Functional Heterogeneity And Dynamic Risk Spillovers In China's Carbon-Green Finance System: A Time-Frequency TVP-VAR Analysis

Ying Huang, Juan Hu*, and Jing Chen

School of Foreign Languages, Wuhan City Polytechnic, Wuhan 430064, China

Corresponding author. E-mail: juanzi0985@163.com

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The diverse roles of green financial sub-markets and their dynamic risk spillovers to the carbon market are important to explain the systemic risks of Chinese low-carbon transition. We employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) model with time-frequency decomposition to explore the connections in China's carbon-green finance system between January 2016 and January 2025. The findings indicate major bidirectional asymmetric spillovers, with the greater impacts of green financial markets on the carbon market. Particularly, functional heterogeneity is strong across the green financial sub-markets. Green equity markets serve as persistent risk transmitters whereas green bonds are transitional, changing from short-term risk transmitters to long-term stabilizers. The carbon market is regularly a net risk recipient due to its policy-driven nature. On the dynamic features, cross-market linkages are highly time-frequency asymmetries, dominated by short-term speculative spillovers and amplified by extreme events and policy shifts. Moreover, there are clear temporal heterogeneities in the risk transmission paths, where short-run flows are sentiment-led and long-run are fundamentals-led. Understanding these dynamics is crucial for both policy-makers and investors in dealing with systemic climate-finance risks.

Keywords: carbon market; green financial market; dynamic risk spillovers; TVP-VAR-DY; TVP-VAR-BK; Computer network

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1. Introduction

The global transformation to a low-carbon economy is an urgent response to the rising climate crisis. As the largest carbon emitter in the world, China is committed to achieving carbon peaking and carbon neutrality (Dual Carbon goals) and has positioned its national carbon emissions trading market as a cornerstone of its climate strategy. The market-based mechanism, designed to price carbon emissions, operates within a broader financial ecosystem. Its linkages with the fast-developing green finance industry of green equities and green bonds make it an interconnected carbon-green finance network. While expanding its funding for sustainable projects, this interconnectedness establishes potent channels for cross-market risk contagion, presenting significant challenges to financial stability and climate policy efficiency.

Initial research mostly utilized GARCH-family model to validate volatility in spillover between carbon, energy and conventional financial markets [1, 2]. With the increasing popularity of green finance, the investigation focused on developed EU Emissions Trading Scheme (ETS) and found obvious spillovers from green bond and enquity markets [3, 4]. In China, time-varying correlations within its carbon-green finance system has also been confimed [5]. A new but essential result shows that these linkages might not be consistent across the sub-sectors of green finance. Chatziantoniou et al. [6] found the green bonds primarily act as net recipients, whereas green equities are the principal channels of shock transmission. Conversely, Wu and Qin [7] revealed that green bonds and ESG markets function as net emitters, while carbon and new energy markets acting as net receivers. Similarly, Huang et al. [8] demonstrated that green bonds and stocks are primarily net transmitters, contrasting with the carbon market as a net receiver. This functional heterogeneity is also evident in the strength of bilateral linkages. Deng et al. [9] found that there's a stronger interaction between China's carbon market and green bonds than with green enquities. Yan and Han [10] highlighted the intricate relationship between carbon prices and green bonds.

The field has methodologically evolved to uncover the dynamic features of these connectivity. The introduction of the TVP-VAR model combined with the Diebold-Yilmaz (DY) spillover index and its frequency-domain extension by Baruník and Křehlík (BK) signifies a major improvement over the traditional rolling-window models. This method avoids subjectivity of window size choice, retains data and is more robust to outliers. It allows investigators to identify short-term (high-frequency) speculative spillovers with long-term (low-frequency) fundamental linkages. When applied to the carbon-green finance system, it elucidates risk transmitters and receivers while revealing short- and long-term transmission mechanisms. As proved by Hui et al. [11] and Qi et al. [12], short-term spillovers dominate long-term ones in the carbon-green energy finance system. Wang and Liu [13] confirmed the carbon market is a short-term risk receiver but a long-term transmitter. Moreover, it has been agreed that cross-market contagion intensifies during extreme events and changes in policy [14, 15].

Nevertheless, the previous studies pay more attention to mature markets such as the EU ETS or treat green finance as a homogeneous sector, failing to reveal the structural and dynamic complexities within China's carbon-green finance system. To bridge these gaps, first, we applied TVP-VAR time-frequency spillover methods to the Chinese context. This technique allows for the precise measurement of dynamic and asymmetric connectedness across markets, providing a new approach for analyzing multi-scale interactions. Second, we challenged the traditional perception of green finance as a homogenous entity and revealed the diverse roles of green bond and green equity in risk transmission. Third, we examined the network topology and time-varying risk transmission pathways within the system. Thus, understanding these dynamics is imperative not only for investors to enhance portfolio resilience but also for policymakers to safeguard financial stability and optimize climate policies.

2. Methods

2.1. Construction of TVP-VAR-DY model

To overcome the drawback of selecting a rolling window width in Diebold and Yilmaz [16], Antonakakis et al. [17] introduced the solution, creating the time-varying information spillover index constructed as per a TVP-VAR model. The study shows that the TVP-VAR method offers better performance when compared to the rolling-window VAR approach in measuring dynamic spillover effects.

