Global NEST Journal, Vol 27, No X, pp 1-11

Dynamic connectedness and time-frequency interaction between china's carbon emission allowances (CEA) and the high-tech industry

Guo W.[1] and Wu R.[2*]
[1]Shanxi College of Applied Science and Technology, Taiyuan, China
[2]School of Economics and Management, Southeast University, Nanjing, China
Received: 30/11/2024, Accepted: 15/02/2025, Available online: 27/02/2025
*to whom all correspondence should be addressed: e-mail: wuran1998@gmail.com
https://doi.org/10.30955/gnj.07087

Graphical abstract

Abstract

This study utilizes the Time-Varying Parameter Vector Auto-Regression (TVP-VAR) Connectedness model and wavelet coherence analysis to investigate, for the first time, the dynamic connection between China's carbon market and high-tech industry. The results show an overall market Connectedness index of 71.47%, indicating significant information transmission across markets. However, the carbon market exhibits relatively independent characteristics, with spillover coefficients generally below 1%. Dynamic analysis reveals that market Connectedness fluctuates between 60% and 70%, with a narrowing range of fluctuation observed since 2023, suggesting the market's increasing maturity. Wavelet coherence analysis highlights interaction characteristics between the carbon market and various sectors over different time scales: in the long-term frequency domain (128 days), the carbon market exerts sustained influence on sectors such as technology and new energy; in the mid-term frequency domain (16-64 days), notable periodic correlations emerge; and in the short-term high-frequency domain (4-8 days), active daily trading interactions are evident. Net spillover effect analysis demonstrates that the Advanced Manufacturing Index and High-End Equipment Index act as primary sources of information transmission, while the carbon market primarily absorbs impacts from other markets. These findings have significant policy implications for improving carbon market mechanisms, promoting low-carbon industrial transitions, and fostering high-tech industry development. They also provide valuable references for investors in asset allocation and risk management.

Keywords: carbon market; connectedness; tvp-var model; wavelet coherence; high-tech industry

1. Introduction

Against the backdrop of intensifying global climate change, China as the world's largest emitter of greenhouse gases, faces unprecedented pressure to reduce emissions (Lian and Li 2024; Wu *et al*. 2024; Zeng *et al*., 2024). To achieve its dual carbon goals–peaking carbon emissions by 2030 and attaining carbon neutrality by 2060–the Chinese government has introduced a series of major policy measures. Among them, the nationwide Carbon Emission Allowance (CEA) trading mechanism stands out as a landmark market-based tool. Since the launch of China's carbon allowance trading market as a regional pilot project in 2011, its development has continued to mature and improve after the establishment of a unified national market in 2017 and the opening of online trading on 16 July 2021. As an important part of the green financial system, the carbon allowance trading market dominates the allocation of carbon resources through the CEA system trading mechanism, allocating progressively reduced emission allowances to enterprises through competitive bidding, with the aim of guiding and positively incentivising enterprises to adopt low-carbon production methods with a view to achieving the goal of industrial carbon emission reduction.

At the same time, China's high-tech industry is booming, and its position in the global technology industry landscape is becoming increasingly prominent (Appelbaum *et al*., 2018; Zeng *et al*., 2023). As the Chinese government and business community continue to invest in high-tech fields such as new energy, semiconductors and advanced manufacturing, and the industrial sector is closely related to carbon emissions, the expected complex interaction between high-tech industries and the carbon market can be expected to form (Zhang *et al*. 2013; Wu and Li, 2024). On the one hand, high-tech firms that emit GHGs during industrial production are undoubtedly affected by carbon market policies (Leggett *et al*., 2019; Zeng, 2024). On the other hand, the technological revolution and innovations generated by high-tech industries, especially the implementation and application of cutting-edge management methods such as artificial intelligence, have allowed us to provide strong technological and ecological support for carbon emissions monitoring, quota allocation, and trading management, which has strongly contributed to the digital transformation of the carbon trading market (Chatterjee *et al*., 2023; Lu and Zeng, 2023). All in all, this two-way potential linkage makes the risk transmission mechanism and price linkage between the carbon trading market and the high-tech industry increasingly significant.

Specifically, the practical implications of this study are threefold. First, this study provides valuable insights for policymakers to design more effective carbon market regulations that take into account the unique characteristics of high-tech industries. Second, we can help investors better understand the risk transmission mechanism across carbon emissions trading and high-tech markets, thereby helping them make more informed investment decisions. Third, we can provide guidance to high-tech firms in managing their carbon assets and effectively developing emission reduction strategies.

However, existing studies have mainly focused on the European Union Emissions Trading System (EU ETS), and few studies have checked the complex dynamic linkages between Chinese carbon market and other markets. To fill this key research gap, this paper selects representative high-tech industry indicators such as Everbright China Manufacturing 2025 Index, China Technology 100 Index, China New Energy Index, China Advanced Manufacturing Index and China High-end Equipment Index. Then the connectedness structure and time-frequency links between the CEA market and various segments of China's high-tech industry are systematically investigated using the TVP-VAR connectedness model and wavelet coherence estimate.

Among them, the TVP-VAR connectedness model has the following significant advantages over traditional VAR-based connectedness models: first, it not only captures the time-varying characteristics of the dynamic relationships between markets, but also quantifies the spillover effects through the extended connectedness metrics, which more accurately depicts the complex interdependencies between markets (Wu *et al*., 2025). In addition, by integrating wavelet coherence analysis, this study investigates the lead-lag linkages between markets in the short and long term in the time-frequency domain (Lu *et al*., 2023).

Based on the theoretical analyses and existing literature, this study proposes the following core hypotheses.

H1 (Time-varying correlation hypothesis):

The correlation between China's CEA market and China's high-tech industry segments exhibits significant time-varying characteristics, with the strength of the relationship fluctuating in response to market conditions and policy changes. This hypothesis rests on several key theoretical foundations: first, the evolutionary nature of China's CEA market suggests a dynamic pattern of integration with other financial markets as the market matures. Second, the rapid development of high-tech industries and the growing concern of market participants about their environmental sustainability suggest that their interaction with the carbon market may change over time and over the term of the transaction. Third, the gradual implementation of carbon emission-related policies and advances in carbon emission monitoring technology can be expected to result in dynamic changes in inter-market linkages.

