

# Dynamic Spillovers between Green Finance and Energy Markets and Their Association with Financial Market Uncertainty: Evidence from China

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**Abstract:** This study examines how return spillovers between China's green finance and energy markets vary across market states and investment horizons, and how those spillovers co-move with financial market uncertainty. The analysis uses 1,539 matched daily observations from June 2017 to January 2025 for carbon allowances, green equities, green bonds, crude oil, liquefied natural gas, coking coal futures, and a new energy index. A quantile vector autoregression model is combined with generalized forecast error variance decompositions, the Diebold-Yilmaz connectedness framework, the Baruník-Křehlík frequency decomposition, and wavelet coherence. Changes in CSI 300 conditional volatility, estimated using a GARCH (1,1) model, serve as the financial market uncertainty proxy. At the median quantile, total connectedness is 21.63%; the corresponding lower- and upper-tail values are 69.06% and 69.15%. The largest share of spillovers occurs within one to five trading days. For this short horizon, connectedness reaches 16.82% at the median, 53.66% in the lower tail, and 55.53% in the upper tail. The respective longer-horizon values are 4.80%, 15.40%, and 13.62%. Green equities and new energy stocks are recurrent transmitters, while the coking coal market changes from a receiver under typical conditions to a transmitter in both tails. Green bonds become an important short-term transmitter in the upper tail. Wavelet evidence shows that the association between connectedness and financial uncertainty is episodic, quantile dependent, and concentrated at different frequencies around the COVID-19 pandemic and the Russia-Ukraine war. The results support state-contingent risk monitoring and horizon-specific portfolio management.

**Keywords:** Green Finance; Energy Markets; Financial Market Uncertainty; Quantile

**Vector Autoregression; Connectedness; Wavelet Coherence**

## 1. Introduction

The transition to a low-carbon economy links financial markets more closely to energy production, carbon pricing, and clean-technology investment. Green finance directs capital toward environmentally beneficial activities and can reduce financing constraints for renewable-energy deployment and other transition projects [1,2]. These channels also expose green assets to shocks originating in fossil-fuel prices, energy demand, and policy expectations. The resulting cross-market dependence is economically relevant because a disturbance in one segment can be transmitted through asset repricing, funding costs, and portfolio rebalancing.

Evidence from oil and clean-energy equities shows that the strength and direction of dependence change over time [3-5]. Green bonds are also connected to conventional bond, equity, commodity, and currency markets, although their transmission role differs across periods and market conditions [6,7]. More recent research extends this setting to broader systems that combine traditional energy and emerging green markets and finds material state and horizon heterogeneity in spillovers [8,9]. These findings caution against treating green finance and energy assets as a stable diversification block.

Financial uncertainty may amplify or redirect these connections. Uncertainty shocks are associated with abrupt changes in investment, risk premia, and market activity, and their effects can be especially pronounced in emerging economies [10,11]. Connectedness studies further show that uncertainty and financial stress propagate across countries and asset classes rather than remaining local to the market in which they originate [12,13]. In green markets, policy uncertainty and carbon-market volatility are related to time-varying changes in connectedness [14,15]. A conditional-mean model may therefore

conceal the dependence that emerges during large negative or positive returns.

This study evaluates these issues in a unified Chinese market system. It addresses three questions. First, does connectedness among carbon allowances, green equities, green bonds, fossil-energy markets, and new energy equities differ between typical and tail states? Second, are spillovers concentrated at short horizons or do they persist beyond five trading days? Third, does the association between system-wide connectedness and financial market uncertainty vary across time, frequency, and quantile? We estimate connectedness from a quantile vector autoregression in both the time and frequency domains. We then use wavelet coherence to examine the total connectedness series together with a market-based proxy for uncertainty.

Our approach brings together aspects of spillovers that are often examined in separate analyses. Estimating the model at the lower tail, median, and upper tail allows us to compare market states. Frequency decomposition distinguishes spillovers associated with rapid information transmission from those that persist. We use wavelet analysis to locate the dates and periodicities at which total connectedness co-moves with financial market uncertainty. The resulting coherence estimates describe local co-movement and phase; we do not interpret these estimates as evidence of a causal relationship.

The results show substantial state dependence. Total connectedness rises from 21.63% at the median to approximately 69% in both tails, and the composition of transmitters and receivers changes. Green equities and new energy equities are recurrent transmitters, while coking coal becomes a net transmitter under extreme conditions. The frequency decomposition indicates that most spillovers occur within five trading days. Wavelet coherence is episodic rather than constant and shifts across quantiles and periodicities around major disruptions. These patterns imply that risk limits based only on average or full-sample dependence can understate exposures in stressed markets.