To formalize this, consider a TVP-VAR model with lag order p:

$$X_t = A_t Z_{t-1} + \varepsilon_t, \varepsilon_t \mid \Omega_{t-1} \sim N\left(0, \Sigma_t\right) \tag{1}$$

$$vec\left(A_t\right) = vec\left(A_{t-1}\right) + \xi_t, \xi_t \mid \Omega_{t-1} \sim N\left(0, R_t\right) \tag{2}$$

$$Z_{t-1} = \begin{pmatrix} X_{t-1} \\ X_{t-2} \\ \vdots \\ X_{t-p} \end{pmatrix} \quad A_t' = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \vdots \\ A_{pt} \end{pmatrix} \tag{3}$$

Where X_t is an m × 1 vector composed of volatility measures from m markets. Ω_{t-1} denotes the information set available at time $t-1$ and earlier periods. Z_{t-1} is an mp × 1-dimensional vector. The time-varying coefficient matrix A_t is an m× mp-dimensional matrix, and vec (A_t) represents the $m^2p \times 1$-dimensional vectorized form of A_t. $\sum_t$ and R_t are time-varying variance-covariance matrices of dimensions $m \times m$ and $m^2p \times m^2p$, respectively.

By transforming the TVP-VAR model into its time-varying parameter vector moving average (TVP-VMA) representation, we obtain:

$$X_t = \sum_{i=1}^{p} A_{it} X_{t-i} = \sum_{j=0}^{\infty} \Psi_{jt} \varepsilon_{t-j}, j = 0, 1, \ldots \tag{4}$$

Based on the generalized variance decomposition (GVD), the contribution of shocks in variable j to the forecast error variance of variable i can be expressed as:

$$\theta_{ij,t}(H) = \frac{\left(\sum_t\right)_{\mathrm{jj}}^{-1} \sum\limits_{\mathrm{h}=0}^{\mathrm{H}} \left[\left(\Psi_h \Sigma_t\right)_{ij,t}\right]^2}{\sum\limits_{h=0}^{H} \left(\Psi_h \Sigma_t \Psi_h'\right)_{ii}} \tag{5}$$

Where $\sum_t$ is the time-varying covariance matrix of errors, and $\Psi_{h,t}$ represents the impulse response coefficients derived from the TVP-VMA representation.

To satisfy the conditions $\sum\limits_{\mathrm{i}=1}^{\mathrm{m}} \tilde{\theta}_{ij,t}(H) = 1$ and $\sum\limits_{\mathrm{j}=1}^{\mathrm{m}} \sum\limits_{\mathrm{i}=1}^{\mathrm{m}} \tilde{\theta}_{ij,t}(H) = m$, a normalization is applied.

The normalized contribution of variable j to the forecast error variance of variable i is then defined as:

$$\tilde{\theta}_{ij,t}(H) = \frac{\theta_{ij,t}(\mathrm{H})}{\sum\limits_{\mathrm{j}=1}^{\mathrm{m}} \theta_{ij,t}(\mathrm{H})} \tag{6}$$

Using this, the total connectedness index across all variables in the system is calculated as:

$$TCI_t(H) = \frac{\sum\limits_{i,j=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(H)}{m} \times 100 \tag{7}$$

$$\mathrm{CTCI}_t(H) = \frac{1}{m-1} \times \left(\sum_{i,j=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(H) \right) \times 100 \tag{8}$$

This index $\mathrm{CTCI}_t(\mathrm{H})$ reflects the average impact of shocks from one variable on all others. A higher value indicates greater systemic risk exposure, and vice versa.

Directional connectedness indices include:

Spillovers to market i from all other markets:

$$\mathrm{FROM}_{i\leftarrow\cdot,t}(H) = \sum_{j=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(H) \times 100 \tag{9}$$

Spillovers from market i to all other markets:

$$TO_{\cdot\leftarrow i,t}(H) = \sum_{i=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(H) \times 100 \tag{10}$$

The net connectedness index from market i is the difference between its outward and inward spillovers:

$$NET_{i,t}(H) = TO_{\cdot\leftarrow i,t}(H) - FROM_{i\leftarrow\cdot,t}(H) \tag{11}$$

Similarly, the net pairwise connectedness between markets i and j is defined as:

$$NPDC_{ij,t}(H) = \tilde{\theta}_{ij,t}(H) - \tilde{\theta}_{ji,t}(H) \tag{12}$$

If $NPDC_{ij,t}(H) > 0$, market j exerts a stronger influence on market i than vice versa.

2.2. Construction of TVP-VAR-BK model

Chatziantoniou et al. [18] developed a framework of BK spillover index based on a TVP-VAR model, building on the approaches of Antonakakis et al. [17] and Baruník and Křehlík [19]. It not only captures the time-varying features of spillovers, but also defines their frequency-domain dynamics, which more effectively describes heterogeneous responses in markets to shocks.

Just as in the construction of the BK spillover index for the traditional VAR models, the process starts with a time-dependent frequency-space response function:

$$\Psi_t\left(e^{-iw}\right) = \sum_{\mathrm{h}=0}^{\infty} e^{-iwh}\Psi_{h,t} \tag{13}$$

Where $\Psi_{h,t}$ represents the time-varying impulse response matrix at lag h.