The validation of the above hypotheses will help academics and market participants gain a deeper understanding of the non-linear dynamic interaction mechanism between China's carbon emission market and high-tech industries. The primary innovation of this study lies in the first-time application of the extended TVP-VAR Connectedness analysis framework to explore the connection between Chinese carbon market and high-tech industry. This framework not only captures the dynamic evolution of inter-market relationships but also accurately quantifies directional spillover effects between different markets. Furthermore, by integrating wavelet coherence analysis, this study examines short-term and long-term linkages between markets within the time-frequency domain, providing a new perspective for understanding multi-scale interaction relationships. These findings not only enrich related theoretical research but also offer crucial empirical evidence for regulatory authorities to formulate differentiated policies and for investors to manage risks effectively. The empirical analysis of this study reveals that although China’s carbon market has integrated into the financial market system, it still operates with relatively independent characteristics. The Total Connectedness Index is 71.47%, indicating significant information transmission across markets. However, the spillover coefficients of the carbon market generally remain below 1%, reflecting its limited susceptibility to external shocks. Dynamic analysis shows that market Connectedness fluctuates steadily within the 60%-70% range, with a further narrowing of volatility observed in 2023, signifying the market’s increasing maturity. Wavelet coherence analysis highlights the interaction characteristics of the carbon market with different sectors across various time scales. In the long-term frequency domain, the carbon market exhibits sustained influence on the technology and new energy sectors. In the mid-term frequency domain, significant periodic correlations are observed. In the short-term high-frequency domain, active daily trading interactions are evident. Net spillover effect analysis shows that the High-End Equipment Index and the Advanced Manufacturing Index act as primary sources of information transmission, while the carbon market mainly absorbs impacts from other markets. These findings deepen the understanding of the operational mechanisms of the carbon market and provide critical references for policy formulation and investment decision-making.

This work makes several theoretical contributions to the existing literature. First, it extends the application of TVP-VAR Connectedness analysis to a novel context, providing insights into the dynamic relationships between carbon and high-tech markets. Second, we combines wavelet coherence analysis, offering a multi-dimensional perspective on market interactions. Third, it advances our understanding of how emerging carbon markets integrate with established financial systems, particularly in the context of developing economies.

The remainder of this paper is organized as follows. The second section reviews the relevant literature. The third section introduces the data sources and research methodology. The fourth section presents the empirical results and provides a discussion. The final section concludes the paper and offers policy recommendations.

2. Literature review

The carbon market, as a crucial governance mechanism to address climate change, has been the focus of academic research, particularly its effectiveness and market linkages. Existing studies primarily explore the carbon market's interaction with the energy market, the impact of carbon market attention, and the transmission mechanisms of market uncertainty. Millischer *et al*. (2023), through empirical analysis, found that China's regional carbon emission trading markets exhibit significant negative net spillover effects, which are particularly pronounced in the short term. This finding suggests that regional carbon markets in China may not be operating as efficiently as intended, potentially due to market fragmentation and varying levels of market maturity across regions. Notably, since 2018, the spillover effects of the natural gas market on the carbon trading market have surpassed those of the coal market, indicating a structural shift in energy market dynamics and their influence on carbon pricing mechanisms.

Li *et al*. (2024) explored the risk spillover and correlation relationship between U.S. business development and clean energy, concluding that clean energy significantly impacts the ADS index both in the short term and long term. This bilateral relationship demonstrates the gradual integration of carbon and sustainable energy considerations into mainstream portfolios, highlighting the growing importance of understanding the dynamics of cross-sustainability and other financial assets in the context of the current sustainability transition.

Moreover, it is an interesting indicator for market attention. Zheng *et al*. (2022) investigated the correlation between carbon market attention and returns on EU carbon allowances (EU ETS). Their study found a significant negative correlation between the two and showed a lagged effect of increasing and then decreasing under bullish market conditions. They conclude that this pattern is significantly different from the pattern of correlations in traditional financial markets, where increased market attention is usually followed by positive price performance changes. This heterogeneous result suggests that carbon markets are subject to unique market psychology and different regulatory frameworks.

Regarding the exploration of the transmission mechanism of market uncertainty, Liu *et al*. (2023) further explored the risk transmission relationship between carbon and energy markets. Their study shows that global economic turmoil and major risk events significantly affect volatility correlations and spillover indices. This high sensitivity to macroeconomic and financial factors distinguishes carbon markets from other commodity markets, which highlights their dual attributes as environmental policy instruments and financial instruments. In particular, the coal market exhibits the strongest volatility link with the carbon market, while spillovers from the renewable energy market to the carbon market are also observed to be increasing. In addition, from the perspective of structural evolution, carbon markets have transformed from information receivers to information disseminators. This evolution reflects the growing maturity of carbon markets.

On the other hand, through VAR-Base's connectedness index model, Xia *et al*. (2022) find that China's carbon trading market mainly acts as a risk taker, with its risks mainly coming from high-carbon emitting industries. However, this risk transmission relationship may be reversed under external risk shocks, especially during major events such as the U.S.-China trade war and COVID-19.

At the same time, the interaction between the high-tech industry and the carbon trading market has inevitably attracted increasing attention from both the academic and practical communities Li *et al*. (2022), using a PSM-DID model, revealed that carbon emission trading policies significantly promote green technological innovation in firms, although this impact varies significantly by region and enterprise type. This heterogeneous effect suggests that market-based environmental policies may need to be complemented by targeted innovation support measures to achieve optimal outcomes across different contexts. Nie *et al*. (2022) uncovered significant short-term spillover effects among clean energy and technology stocks, and index of carbon allowances, with technology stocks exerting a particularly prominent influence on renewable energy stocks. Qi *et al*. (2022) further confirmed the high-tech industry's dominant position in market systems, acting as a primary propagator of shocks to other variables. This finding positions the high-tech sector as a potential catalyst for market-wide transitions toward low-carbon development.

In terms of environmental impacts, Rasool *et al*. (2022) found a significant negative correlation between the development of China's high-tech industry and environmental degradation, indicating that the advancement of the high-tech sector contributes to environmental improvement. This relationship suggests that technological advancement and environmental protection can be mutually reinforcing, challenging the traditional trade-off narrative between economic development and environmental conservation.

While currently available research has delved into the dynamics between carbon markets and other financial markets, there remains a critical gap in research on the linkages between carbon markets and high-tech stock markets. This gap provides a key entry point for this study.

3. Methodology and data

3.1. TVP-VAR connectedness method

Antonakakis *et al*. (2020) developed the connectedness framework introduced by Diebold and Yılmaz (2012; 2014) into a TVP-VAR method. This version of connectedness method was designed to accurately measure the dynamics of connectedness. By utilizing a rolling window technique, it allowed for the calculation of spillover indices that changed over time while maintaining the integrity of the initial sample estimations. Furthermore, it was robust against the influence of outliers in the dataset. Let us assume an *N*-dimensional TVP-VAR framework with *p* lags:

$$\begin{aligned} &\mathrm{Y}_t = \mathrm{A}_t \mathrm{X}_{t-1} + \varepsilon_t, \varepsilon_t \mid \Omega_{t-1} \sim \mathrm{N}(0, \Sigma_t), \\ &\mathrm{vec}(\mathrm{A}_t) = \mathrm{vec}(\mathrm{A}_{t-1}) + \xi_t, \xi_t \mid \Omega_{t-1} \sim \mathrm{N}(0, \Xi_t) \end{aligned} \tag{1}$$

Where $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{N-1,t}, y_{N,t})$ is an $N \times 1$ vector indicating *N* dimensional market returns at time *t*, and X_{t-1} is a *Np* by 1 matrix, which equals to $(Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})'$ denoting the past values of Y_t with *p* lags. In this article, we select the lag order *p* by applying the BIC. A_t is a *N* by *Np* matrix containing the coefficient matrix with *p* lags. Namely, $\mathrm{A}_t = (\mathrm{A}_{1t}, \mathrm{A}_{2t}, \ldots, \mathrm{A}_{pt})$. More specifically, in the matrix A_t, each *N* columns of matrix, A_{mt}, is an *N* by *N* parameter matrix measuring the effect of Y_{t-m}, where $m = 1 \ldots p$. vec (A_t) is an $N^2 p$ by 1 dimensional vector denoting the vectorisation of A_t. In addition, ε_t and ξ_t are error vectors with zero mean, and Ω_{t-1} is the set of information available at $t-1$. Finally, Σ_t and Ξ_t are the dynamic variance covariance matrices of ε_t and ξ_t.

