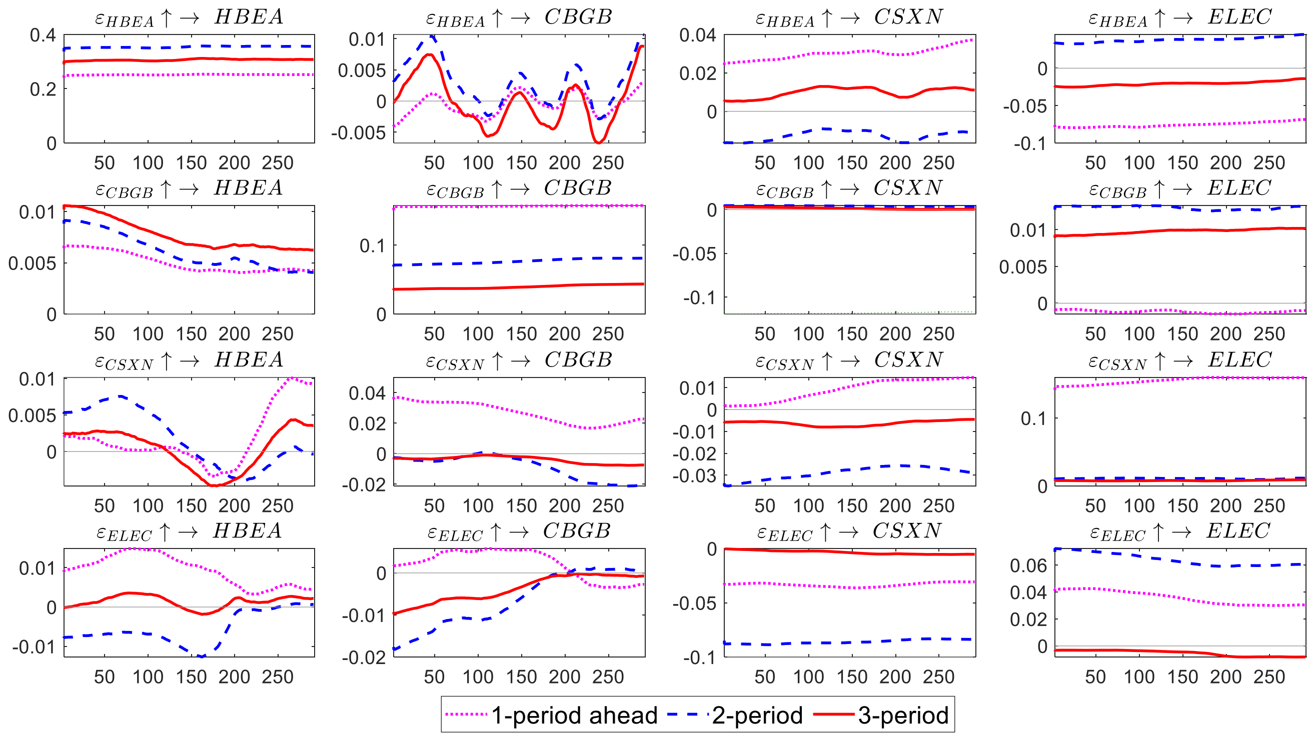

Figure 7. Equal interval impulse response diagram of the Hubei carbon market.

5. Conclusions

This study empirically analyzes the dynamic non-linear linkages between carbon markets, green bonds, clean energy, and electricity markets. Initially, a non-linear BDS examination was performed on the entire yield data, followed by the utilization of a DCC-GARCH framework to investigate the dynamic relationship among the four markets. The CSI New Energy Index shows a strong correlation with the electricity index, suggesting that the construction of the new electricity system dominated by new energy will necessarily require the complementarity of the two markets. When COVID-19 emerged, the strong relationship of volatility between markets increased, indicating that major events have a notable effect on the connection between the four markets.

To better explore the intrinsic effects and transmission mechanisms between markets, this study constructs a TVP-VAR-SV model for empirical analysis. Through impulse response analysis of two types of impulse response functions at equal time intervals and at different time points, our findings suggest that the connectivity between different markets is time-varying:

(1) The Hubei carbon market has a positive impact on the CSI New Energy Index in the short and medium terms, but a transformative impact in the long term, indicating that the new energy market cannot respond to the carbon market in the same period and needs the indirect synergy of multiple markets. There was a notable increase in the electricity market in the short and medium terms after 2020, with a lesser negative impact in the long term. This could be due to traditional electric power enterprises making preparations for industrial restructuring for the long-term sustainable development of their enterprises. Specially, the carbon market has a clear fluctuation in 2020 when the other three markets are affected.

(2) The green bond market has a significant negative impact on the electricity market before 2021, after turning to positive effect and gradually increasing, which is due to the early power enterprises experiencing green transformation, and the trial error costs are high when the law of power generation has not yet been mastered. In recent years, most power companies have been supported by green bond funding, and the development of enterprises has slowly smoothed out.

(3) The New Energy Index had a dampening effect on the Hubei carbon market in the short to medium terms, and turned into a boosting effect after July 2021, indicating that the degree of dependence between the two markets increased significantly during COVID-19. The electricity market reacted negatively, but turned positive after 2020, fully demonstrating the uncertainty, volatility, and anti-peak regulation characteristics of the renewable power generation output, which bring great challenges to the system power balance.

This paper suggests that policy makers could prioritize improving the connection between the carbon market and new electricity market reform and utilize the price discovery function of the carbon market to guide investment decisions in the renewable energy sector. We also suggest developing and enhancing the eco-friendly financial system to encourage financial institutions to actively create green financial products and boost investments in renewable energy, leading to the advancement of businesses' industrial structure. Power companies could be cautious of the effects of carbon price fluctuations on production costs in the near future and make timely adjustments to carbon asset allocation. Over time, it is important to boost the share of renewable energy in electricity production to lessen the impact of power generation expenses on carbon prices, ultimately mitigating the threat of fluctuations in carbon prices. In terms of advancing carbon market development, it is crucial to understand how information is shared in the 'carbon-electricity' system and oversee the progress of the energy industry, particularly focusing on companies that have significant power generation capabilities and rely heavily on thermal power generation.

Although the above study has obtained some key conclusions, there are still some limitations. (1) The existing carbon price data from the pilot regions cannot fully represent the comprehensive operation of China's carbon market, and therefore, as the development of the national carbon market is accelerated and promoted and after the sample size of the unified national carbon market is sufficient, we will consider analyzing the trading data for the national carbon market and exploring the risk transmission mechanism between it and the power market as well as the renewable energy market. (2) We will also further study the inclusion of the remaining carbon-intensive industries (such as non-ferrous metals, iron and steel, chemicals, etc.) that are also undergoing a clean energy transition, and include the energy market and climate risk as intermediary variables to make the research framework more complete. (3) This study focuses on inter-market connectivity in terms of returns and volatility. Higher-order moment risk is important in asset pricing, volatility modeling, risk hedging, and portfolio optimization, and therefore the effect of risk shocks at the level of higher-order moments will be considered in subsequent studies (Zhou et al., 2023).

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Use of AI tools declaration

The author declare they have not used artificial intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

Data availability statement

The data that support the findings of this study are available on Wind database.

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