Consequently, the spectral density of X_t at frequency w can be expressed as:

$$S_X(w) = \sum_{h=-\infty}^{\infty} E\left(X_t X'_{t-h}\right) e^{-iwh} = \Psi_t\left(e^{-iwh}\right) \sum_t \Psi'_t\left(e^{+iwh}\right) \tag{14}$$

The generalized variance decomposition at frequency w is then defined as:

$$\theta_{ij,t}(w) = \frac{\left(\sum_t\right)^{-1}_{\mathrm{jj}} \left| \sum\limits_{h=0}^{\infty} \left(\Psi_t\left(e^{-iwh}\right)\Sigma_t \right)_{ijt} \right|^2}{\sum\limits_{h=0}^{\infty} \left(\Psi_t\left(e^{-iwh}\right)\Sigma_t \Psi_t\left(e^{iwh}\right) \right)_{ii}} \tag{15}$$

Normalizing this yields:

$$\tilde{\theta}_{ij,t}(w) = \frac{\theta_{ij,t}(w)}{\sum_{j=1}^{m} \theta_{ij,t}(w)} \tag{16}$$

To assess short-term and long-term connectivity, consider a frequency band $\mathrm{d} = (\mathrm{a},\mathrm{b})$, where $\mathrm{a},\mathrm{b} \in (-\pi,\pi)$ and $\mathrm{a} < \mathrm{b}$. The spillover connectivity over band d is computed as:

$$\tilde{\theta}_{ij,t}(d) = \int_a^b \tilde{\theta}_{ij,t}(w)dw \tag{17}$$

Following Baruník and Křehlík [19], the contribution of each frequency band is weighted by its share of total variance. The weights are defined as:

$$\Gamma(d) = \frac{\sum\limits_{i,j=1}^{m} \tilde{\theta}_{ij,t}(d)}{m} \tag{18}$$

Therefore, the total connectedness index across all variables in the system can be expressed as:

$$TCI_t(d) = \Gamma(d) \times \frac{\sum\limits_{i,j=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(d)}{m} \times 100 \tag{19}$$

or equivalently,

$$\mathrm{CTCI}_t(d) = \Gamma(d) \times \frac{1}{m-1} \times \sum_{i,j=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(d) \times 100 \tag{20}$$

Directional connectedness indices within frequency band d include:

Spillovers to market i from all other markets:

$$\mathrm{FROM}_{i\leftarrow\cdot,t}(d) = \Gamma(d) \times \sum_{j=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(d) \times 100 \tag{21}$$

Spillovers from market i to all other markets:

$$TO_{\cdot\leftarrow i,t}(d) = \Gamma(d) \times \sum_{i=1,i\neq j}^{m} \tilde{\theta}_{ij,t}(d) \times 100 \tag{22}$$

The net connectedness index for market i is defined as the difference between its outward and inward spillovers:

$$NET_{i,t}(d) = TO_{\cdot\leftarrow i,t}(d) - FROM_{i\leftarrow\cdot,t}(d) \tag{23}$$

The net pairwise connectedness between markets i and j is the weighted difference of their mutual spillovers:

$$NPDC_{ij,t}(d) = \Gamma(d) \times \left(\tilde{\theta}_{ij,t}(d) - \tilde{\theta}_{ji,t}(d)\right) \tag{24}$$

The relationship between the DY spillover index [16, 20] and the BK spillover index [19] constructed via TVP-VAR models can be summarized as follows:

$$TCI_t(H) = \sum_{d} TCI_t(d) \tag{25}$$

$$\mathrm{CTCI}_t(H) = \sum_{d} \mathrm{CTCI}_t(d) \tag{26}$$

$$FROM_{i\leftarrow\cdot,t}(H) = \sum_{d} FROM_{i\leftarrow\cdot,t}(d) \tag{27}$$

$$TO_{\cdot\leftarrow i,t}(H) = \sum_{d} TO_{\cdot\leftarrow i,t}(d) \tag{28}$$

$$\mathrm{NET}_{i,t}(H) = \sum_{d} \mathrm{NET}_{i,t}(d) \tag{29}$$

$$NPDC_{ij,t}(H) = \sum_{d} NPDC_{ij,t}(d) \tag{30}$$

2.3. Model estimation and implementation details

The time-varying parameters of the TVP-VAR model in this study are estimated using a recursive Kalman filter algorithm. The specific configurations are as follows.

First, within the state-space model framework, the time-varying coefficients and their covariance matrices under the Gaussian assumption are updated via the forward recursion of the Kalman filter. Second, the decay factor is set to 0.99 to balance the sensitivity to new information against the smoothness of the parameter evolution. The initial prior for the vector of time-varying coefficients is set to a zero vector, and the initial covariance matrix is specified as 100 × I (the identity matrix). This diffuse prior setting allows the data to rapidly update the prior beliefs during the initial phase of estimation. Finally, to ensure the local stationarity of the model, the eigenvalues of the VAR system are computed at each time point using the parameters estimated at that specific period. It has been verified that all eigenvalues lie inside the unit circle, satisfying the stability condition of the model. The computations were implemented in the R programming environment, adapting the TVP-VAR code framework from Antonakakis et al. [17] and Chatziantoniou et al. [18].

2.4. Data selection and pre-processing

Since 2013, China has launched pilot programs for carbon emission allowance trading in eight regions including Beijing, Shanghai, Guangdong, Hubei and etc. China's National Carbon Emissions Trading Market (CNCETM) was officially launched on July 16, 2021. Due to its relatively recent establishment and limited data availability, this study adopts the Hubei carbon market as a representative case for analysis. Among the pilot markets, the Hubei carbon market is the most liquid and institutionally mature. It is widely regarded as an effective barometer for the Chinese carbon market [8]. Moreover, risk spillover analysis focuses on the comovement in volatility rather than absolute price levels. Given the high correlation in return dynamics between Hubei and national carbon prices, Hubei carbon allowance (hbea) trading price is employed as a proxy for Chinese carbon market. Concurrently, China's green financial market has been categorized into green bond and green stock markets, represented respectively by the ChinaBond China Green Bond Wealth Index (gb) and the CSI 300 Green Leading Stock Index(gs).