The fundamental concept behind the spillover index method was to gauge the *H*-step ahead GFEVD using the TVP-VAR(p) model, as outlined below:

$$Y_t = A_t X_{t-1} + \varepsilon_t = \sum_{h=0}^{\infty} B_{h,t} \varepsilon_{t-h} \tag{2}$$

Where $B_{h,t} = \sum_{l=1}^{p} A_{l,t} B_{h-p,t}$ denotes the response function. $B_{0,t}$ is the unit matrix and $B_{h,t} = 0$ when $h<0$; Accordingly, the *H* step-head GFEVD is calculated as follows:

$$\Phi_{jk,t}(H) = \frac{\Sigma_{kk,t}^{-1} \sum_{h=0}^{H-1} \left(\theta_j' B_{h,t} \Sigma_t \theta_k \right)^2}{\sum_{h=0}^{H-1} \left(\theta_j' B_{h,t} \Sigma_t B_{h,t}' \theta_j \right)} \tag{3}$$

Where θ_k are $N \times 1$ selection vectors with the *k*-th parameters are 1, otherwise 0; θ_j works in the same manner. When $j \neq k$, $\Phi_{jk,t}(H)$ denote the share of the *H*-step prediction error variance *j* due to impacts of *k*. To define that the amount of variables in every row is 1, we normalize each entry:

$$\mathring{\Phi}_{jk,t}(H) = \frac{\Phi_{jk,t}(H)}{\sum_{j=1,k=1}^{N} \Phi_{jk,t}(H)} \times 100 \tag{4}$$

$\sum_{k=1}^{N} \mathring{\Phi}_{jk,t}(H) = 1$ and $\sum_{j=1,k=1}^{N} \mathring{\Phi}_{jk,t}(H) = N$. Thus, we can ensure the dynamic TCI at time *t* in the TVP-VAR structure as:

$$TCI_t(H) = \frac{\sum_{k=1,j\neq k}^{N} \mathring{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^{N} \mathring{\Phi}_{jk,t}(H)} \times 100 \tag{5}$$

TCI could be applied to account the total strength of connectedness between all the assets in the system. Further, we can also explore the connection between markets by calculating the directional spillover effect. The directional spillover effect measures the market *j* receives from other assets at time *t* as follows：

$$FROM_{j\leftarrow *,t}(H) = \frac{\sum_{k=1,j\neq k}^{N} \mathring{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^{N} \mathring{\Phi}_{jk,t}(H)} \times 100 \tag{6}$$

The natural way to measure directional overflow from asset *j* to all the other assets at time *t* is then as follows:

$$TO_{j\to *,t}(H) = \frac{\sum_{k=1,k\neq j}^{N} \mathring{\Phi}_{kj,t}(H)}{\sum_{j=1,k=1}^{N} \mathring{\Phi}_{jk,t}(H)} \times 100 \tag{7}$$

Next, to calculate the net directional connectedness of the variables, i.e. the difference between the directional TO and FROM connectedness, we calculated this as:

$$NET_{j,t}(H) = TO_{j\to *,t}(H) - FROM_{j\leftarrow *,t}(H) \tag{8}$$

It can be seen from the equation (8): A positive net connecteness index indicates that asset *j* is a net transfer shock to other variables, otherwise it is a net recipient. Finally, to assess the connectedness between two specific assets, we establish the net pairwise directional connectedness (NPDC) between market *j* and *k* as:

$$NPDC_{jk,t}(H) = \left(\frac{\mathring{\Phi}_{kj,t}(H)}{\sum_{j=1,k=1}^{N} \mathring{\Phi}_{jk,t}(H)} - \frac{\mathring{\Phi}_{jk,t}(H)}{\sum_{j=1,k=1}^{N} \mathring{\Phi}_{jk,t}(H)} \right) \times 100 \tag{9}$$

Similarly, a positive NPDC indicates that the connectedness *k* to *j* is stronger than the spillover effect to, denoting that market *j* dominates the return transmission with *k*, and vice versa.

3.2. Wavelet coherence

Following the definition of Torrence and Compo (1998), we let WC equals to

$$R_{xy}^2(a,b) = \frac{\left| S\left(b^{-1} W_{xy}(a,b)\right) \right|^2}{S\left(b^{-1} W_x(a,b)\right)^2 S\left(b^{-1} W_y(a,b)\right)^2} \tag{10}$$

where $W_{xy}(a, b) = W_x(a, b)\, W_y(a, b)$ is indicated as the cross wavelet transform and S stands for the smoothing parameter, $0 \leq R_{xu}^2(a, b) \leq 1$.

Then the phase difference in the wavelet as,

$$\phi_{xy} = arctan\left(\frac{Im\left[S\left(b^{-1}W_{xy}(a,b)\right)\right]}{Re\left[S\left(b^{-1}W_{xy}(a,b)\right)\right]}\right), with\, \phi_{xy} \in [-\pi, \pi] \tag{11}$$

Where, *Im* and *Re* indicate the imaginary and real sections of the smoothed power spectrum. The phase ϕ_{xy} offers understandings into the connection and potential leading-lag causality between two markets.

This study uses daily data spanning from July 19, 2021, to May 22, 2023, including the price of China's national carbon emission allowances (CEA) and five representative high-tech-related indices: the Everbright China Manufacturing 2025 Index (GD), the China Tech 100 Index (TECH), the China New Energy Index (NE), the China Advanced Manufacturing Index (AM), and the China High-End Equipment Index (HE). The data is sourced from the Wind Financial Database. The starting date of the sample is determined based on the official launch of trading in China's national carbon market, while the end date corresponds to the latest available data.

The descriptive statistics in **Table 1** indicate that the average returns of the six indices are generally low, with the TECH index showing the worst performance (-0.074) and the NE index demonstrating the best performance (0.012). Additionally, the NE index has the highest variance (4.21), reflecting a higher risk profile, while the GD index has the lowest variance (0.595), indicating relative stability. Skewness data reveal that the CEA index exhibits the most pronounced right-skewed distribution (0.345), whereas the HE index shows the most pronounced left-skewed distribution (-0.351). In terms of kurtosis, the CEA index significantly surpasses the others (6.308), suggesting a sharper peak in its return distribution. The Jarque-Bera test results are all significant at the 1% level, indicating that the return distributions of all indices deviate from normality. Moreover, the ERS unit root test results are all significantly negative at the 1% level, suggesting that all-time series are stationary and suitable for subsequent econometric analysis.

Table 1. Descriptive statistics

	CEA	GD	HE	NE	TECH	AM
Mean	-0.052	-0.02	-0.008	0.012	-0.074	-0.052
Variance	3.913	0.595	2.25	4.21	2.306	2.88
Skewness	0.345	-0.017	-0.351	0.082	0.005	0.043
Kurtosis	6.308	1.391	1.663	1.026	1.126	1.469
JB	746.682***	35.911***	60.399***	20.013***	23.502***	40.128***
ERS	-3.571***	-5.587***	-9.877***	-8.635***	-9.718***	-6.741***

*Notes: The JB (Jarque-Bera) test is used to test whether the series follows a normal distribution, and the ERS (Elliott-Rothenberg-Stock) test is used to test for the presence of a unit root (i.e., to test for the smoothness of the series), where *** denotes that it is significant at the 1% significance level.*

Table 2. Granger causality test results

Variable	CEA to Others	Others to CEA
GD	2.3042	10.7957
HE	7.3227	10.1215
NE	8.7984	9.4408
TECH	7.8594	10.1947
AM	8.5012	9.8527

Notes: The critical F-statistic value at the 5% significance level is 2.21

According to the Granger causality results in **Table 2**, there exists significant bidirectional causality between all high-tech industries and CEA. The influence of high-tech industries on CEA is generally stronger than the reverse effect, with GD exhibiting the most substantial impact on CEA (10.7957). The bidirectional relationship between NE and CEA demonstrates the highest degree of balance, with F-statistics of 8.7984 and 9.4408, respectively. All F-statistics exceed the critical value of 2.21 at the 5% significance level, indicating statistical significance across all relationships.

4. Empirical results

From the perspective of static Connectedness presented in **Table 3**, the TVP-VAR Connectedness model reveals the degree of mutual influence among different variables. The values in the table show a strong connection between the China AM, the TECH, and the GD Index, with most of the transmission coefficients between them exceeding 20%. Notably, the transmission coefficient from GD to TECH is 27.74%, from TECH to GD is 25.79%, and from AM to TECH is 23.54%. These high transmission coefficients indicate a close mutual influence among these variables. In contrast, the Connectedness between the CEA market and other variables is weaker, with transmission coefficients generally below 1%. The highest external transmission from CEA is only 0.9% (to the China New Energy Index, NE), indicating that the carbon market is relatively independent and less affected by the fluctuations of other indices.

Examining the FROM column, it can be observed that the FROM values for AM, GD, and TECH are all above 87%, indicating that these indices are significantly influenced by other variables in the system.

A particularly noteworthy observation is the Total Connectedness Index (TCI) of 71.47%, which suggests that, on average, 71.47% of the forecast error variance during the sample period is driven by interactions among the variables rather than by shocks specific to individual variables. In other words, over 70% of market dynamics arise from the mutual interactions of variables, reflecting a highly integrated market system. When compared to TCI values reported in similar studies of financial markets, which typically range from 50% to 65%, this relatively high level of connectedness indicates that the carbon market has achieved a substantial degree of integration with other market segments. However, the remaining approximately 30% of variance attributable to individual shocks suggests that there is still room for further market development and maturation. This intermediate level of integration might reflect the carbon market's unique position as both a policy-driven environmental tool and a financial instrument, where market forces operate within regulatory constraints. Higher TCI values emphasise that investors should focus on the systematic risk among indices rather than the relative importance of individual indices in the system when making investment decisions (Zeng and Ahmed, 2024).

From the point of view of NET, HE and AM are the net spillover senders and their net spillover values are 5.31% and 5.48% respectively, indicating that these two indices are the most significant shocks to the other indices in the system. In contrast, the GD Index and CEA are net receivers, with NET values of -5.82% and -1.92%, respectively, reflecting that they primarily absorb shocks from other indices.

Looking at the TO column, the TO values for AM and TECH are 94.79% and 89.47%, respectively, further confirming their roles as key sources of information transmission.

Further analysis of the Net Pairwise Connectedness (NPDC) ranking shows that HE, AM, and TECH rank as the 5th, 4th, and 3rd most significant indices, respectively. These rankings align with their NET values and transmission coefficients, reflecting their importance in the system. From the overall transmission structure, the relationships among indices exhibit clear hierarchical characteristics. Upstream indices, such as AM and HE, dominate the direction of information transmission, while downstream indices, such as the GD Index and CEA, primarily act as receivers, absorbing and responding to these impacts.

Table 3. Connectedness Table

	CEA	GD	HE	NE	TECH	AM	FROM
CEA	96.95	0.79	0.27	0.9	0.53	0.56	3.05
GD	0.39	11.01	19.84	14.44	27.74	26.58	88.99
HE	0.11	17.94	18.45	21.94	19.8	21.76	81.55
NE	0.16	14.54	24.51	21.16	17.87	21.77	78.84
TECH	0.23	25.79	20.44	16.52	12.89	24.12	87.11
AM	0.24	24.12	21.8	19.63	23.54	10.69	89.31
TO	1.13	83.17	86.86	73.43	89.47	94.79	428.85
NET	-1.92	-5.82	5.31	-5.42	2.36	5.48	TCI=71.47%
NPDC	0	2	5	1	3	4	

Notes: TCI indicates the total connectedness index

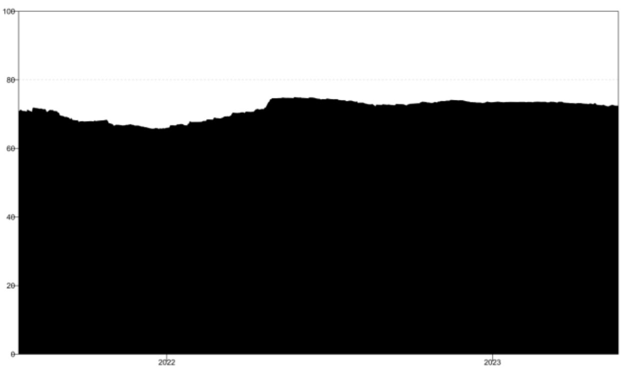

Figure 1. Dynamic TCI

From the perspective of dynamic Connectedness, **Figure 1** illustrates the overall Connectedness changes within the market system during the sample period. The upper boundary of the black-shaded area in the figure shows that Connectedness levels generally fluctuate within the 60-70% range. This relatively stable range indicates that the information transmission mechanisms among market indices operate smoothly, with the system demonstrating strong resilience. Over the time dimension, a slight decline in Connectedness levels can be observed in the first half of 2022, gradually decreasing from approximately 70% to around 65%. This may reflect a temporary weakening of the linkage among market sectors during that period. In the second half of 2022, the Connectedness levels stabilized and slightly rebounded, reaching a small peak by the end of 2022. Entering 2023, the Connectedness levels remained relatively stable, consistently hovering around 70%, with further narrowing of the fluctuation range.