With the growing financialization of carbon markets, this paper incorporates the conventional financial sectors to study their mechanisms of interaction. Specifically, we employ the ChinaBond Treasury Wealth (Total Value) Index as the proxy varialbe for China's national bond market (nb). The stock market (s), commodity futures market (cf), energy market (coal) and the gold market (gold) are proxied by the CSI 300 Index, the CSI Commodity Futures Composite Index, the CSI Coal Futures Component Index and the Shanghai Futures Exchange gold futures price index respectively.

The data for each market, spanning from January 5th, 2016 to January 6th, 2025, was obtained from the Wind database. Daily closing prices are used in all the variables where non-synchronous trading days in all the markets are not taken into account, leaving 2,126 observations. The sample range covers the development of Hubei carbon market and the stabilization of CNCETM, thus enabling a comprehensive analysis of market interdependence dynamics under the "dual-carbon" policy framework.

Table 1. Results of descriptive statistics.

Yield Variable	Mean (%)	Maximum value (%)	Minimum value (%)	Standard Deviation	ADF
hbea	0.0262916	11.08045	-19.72102	2.828749	-44.486***
gb	0.0187945	0.8008372	-0.8183246	0.0794773	-29.159***
gs	-0.0044412	10.32083	-10.32339	1.656642	-46.319***
nb	0.0170615	0.9078048	-0.9505837	0.1161551	-35.975***
s	0.0112057	8.141981	-7.312301	1.189951	-44.870***
cf	0.0521947	5.014076	-4.706516	0.9796816	-42.795***
coal	0.0802521	6.905273	-11.58774	1.678546	-31.608***
gold	0.0470312	5.398978	-4.632807	0.781912	-44.902***

Note: $^{***}, ^{**}, ^{*}$ represents statistical significance at the 1%, 5% and 10% level respectively.

Table 2. Total static spillover indices.

Variable	hbea	gb	gs	nb	s	cf	coal	gold	FROM
hbea	94.51	0.94	0.95	0.87	0.83	0.67	0.65	0.57	5.49
gb	0.54	56.07	1.43	36.89	1.68	1.23	1.33	0.82	43.93
gs	0.57	0.74	46.84	1.84	43.93	4.13	1.33	0.81	53.16
nb	0.48	29.91	2.36	60.37	2.60	1.72	1.33	1.23	39.63
s	0.50	0.89	43.68	2.02	46.63	4.30	1.16	0.82	53.37
cf	0.49	0.76	5.38	1.46	5.66	64.03	17.47	4.74	35.97
coal	0.53	1.16	2.35	1.66	2.42	25.57	65.30	1.00	34.70
gold	0.56	1.19	1.48	1.86	1.50	6.46	1.30	85.66	14.34
TO	3.68	35.60	57.64	46.61	58.63	44.08	24.37	9.99	280.59
NET	-1.82	-8.32	4.48	6.98	5.26	8.11	-10.33	-4.35	TCI
NPDC	0	2	6	4	7	5	3	1	35.07

In this paper, we analyze the dynamic spillover effects among return series. To achieve this, we convert all original price data into the logarithmic returns using daily closing prices, defined as $r_t = 100 \times \ln\left(p_{i,t}/p_{i,t-1}\right)$, where p_t denotes the closing price at time t. Table 1 summarizes the descriptive statistics of the market returns. First, the mean value of the carbon yield is higher and the standard deviation are larger than other markets, which indicates the carbon market is characterized by higher yield and high volatility. This volatility pattern highlights the practical significance of studying cross-market spillover effects for carbon market risk management. Second, the green bond market exhibits remarkably low volatility, with its standard deviation approaching zero. This characteristic suggests the green bond has the nature of a hedge asset. Finally, the time series of market yields are found to be stable by Augmented Dickey-Fuller (ADF) test.

3. Results and discussion

3.1. Static time-domain spillover analysis

The TVP-VAR-DY model is used to examine total spillover effects in the static time-domain. Following the Akaike Information Criterion (AIC) and Schwarz Criterion (SC), the optimal lag order for the autoregressive process is identified as 1, with the Generalized Forecast Error Variance Decomposition (GFEVD) horizon standardized to 10 periods. Table 2 presents the calculated total connectedness index (TCI), directional spillover indices (FROM and TO), net spillover indices (NET), and net pairwise spillover indices (NPDC), derived from Eqs. (7) to (12).

The results show significant interactions among China's carbon, green and conventional financial markets, with a TCI of 35.07%. Notably, commodity futures, treasury bonds, equities, and green equities exhibit positive net spillover indices, acting as net contributors to systemic risk. These traditional financial and commodity markets typically function as primary risk transmitters due to their high liquidity, large trading volumes, and sensitivity to macroeconomic shifts. In contrast, coal, green bonds, gold, and carbon markets display negative net spillover indices, operating primarily as net absorbers of external shocks. The carbon market is susceptible to energy price volatility and policy adjustments, resulting in asymmetric vulnerability to external spillovers.