These dynamic characteristics convey several important insights. First, the Connectedness level of 60-70% indicates significant mutual influence among market indices, but the degree of influence is not sufficient to trigger severe market volatility. Second, the relative stability of Connectedness levels suggests that the fundamental structure of the market remained unchanged during the observation period, which helps market participants form stable expectations. Lastly, the gradual narrowing of fluctuations may imply an improvement in market maturity, with inter-index relationships becoming more normalized. These observations support the confirmation of H1.

From the dynamic perspective of NET shown in **Figure 2**, the indices exhibit varying spillover characteristics and trends between 2022 and 2023. The TECH demonstrates a transition from weak net spillover to strong net spillover. During 2022, its net spillover effect remained relatively stable and weak, but entering 2023, particularly in the latter half of the year, the net spillover effect strengthened significantly, indicating a growing influence of TECH on other indices. This transformation reflects the technology sector's evolving role in China's economic landscape. The strengthening spillover effect suggests that the tech sector has become increasingly central to market dynamics, potentially due to its pivotal role in driving digital transformation and green innovation. The timing of this shift is particularly noteworthy as it coincides with China's intensified focus on indigenous technological development and the implementation of various supportive policies for high-tech industries. The driver behind this change may be related to the strong performance of China's tech sector in recent times.

In addition, we note that AM exhibits significant volatility. It reaches a high level of net spillovers (around 10 per cent) in the first half of 2022, followed by a significant decline, but then shows signs of recovery towards the end of 2023. This change may indicate that while AM generally maintains a net spillover effect, the intensity of its impact adjusts dynamically over time. The China High-End Equipment Index (HE) shows relatively stable net spillover characteristics, with values mostly remaining positive and with small fluctuations. This suggests that HE consistently acted as a stable information transmitter throughout the sample period.

In contrast, the GD Index and the China New Energy Index (NE) mostly acted as net receivers. The GD Index maintained a negative NET value throughout the period, with its net receiver role strengthening toward the end of 2023. NE demonstrated even more pronounced net receiver characteristics, particularly with a significant negative NET value in early 2022. Although its position improved slightly later, it still predominantly acted as a net receiver.

The CEA market exhibited the most stable characteristics, with a narrow NET value range consistently hovering around slight negative values. This aligns with its relatively independent market nature. These dynamic evolutionary characteristics indicate that while the overall market Connectedness level (TCI = 71.47%) remains stable, the influence relationships among individual indices are dynamically changing. In particular, the rising influence of the TECH sector and the cyclical fluctuations of AM reflect subtle structural changes in the market. For investors, this dynamic feature carries significant implications, as it suggests potential shifts in market leadership roles. This may necessitate timely adjustments to risk management strategies to align with the evolving market dynamics.

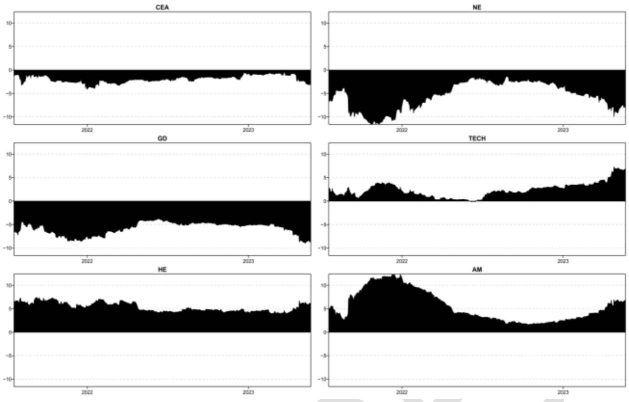

Figure 2. Dynamic NET of all indices

From the analysis of Net Pairwise Directional Connectedness (NPDC) in **Figure 3**, the dynamic interactions between the CEA market and other indices exhibit distinct characteristics. The relationship between CEA and NE is particularly pronounced. We note that the net effect of NE on CEA reaches its lowest value of about -4 per cent in mid-2022, and although this improves as we move into 2023, the net effect is still negative.

On the other hand, the connectedness between CEA and the GD index also shows a significant negative correlation, with a nadir of about -2 per cent in mid-2022. In contrast, the relationships between CEA and the TECH as well as the China AM are relatively weaker, with fluctuations mostly ranging between -1% and 0. This suggests that while the development of the technology and advanced manufacturing sectors is linked to the carbon market, the degree of influence is relatively limited. This may be because these sectors inherently emphasize energy efficiency and emissions reduction, resulting in a lower dependency on carbon allowances.

The relationship between CEA and the China High-End Equipment Index (HE) is the most stable, with the smallest fluctuation range, consistently remaining in a slightly negative range. This indicates that the development of the high-end equipment manufacturing sector has a relatively mild and stable impact on the carbon market.

Overall, the figure demonstrates that the carbon market primarily acts as a net receiver, consistent with the earlier NET analysis. The impact of different sectors on the carbon market varies significantly, with the most notable effects coming from the new energy and traditional manufacturing sectors. These relationships generally stabilized in 2023, supporting the confirmation of H2.

These findings offer critical insights for market participants and policymakers. The carbon market's pricing mechanism is influenced by multiple related markets, particularly the significant impact of the new energy sector, which underscores the need for carbon market participants to closely monitor developments in the new energy industry. The negative association with traditional manufacturing suggests that the carbon market may face pricing pressures during the manufacturing sector's transformation and upgrading. In contrast, the weaker correlation with high-tech and advanced manufacturing sectors indicates that these industries may have already adapted well to carbon reduction requirements. Future efforts may need to focus more on supporting emission reduction transitions in traditional industries.

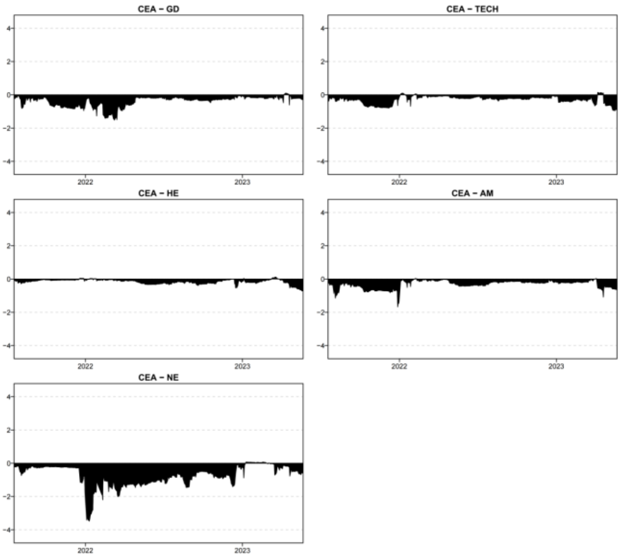

Figure 3. NPDC of CEA and other indices

From the color-coded network diagram in **Figure 4**, the roles of each index in the spillover effects are more clearly illustrated. Blue nodes represent spillover transmitters, including the China High-End Equipment Index (HE), the TECH, and the China AM. These indices predominantly transmit information and shocks to other markets. Yellow nodes represent spillover receivers, including the CEA market, the China New Energy Index (NE), and the GD Index. These indices mainly absorb impacts from other markets.

Particular attention should be given to the position and color of CEA. As a yellow node, CEA not only occupies a peripheral position in the network but is also connected to the network solely through NE. This structural feature conveys two key insights. First, CEA's role as a spillover receiver is evident, consistent with the negative NET values observed in earlier analyses. Second, its connection to the network through another spillover receiver (NE) reflects a "weak-to-weak" linkage structure, which may exacerbate its sensitivity to external shocks.

In terms of transmission pathways, information primarily flows from blue nodes (HE, TECH, AM) to yellow nodes. CEA receives influences indirectly through NE as an intermediary node. This indirect transmission pathway could dilute the intensity of external shocks, explaining why CEA, despite being a net receiver, is relatively less affected by spillovers.

This structured spillover pattern provides a novel perspective for understanding the price formation mechanisms of the carbon market. It also highlights that the future development of the carbon market may benefit from strengthening direct connections with information-dominant blue nodes (transmitters) to enhance market efficiency and pricing capabilities.

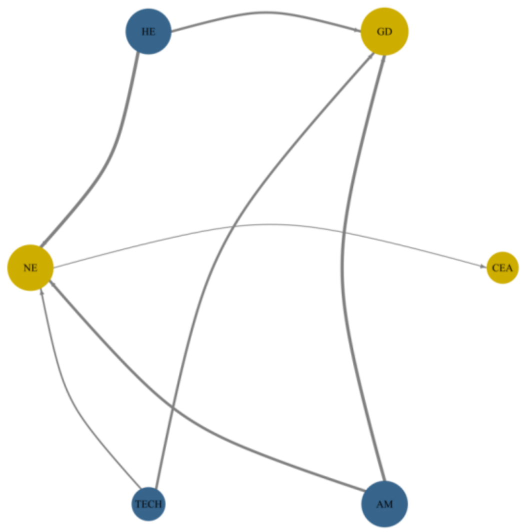

Figure 4. Network spillover structure of CEA and other indices

Figure 5 illustrates the dynamic relationship between China's CEA trading market and the TECH during the observation period. In the long-term frequency domain (128 days), a sustained high-correlation region (deep red) is observed from the fourth quarter of 2022 to early 2023, indicating a significant long-term impact of the carbon market on the technology sector. In the mid-term frequency domain (16-64 days), several regions of strong correlation are also evident, particularly in mid-2022, reflecting the phase-specific influence of carbon market price fluctuations on the technology sector.

In the short-term high-frequency domain (4-8 days), multiple scattered regions of high correlation appear, notably in early 2023, highlighting the active short-term interaction between the two markets during daily trading activities.

These multi-layered correlation characteristics suggest that the carbon market is driving the transition of technology enterprises toward low-carbon and environmentally friendly development through price mechanisms.

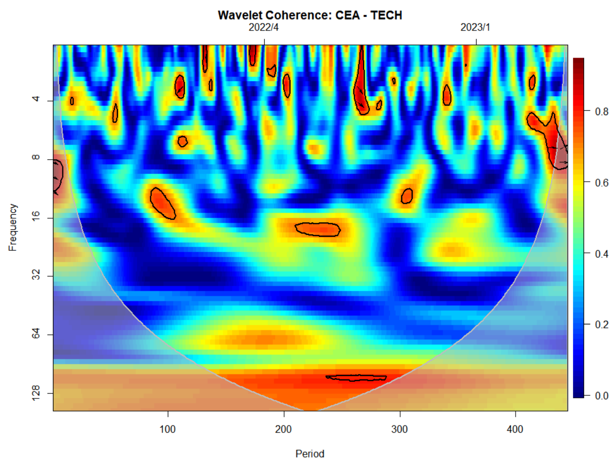

Figure 5. Wavelet coherence between CEA and TECH

Notes: The spectrum displayed colour transitions varying from crimson (elevated consistency) to azure (reduced consistency), which illustrated movement correlations. Crimson demonstrated robust parallel shifts, whereas azure exhibited minimal synchronisation. Directional markers → and ← revealed synchronous and asynchronous market yield patterns, correspondingly. Synchronous (asynchronous) patterns reflected affirmative (adverse) linkages amidst market yields. Moreover, (↗) highlighted leading preceding parameters; (↘) and (↖) emphasised leading subsequent parameters; whilst (↙) manifested leading preceding parameters. Such interpretative guidelines remained uniform across all graphical presentations.

Figure 6 reveals the multi-layered correlation characteristics between China's CEA trading market and the China New Energy Index (NE) during the observation period. In the long-term frequency domain (64 days), a prominent high-correlation region emerges in mid-2022, indicating a sustained impact of the carbon market on the new energy sector.

In the mid-term frequency domain (16-32 days), several significant correlation regions are observed, particularly in the fourth quarter of 2022, reflecting the phase-specific influence of carbon market price fluctuations on the new energy sector.

In the short-term high-frequency domain (4-8 days), multiple scattered high-correlation regions appear, with notably stronger correlations (deep red regions) in early 2023, suggesting close short-term interactions between the two markets during daily trading activities.

These multi-layered correlation patterns demonstrate that the development of the carbon market is effectively fostering innovation and market expansion in the new energy sector through market mechanisms.

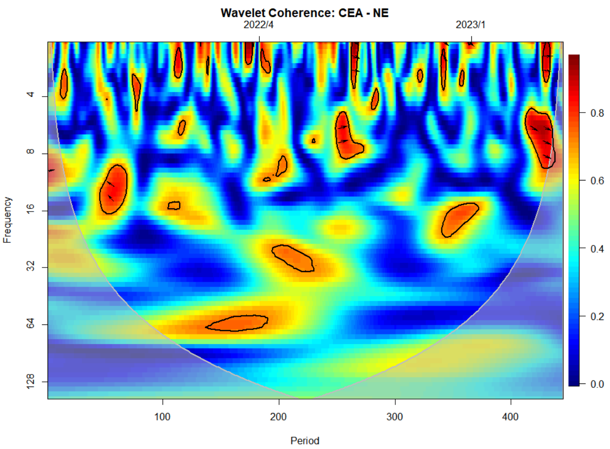

Figure 6. Wavelet coherence between CEA and NE

Figure 7 highlights the dynamic correlation characteristics between China's CEA trading market and the HE index from the fourth quarter of 2022 to early 2023. In the long-term frequency domain (128 days), the correlation is relatively weak. However, in the mid-term frequency domain (16-32 days), a significant high-correlation region emerges, particularly in the second half of 2022, indicating that fluctuations in carbon market prices have had a substantial impact on the high-end equipment sector.