Most importantly, spillover dynamics between the carbon and green financial markets reveal bidirectional asymmetric interactions. The pairwise spillover indices are 0.54% for carbon-to-green bonds and 0.94% for green bonds-to-carbon, where the feedback effects of green finance to carbon market are stronger. Likewise, there is an imbalanced risk reciprocity with indices between carbon and green equity markets recording 0.57% (carbon-to-green equities) and 0.95% (green equities-to-carbon). As a core policy instrument for decarbonization, the carbon market exerts an active incentive effect on corporate green investments, a trend reflected in its outward spillovers to green equities (0.57%) and green bonds (0.54%). In the meantime, the market absorbs a combined inward spillover intensity of 1.89% from green financial markets. This substantial net inflow indicates that the carbon market currently relies heavily on signals from the financial market for price discovery. This reveals a symbiotic yet asymmetric relationship, in which the green financial market essentially dominates the formation of carbon price trends.

3.2. Static frequency-domain spillover analysis

We use the BK technique to extend our study to situations in high-frequency (1 to 5 days, short-term), medium-frequency (6-22 days, medium-term) and low-frequency (beyond 22 days, long-term) frequency ranges. Here, a 22-day cycle is used to represent the monthly frequency, corresponding to the standard number of trading days. The results for these frequency bands are systematically presented in Tables 3 to 5.

Across frequency bands, the TCI values exhibit significant time variation. The magnitude of spillover effects is the highest in the short term (25.04%), decreasing to 7.25% in the medium term and 2.78% in the long term. Specifically, in the short run, the carbon market exerts the strongest spillover effects on the green equity market, whose shocks also drive carbon price fluctuations most sensitively. Over medium- and long-term horizons, the spillover effects from the carbon to the green bond market grow stronger. As this relationship develops, carbon prices also become increasingly governed by the green bond market.

Across all examined time horizons, the carbon market predominantly receives risk from other markets, with its own spillover influence fading as the time extends. In contrast, the role of the green bond market is dynamic [21]. It acts as a net risk transmitter with the highest positive net spillover among all markets in the short term. In the medium and long term, however, it transitions to the primary risk absorber, characterized by the strongest negative net spillover. This dual role allows it to amplify near-term risk shocks, yet absorb them over longer periods. The green equity market, in contrast, consistently sends out more risk than it receives, although the strength of this transmission steadily weakens across time horizons.

3.3. Dynamic spillover analysis

3.3.1. Dynamic total spillover analysis in time and frequency domains

Fig. 1 illustrates significant time-varying spillover effects among China's carbon, green financial, and traditional financial markets. Between 2018 and 2019, the TCI was pushed upward by increased systemic risks due to macroeconomic shocks, including U.S.-China trade tensions, sustained RMB depreciation, and stock market volatility. In 2020, the COVID-19 pandemic triggered widespread market panic, amplifying systematic spillovers and driving the TCI to its peak. As the index had dropped in early 2021 amid the successful pandemic containment and economic stabilization, it climbed again following the introduction of CNCETM in July 2021, tightening links between carbon-green financial markets. Notably, 2024 witnessed accelerated market integration by three major reforms. Chinese Certified Emission Reduction (CCER) was resumed and the steel and cement industries were incorporated into the CNCETM. Besides, the Interim Regulations on Carbon Emissions Trading was officially implemented. Collectively, they drove the TCI to a record level.

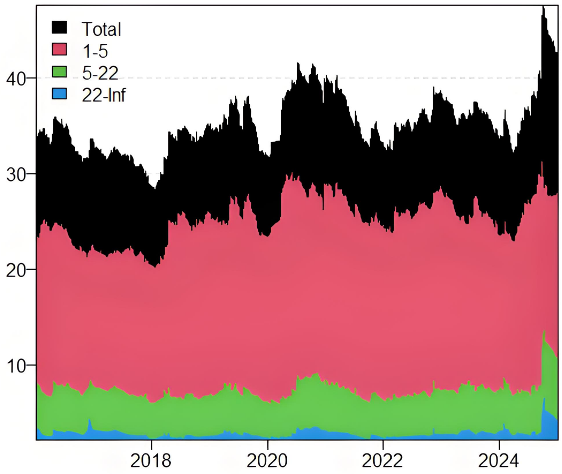

Fig. 1. Dynamic TCI Spillovers in Time and Frequency Domains.

Frequency-domain analysis further reveals that the short-term spillover index consistently dominated the medium- and long-term indices. Therefore, when exogenous shocks such as the pandemic and intensive policy adjustments impacted all ranges, cross-market linkage is primarily driven by short-term speculative sentiment and liquidity flows rather than long-term fundamental shifts.

Table 3. Short-term spillover indices.

Variable	hbea	gb	gs	nb	s	cf	coal	gold	FROM
hbea	80.81	0.74	0.78	0.74	0.67	0.57	0.53	0.51	4.54
gb	0.33	32.38	0.71	18.43	0.83	0.57	0.58	0.45	21.91
gs	0.48	0.53	37.50	1.35	34.96	3.32	0.82	0.64	42.11
nb	0.35	21.38	1.62	42.30	1.78	1.14	0.77	0.90	27.95
s	0.43	0.64	35.08	1.49	37.31	3.42	0.83	0.64	42.53
cf	0.45	0.56	4.43	1.15	4.63	51.93	13.76	3.69	28.67
coal	0.44	0.74	1.42	1.08	1.46	15.40	44.75	0.65	21.20
gold	0.44	0.88	1.23	1.37	1.24	5.26	0.99	69.13	11.40
TO	2.92	25.47	45.27	25.61	45.57	29.68	18.28	7.48	200.29
NET	-1.61	3.56	3.16	-2.33	3.05	1.02	-2.92	-3.92	TCI
NPDC	0	4	7	4	6	4	2	1	25.04

Table 4. Mid-term spillover indices.

Variable	hbea	gb	gs	nb	s	cf	coal	gold	FROM
hbea	10.11	0.15	0.13	0.10	0.11	0.08	0.09	0.04	0.70
gb	0.15	16.84	0.51	13.02	0.60	0.46	0.52	0.26	15.53
gs	0.06	0.16	6.86	0.35	6.59	0.59	0.22	0.12	8.09
nb	0.10	6.18	0.53	13.09	0.60	0.42	0.40	0.24	8.46
s	0.05	0.18	6.32	0.38	6.84	0.64	0.24	0.13	7.94
cf	0.03	0.15	0.70	0.23	0.76	8.89	2.72	0.77	5.36
coal	0.07	0.31	0.67	0.43	0.70	7.36	14.92	0.25	9.79
gold	0.08	0.22	0.18	0.36	0.20	0.89	0.23	12.17	2.16
TO	0.55	7.35	9.04	14.88	9.54	10.43	4.42	1.82	58.03
NET	-0.15	-8.18	0.95	6.41	1.60	5.08	-5.37	-0.34	TCI
NPDC	2	0	6	4	7	5	2	2	7.25

Table 5. Long-term spillover indices.

Variable	hbea	gb	gs	nb	s	cf	coal	gold	FROM
hbea	3.59	0.06	0.05	0.04	0.04	0.03	0.03	0.02	0.25
gb	0.06	6.86	0.21	5.44	0.25	0.20	0.22	0.11	6.49
gs	0.02	0.06	2.48	0.13	2.39	0.22	0.09	0.04	2.95
nb	0.04	2.35	0.20	4.98	0.23	0.16	0.16	0.09	3.22
s	0.02	0.07	2.29	0.14	2.48	0.24	0.09	0.05	2.90
cf	0.01	0.05	0.25	0.09	0.27	3.21	0.99	0.28	1.95
coal	0.02	0.12	0.25	0.15	0.27	2.81	5.63	0.10	3.71
gold	0.03	0.09	0.06	0.13	0.07	0.31	0.08	4.36	0.78
TO	0.20	2.79	3.32	6.12	3.51	3.96	1.67	0.68	22.26
NET	-0.05	-3.70	0.37	2.90	0.61	2.01	-2.04	-0.09	TCI
NPDC	2	0	6	3	7	5	3	2	2.78

3.3.2. *Dynamic net spillover analysis*

Fig. 2 presents the dynamic net spillover indices, highlighting the evolving risk roles of specific markets over time, which is distinct from their static topological positions.

To start with, the carbon market has characteristic cyclical volatility. Although it is by and large a net receiver of spillovers, it turns into a net transmitter in meeting compliance deadlines. This shift occurs because trading activity increases near these deadlines, causing the carbon market to temporarily export risk. On the other hand, the COVID-19 pandemic cut down activity since the beginning of 2020, which strengthens its position as a net receiver, showing the market's sensitivity to extraordinary events.

Second, a comparative analysis reveals a distinct functional difference and linkage between bond markets. Green bond market tends to be a net receiver as compared to treasury bond market which is usually a net transmitter. The fact that their changes coincide with each other is evidence of high interconnectedness.

Third, major structural changes occurred in 2024. The inflows of risks in the coal market increased, and the outflows in equity market (including green equities) intensified. This dynamic is based on the expanded CNCETM that directly raises compliance expenses of coal-dependent business. Compelled to purchase emission quotas, these companies are redirecting capital toward low-carbon initiatives, transforming coal markets into risk absorption basins. In the meantime, the CCER relaunch has increased investments in green projects to intensify the spillover impacts of green equity markets.

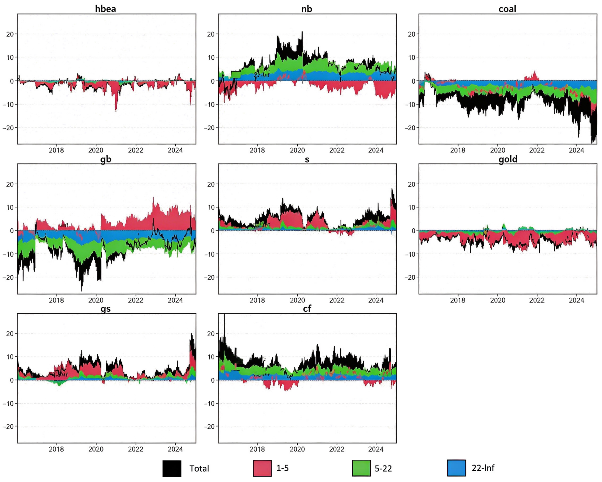

Fig. 2. Dynamic NET Spillovers in Time and Frequency Domains.

3.3.3. *Dynamic frequency-domain net spillover analysis*

Fig. 2 illustrates the dynamic NET indices among China's carbon, green, and conventional financial markets across different frequency bands. This analysis highlights the frequency-dependent stability of each market's role as a net transmitter or receiver.

To begin with, carbon market is consistently vulnerable across all ranges. It mainly serves as a net recipient of the spillovers irrespective of time domain. Notably, it is most sensitive to external shocks in the short run, where it absorbs significant spillover inflows, especially from green financial markets. The net inflows prevail but reduce in the medium and long-term, indicating that the long term fundamentals exert a stabilizing influence compared to short-term sentiment.