In the short-term high-frequency domain (4-8 days), multiple scattered high-correlation regions are observed, with particularly strong correlations in early 2022, reflecting the close short-term interactions between the two markets during daily trading activities.

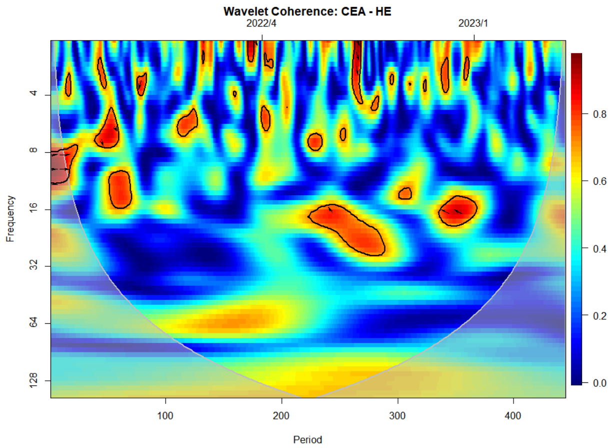

Figure 7. Wavelet coherence between CEA and HE

Overall, these dynamic correlation characteristics suggest that the carbon market, through price signals and policy guidance, is driving the transformation of China's high-end equipment manufacturing industry toward more environmentally friendly and low-carbon practices.

Figure 8 depicts the complex dynamic relationship between China's CEA trading market and the GD from the fourth quarter of 2022 to early 2023. In the long-term frequency domain (128 days), significant correlation regions (red areas) are observed, reflecting the sustained influence of the carbon market on the transformation of the manufacturing sector.

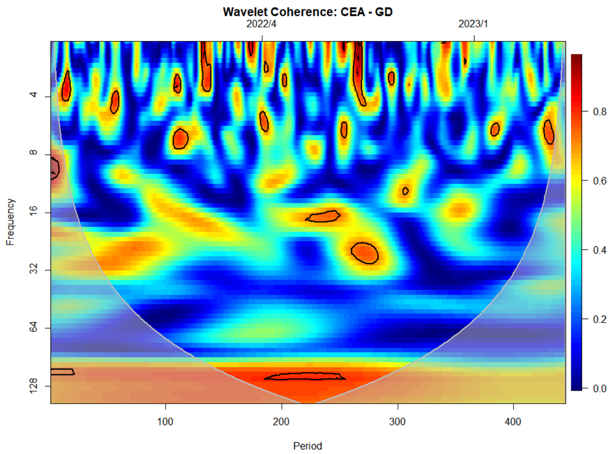

Figure 8. Wavelet coherence between CEA and GD

In the mid-term frequency domain (16-32 days), several notable correlation regions emerge, particularly the high-correlation region in mid-2022, indicating the phase-specific impact of carbon market price fluctuations on the manufacturing index.

In the short-term high-frequency domain (4-8 days), multiple scattered high-correlation regions are observed, illustrating the short-term linkage effects between the two markets during daily trading activities.

These multi-layered correlation characteristics indicate that, as an emerging yet pivotal financial market, carbon emissions trading is exerting a substantive impact on the green transformation of China's manufacturing sector through price signals and policy guidance.

Figure 9 illustrates the multi-layered correlation characteristics between China's CEA trading market and the AM during the observation period. In the long-term frequency domain (128 days), strong correlation regions (red areas) are observed from the fourth quarter of 2022 to early 2023, reflecting the profound impact of the carbon market on the long-term development trajectory of the advanced manufacturing sector.

In the mid-term frequency domain (16-32 days), several significant correlation regions emerge, particularly in mid-2022, indicating the noticeable mid-term effects of carbon market price fluctuations on the advanced manufacturing index.

In the short-term high-frequency domain (4-8 days), numerous scattered high-correlation regions (small red patches) are observed, highlighting frequent interactive relationships between the two markets in daily trading activities.

These multi-dimensional correlation features suggest that the carbon market, as an emerging financial instrument, is exerting a profound influence on the low-carbon transformation and innovative development of China's advanced manufacturing sector through market mechanisms.

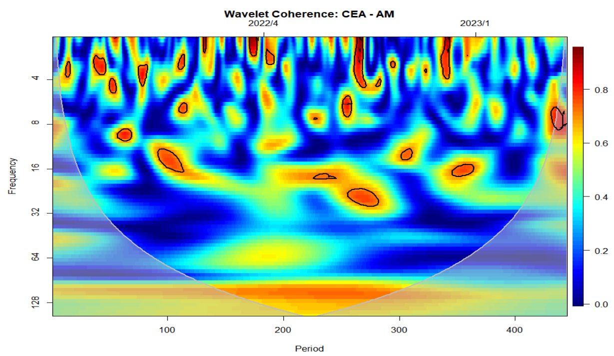

Figure 9. Wavelet coherence of CEA and AM

5. Conclusions

The findings of this study reveal a complex and dynamic interaction between China's carbon market and the high-tech industry. The Total Connectedness Index (TCI) reached 71.47%, indicating a significant mechanism of information transmission across markets. This high level of market integration suggests that over 70% of market changes are driven by interactions between variables. However, the carbon market exhibits relatively independent characteristics, with outward transmission coefficients generally below 1%, peaking at only 0.9% (to the China New Energy Index). This unique market feature suggests that while the carbon market has become an integral part of the financial market system, it still maintains a relatively independent operating mechanism.

From the perspective of dynamic Connectedness, the market system as a whole fluctuates within a stable range of 60-70%, demonstrating strong system resilience. Notably, the stabilization trend beginning in the second half of 2022, coupled with further stabilization and narrowing fluctuations in 2023, reflects a maturing market. The transition of the TECH from weak to strong net spillover and the cyclical fluctuations of the China AM suggest subtle changes in market structure.

Wavelet coherence analysis further reveals the interaction characteristics of the carbon market with various sectors across different time dimensions. In the long-term frequency domain (128 days), the carbon market exerts sustained influence on sectors such as technology and new energy, particularly prominent from the fourth quarter of 2022 to early 2023. In the mid-term frequency domain (16-64 days), the appearance of multiple significant correlation regions reflects the phase-specific impacts of carbon market price fluctuations on different sectors. In the short-term high-frequency domain (4-8 days), scattered regions of high correlation indicate active daily trading interactions among markets. This multi-layered correlation structure underscores the real-world role of the carbon market in driving low-carbon transitions across industries through price mechanisms.