Second, the green equity market demonstrates remarkable stability as a dominant risk source. It is always a net emitter of spillovers in all the frequency ranges which means that it will continually affect the pricing behaviour of other assets [22]. Conversely, the green bond market demonstrates a high degree of functional transformation: it will become a net transmitter in the short term but net receiver in the medium to long term [23]. Interestingly, national bond market shows the opposite trend to the green bond market in all frequencies, implying tight internal relationship within bond markets.

Third, the NET indices in the commodity futures market increase from the short to medium term before reducing in the long term. Specifically, the coal market experiences climbing net spillover inflows in the short-to-medium horizons and ultimately dissipate. Similarly, the gold market continues to be a major risk receiver from other financial markets, with these inflows decreasing in the long term.

3.4. Spillover network analysis

To further investigate the structural interconnectedness and contagion pathways, we apply a complex network approach to visualize the topology of return-based spillovers. Fig. 3 depicts the risk spillover network within China's carbon–finance system, where node sizes correspond to the magnitude of net pairwise spillover, and arrow direction and thickness indicate the direction and intensity of spillover, respectively. In the short run, the central risk transmitters are the green equity and broad equity markets. The transmission pathway has a certain process: it originates from (green) equities, continues into commodity futures, and then (green) bonds and energy (coal) market, and finally to the carbon market. This structure suggests that market sentiment and capital liquidity are the main drivers of short-term risk. In the medium to long run, the network structure changes to a fundamental value linkage, as documented by Baruník and Křehlík [19] and Baruník and Ellington [24]. This enables commodity futures markets to be the main nodes of the information propagation and the bond markets the secondary but significant position. The long-term pathway diverges, flowing from (green) equities and commodity markets into general bonds, then reaching the carbon and coal sectors. With this structure, the green bond markets serve as the ultimate receivers and price anchors, where fundamental factors and funding costs become the dominant forces.

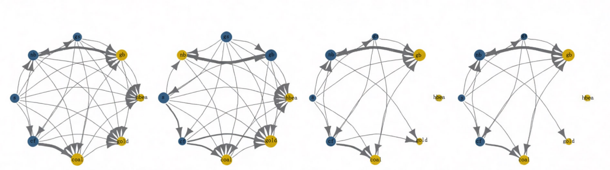

Fig. 3. Spillover Networks in Time, High-, Medium- and Low- Frequency Domains.

3.5. Robustness test

To ensure the reliability of our empirical findings, we conduct robustness as follows. The results of these tests consistently corroborate our main conclusions.

We first assess the robustness of the empirical analysis by replacing the primary index from the Hubei carbon market with that of the Guangdong carbon market (gdea). This substitution examines the generalizability of our findings across different pilot carbon trading markets. The results in Figs. 4 to 6 demonstrate nearly identical dynamic spillover patterns. This confirms that our core findings are not driven by peculiarities of any specific pilot market.

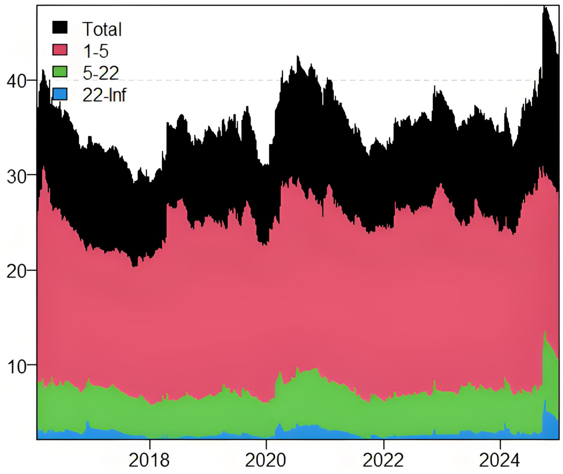

Fig. 4. Dynamic TCI spillovers in Time and Frequency Domains (gdea).

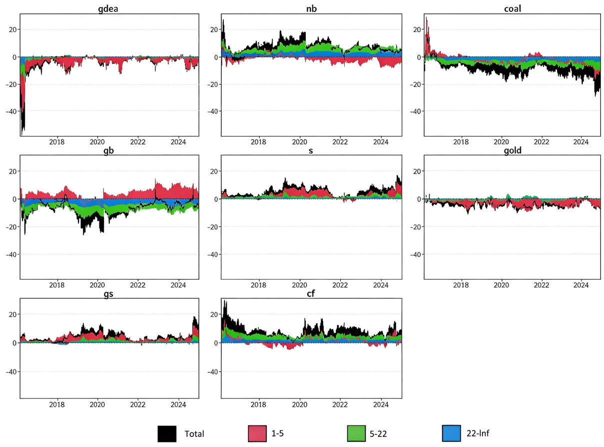

Fig. 5. Dynamic Net Spillovers in Time and Frequency Domains (gdea).

We further investigate the potential influence of policy shifts by analyzing two distinct sub-sample periods: the pre-CNCETM era (January 5th, 2016-July 15th, 2021) and the post-CNCETM era (July 16th, 2021-January 6th, 2025).

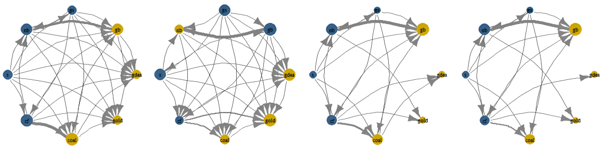

Fig. 6. Spillover Networks in Time, High-, Medium- and Low- Frequency Domains (gdea).

As shown in Tables 6 and 7, the pre-CNCETM sub-samples exhibit slightly lower spillover levels compared with the full sample. This pattern is consistent with our earlier finding that risk spillovers increase significantly during the CNCETM operation periods, thereby confirming the expected difference.

4. Conclusions

Based on TVP-VAR-DY and TVP-VAR-BK models, this study has examined the dynamic spillover effects between China's carbon market and green financial markets. The findings reveal the following conclusions.

First, the study identifies a major bidirectional asymmetric spillover effect within China's carbon-green financial system, with green financial markets exerting a stronger influence on the carbon market than the reverse. The carbon market serves as a policy-driven net risk recipient, which means it lacks an independent pricing ability. Consequently, policies should aim at refining the core pricing mechanism of the carbon market so that it can mitigate passive acquisition of external risks. Specific measures include optimizing quota allocation, clarifying the legal attributes of carbon assets, and exploring the establishment of a carbon price stabilization fund. Meanwhile, it is essential to actively integrate corporate carbon performance and carbon asset returns in financial decision by implementing green credit approval and green bond issuance, and hence leading green finance capital to establish a positive feedback mechanism and turning the carbon market from a passive receiver to an active guide.

Second, the green finance system is marked by func-

Table 6. Comparison of NET spillover indices between pre- and post-CNCETM periods.

index	pre-CNCETM period			post-CNCETM period		
	hbea	gb	gs	hbea	gb	gs
time-domain NET	-2.13	-10.81	4.70	-0.98	-4.58	4.05
short-term NET	-1.80	1.38	3.62	-1.05	6.51	2.62
mid-term NET	-0.24	-8.41	0.79	0.05	-7.60	1.02
long-term NET	-0.09	-3.78	0.29	0.02	-3.49	0.41

Table 7. Comparison of TCI spillover indices between pre- and post-CNCETM periods.

index	pre-CNCETM period	post-CNCETM period
time-domain TCI	34.40	35.97
short-term TCI	24.63	25.64
mid-term TCI	7.06	7.47
long-term TCI	2.71	2.86

tional diversity, challenging the conventional view of a homogeneous market. We find that the carbon market's interaction with green assets is time-varying and frequency-dependent. In the short run, the carbon market shares the strongest bidirectional linkage with the green equity market, which acts as a persistent risk amplifier fueled by market sentiment. Over the medium to long term, however, the carbon market's dependence shifts toward the green bond market. Green bonds demonstrate a unique dynamic conversion mechanism [21]. They initially spread short-term spillover but later evolve into net risk receivers and value anchors. This dichotomy calls for targeted responses. On one hand, the compilation of green stock indices should be strictly standardized to mitigate irrational sentiment. On the other hand, the issuance of medium-to-long-term carbon neutrality bonds should be expanded, and a green bond-carbon quota linkage mechanism established to reinforce the market's function as a systemic stabilizer.

Third, systemic interconnectedness of carbon, green and conventional financial markets is time-varying, dominated by short-term spillovers and highly sensitive to extreme events. This calls for the formation of a multi-dimensional, dynamic risk prevention and control framework. The framework should focus on the creation of inter-departmental joint monitoring platform, incorporating high frequency data from equity, futures, bond and carbon markets to separately track sentiment-driven fluctuations and fundamental risks. Besides, emergency response plans for extreme events should be developed, ensuring prompt activation of tools like temporary liquidity support and risk circuit-breakers during periods of systemic stress.

Fourth, this study demonstrates temporal heterogeneity and dynamic path shifts in risk transmission within China's carbon-finance system. Short-term risks propagate primarily through sentiment-driven channels, whereas long-term transmission is governed by fundamentals. Therefore, a dynamic, precise time-varying regulation framework should be established. Short-term oversight should focus on source control and shock mitigation to curb the rapid spillover of sentiment-driven volatility into the carbon market. In the long term, channel guidance and value anchoring must be prioritized. Innovative instruments can help solidify the role of green bonds as terminal value anchors and risk absorbers, such as issuing ultra-long-term carbon neutrality bonds and establish a green bond-carbon quota linkage mechanism.

Although this paper uncovers the dynamic spillovers in China's carbon-green finance system, there are a few ways that can be explored further. First, we directly analyze the linkage at the return level, using it as a proxy for the risk contagion network, while more precise volatility risk contagion awaits further exploration using volatility series in the future. Second, given China's 2024 policy drive to effectively integrate green finance with transition finance based on market principles, it's necessary in future research to introduce transition finance in the analysis. Comparing its differential impact against the traditional and green finance will give a more comprehensive picture of China's low-carbon transition. Third, although extreme risk contagion is a fast advancing area of research [25, 26], the importance of idiosyncratic risk spillovers is under-researched [27]. Future research should use sophisticated techniques to capture tail dependencies and decouple particular risk sources, including the quantile regression, Conditional Value at Risk and Elastic-Net VAR. These tools would allow for a more precise assessment of systemic risk and help improve the accuracy of risk early-warning mechanisms in the carbon-green financial system.

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Data and code availability

The data that support the findings of this study are available from the Wind Database. All empirical analysis were conducted in R (RStudio 4.4.2). The dynamic spillover calculations adapt the TVP-VAR code framework from Antonakakis et al. (2020) and Chatziantoniou et al. (2024) to the specifications of this study (TVP-VAR-DY and TVP-VAR-BK). The data and core analysis code are available from the corresponding author upon reasonable request.

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