For policymakers, the findings offer several key policy implications. First, policymakers need to further improve the underlying system of the carbon market in response to changes in the market environment. This may often include optimising the quota allocation mechanism, continuously improving the trading rules and strengthening the timely regulation of potential emerging issues or emergencies. Second, policymakers need to continuously improve the liquidity and price discovery function of the carbon market. This may be achieved by introducing multiple market players and developing more carbon financial derivatives.

For investors, it is recommended to strengthen multi-dimensional risk management in investment practice, focusing on the interaction between the carbon trading market and related industries such as new energy and manufacturing, so as to optimise investment portfolios according to their own risk appetite. At the same time, we should pay attention to the changes in the market pattern that may be brought about by the cutting-edge development and innovation in the technology industry, and use this as the basis for updating our investment portfolio. In addition, it is recommended to keep track of carbon market policy trends in order to grasp potential investment opportunities, with special attention to macroeconomic and financial policies that promote synergies between technological innovation and emissions reduction.

The limitation of this study is that it has not explored in depth the interaction between the carbon market and macroeconomic policies, such as the impact of monetary and fiscal policies. Future research could further focus on the transmission mechanism of monetary policy affecting the liquidity of the carbon market and the interaction between fiscal policy and the carbon market. In addition, the integration of the international carbon market is also an important direction, including the harmonisation of trading rules and the further development of uniform carbon accounting standards. The role of technological innovation in promoting market integration and reducing cross-platform transaction costs also deserves attention.

References

Antonakakis N., Chatziantoniou I. and Gabauer D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management*, **13**(4), 84.

Appelbaum R.P., Cao C., Han X., Parker R. and Simon D. (2018). *Innovation in China: Challenging the global science and technology system*. John Wiley and Sons.

Chatterjee S., Chaudhuri R., Kamble S., Gupta S. and Sivarajah U. (2023). Adoption of artificial intelligence and cutting-edge technologies for production system sustainability: a moderator-mediation analysis. *Information Systems Frontiers*, **25**(5), 1779–1794.

Diebold F.X. and Yilmaz K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of forecasting*, **28**(1), 57–66.

Diebold F.X. and Yılmaz K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of econometrics*, **182**(1), 119–134.

Gao Q., Zeng H., Sun G. and Li J. (2023). Extreme risk spillover from uncertainty to carbon markets in China and the EU—A time varying copula approach. *Journal of Environmental Management*, **326**, 116634.

Leggett J.A., Logan J. and Mackey A. (2019). *China's greenhouse gas emissions and mitigation policies*. Congressional Research Service.

Li M., Işık C., Yan J. and Wu R. (2024). The nexus between clean energy market risk and US business environment: evidence from wavelet coherence and variance analysis. *Stochastic Environmental Research and Risk Assessment*, 1–16.

Li X., Guo D. and Feng C. (2022). The carbon emissions trading policy of China: Does it really promote the enterprises' green technology innovations?. *International Journal of Environmental Research and Public Health*, **19**(21), 14325.

Lian C. and Li J. (2024). Legitimacy-seeking: China's statements and actions on combating climate change. *Third World Quarterly*, **45**(1), 171–188.

Liu J., Hu Y., Yan L. Z. and Chang C. P. (2023). Volatility spillover and hedging strategies between the European carbon emissions and energy markets. *Energy Strategy Reviews*, **46**, 101058.

Lu R. and Zeng H. (2023). VIX and major agricultural future markets: dynamic linkage and time-frequency relations around the COVID-19 outbreak. *Studies in Economics and Finance*, **40**(2), 334–353.

Lu R., Xu W., Zeng H. and Zhou X. (2023). Volatility connectedness among the Indian equity and major commodity markets under the COVID-19 scenario. *Economic Analysis and Policy*, **78**, 1465–1481.

Millischer L., Evdokimova T. and Fernandez O. (2023). The carrot and the stock: In search of stock-market incentives for decarbonization. *Energy Economics*, **120**, 106615.

Nie D., Li Y., Li X., Zhou X. and Zhang F. (2022). The Dynamic Spillover between Renewable Energy, Crude Oil and Carbon Market: New Evidence from Time and Frequency Domains. *Energies*, **15**(11), 3927.

Qi X., Zhang G. and Wang Y. (2022). Distributional Predictability and Quantile Connectedness of New Energy, Steam Coal, and High-Tech in China. *Sustainability*, **14**(21), 14176.

Rasool S.F., Zaman S., Jehan N., Chin T., Khan S. and uz Zaman Q. (2022). Investigating the role of the tech industry, renewable energy, and urbanization in sustainable environment: Policy directions in the context of developing economies. *Technological Forecasting and Social Change*, **183**, 121935.

Torrence C. and Compo G.P. (1998). A practical guide to wavelet analysis. *Bulletin of the American Meteorological society*, **79**(1), 61–78.

Wu R. and Li M. (2024). Optimization of shipping freight forwarding services considering consumer rebates under the impact of carbon tax policy. *Ocean & Coastal Management*, **258**, 107361.

Wu R., Li M., Liu F., Zeng H. and Cong X. (2024). Adjustment strategies and chaos in duopoly supply chains: The impacts of carbon trading markets and emission reduction policies. *International Review of Economics & Finance*, **95**, 103482.

Wu R., Zeng H., Abedin M.Z. and Ahmed A.D. (2025). The impact of extreme climate on tourism sector international stock markets: A quantile and time-frequency perspective. *Tourism Economics*, 13548166241311633.

Xia M., Chen Z.H. and Wang P. (2022). Dynamic Risk Spillover Effect between the Carbon and Stock Markets under the Shocks from Exogenous Events. *Energies*, **16**(1), 97.

Zeng H. (2024). Risk transmission and diversification strategies between US real estate investment trusts (REITs) and green finance indices. *Kybernetes*.

Zeng H. and Ahmed A.D. (2024). Risk Transmission and Hedging Strategies Between Chinese Stock Market and Major Trading Partners Along the Belt and Road in COVID-19 Scenario. *American Business Review*, **27**(2), 1.

Zeng H., Abedin M.Z. and Upreti V. (2024). Does climate risk as barometers for specific clean energy indices? Insights from quartiles and time-frequency perspective. *Energy Economics*, 108003.

Zeng H., Lu R. and Ahmed A.D. (2023). Return connectedness and multiscale spillovers across clean energy indices and grain commodity markets around COVID-19 crisis. *Journal of Environmental Management*, **340**, 117912.

Zhang S., Andrews-Speed P., Zhao X. and He Y. (2013). Interactions between renewable energy policy and renewable energy industrial policy: A critical analysis of China's policy approach to renewable energies. *Energy policy*, **62**, 342–353.

Zheng Y., Wen F., Deng H. and Zeng A. (2022). The relationship between carbon market attention and the EU CET market: Evidence from different market conditions. *Finance Research Letters*, **50**, 103140.