The remainder of the paper reviews the related literature, describes the data and empirical methods, reports the connectedness and coherence results, discusses their implications and limitations, and concludes.

## 2. Literature Review

### 2.1 Green Finance and Energy Market Linkages

Green finance comprises instruments and institutions that allocate capital to activities with environmental benefits. In market-based empirical work, green finance is commonly represented by green bonds, environmentally screened equities, clean-energy stocks, and carbon-related assets. These segments differ in cash-flow structure and investor base. Green bonds retain fixed-income characteristics, green equities reflect corporate earnings and discount rates, and carbon allowances are policy-created assets whose prices depend on expected emissions, energy demand, and regulatory design. Their joint analysis is therefore more informative than reliance on a single green index.

Energy markets connect to green assets through both substitution and cost channels. Higher fossil-fuel prices can improve the relative competitiveness of renewable technologies, but energy-price shocks can also increase production costs, tighten financial conditions, and raise discount rates. Early evidence documented links between oil prices and alternative-energy equities [3] and volatility transmission between oil, clean-energy, and technology stocks [4]. Dependence is nonlinear and can intensify in adverse states, which limits diversification benefits precisely when they are most valuable [5].

The expansion of green bond and carbon markets adds further transmission channels. Green bond volatility is distinct from, but not insulated from, conventional asset-market volatility [6]. Price connectedness between green bonds and financial markets varies by asset class and horizon [7]. In systems that explicitly combine fossil-energy and emerging green markets, spillovers respond to changing transition expectations and large external disturbances [8].

### 2.2 State Dependent Connectedness

Connectedness measures based on forecast error variance decompositions summarize how much of each variable's forecast uncertainty is attributable to shocks elsewhere in the system. The directional framework of Diebold and Yilmaz [16] distinguishes spillovers received from other variables, spillovers transmitted to them, and net transmission. Its generalized identification makes the results invariant to variable ordering, which is useful for systems without an uncontroversial contemporaneous ordering.

A mean-based VAR describes dependence around the center of the conditional distribution. Tail states can behave differently because liquidity, leverage constraints, risk aversion, and policy expectations change during large price movements. Quantile VAR models address this limitation by estimating the system at selected conditional quantiles. White et al. [17] formalize multivariate quantile dynamics, while recent financial applications use quantile networks to document stronger and changing spillovers under stress [13]. Green finance and policy-uncertainty systems likewise exhibit higher connectedness away from the median [14].

### 2.3 Frequency Heterogeneity and Financial Uncertainty

Market participants operate at different horizons. Traders and risk managers respond to daily information, whereas institutional investors and policymakers may focus on persistent changes. Baruník and Křehlík [18] decompose variance-based connectedness into frequency bands, allowing total and directional spillovers to be attributed to short- or long-lived shocks. Applications to green and traditional energy markets generally find that high-frequency transmission accounts for a large share of overall connectedness, although the balance changes during disruptive events [9].

Uncertainty can alter this balance by changing risk tolerance, liquidity demand, and expectations about future cash flows. Stock-market volatility provides a market-based measure of uncertainty because it rises when the distribution of expected outcomes widens and risk-bearing capacity weakens [10]. Global disturbances can generate time-varying uncertainty spillovers [12], while trade-policy and geopolitical shocks affect commodity prices in ways that depend on time and regime [19]. The COVID-19 pandemic produced abrupt changes across financial markets [20], and the Russia-Ukraine war combined geopolitical uncertainty with direct energy-supply concerns. These episodes motivate an approach that localizes the connectedness-uncertainty relationship in both time and frequency.

The literature therefore supports three expectations: system-wide connectedness should be stronger in the tails than at the median; short-horizon spillovers should account for most transmission; and the relationship between connectedness and market uncertainty should be

episodic and state dependent. The following analysis evaluates these expectations using a common sample and consistent market definitions.

## 3. Data and Methodology

### 3.1 Data and Variable Construction

The market system contains seven return series. The green finance block comprises carbon emission allowances, green equities, and green bonds. The energy block comprises crude oil, liquefied natural gas, coking coal futures, and new energy equities. The carbon series is the arithmetic mean of closing prices in the Hubei and Guangdong pilot allowance markets. Green equities are represented by the CSI Green Investment Equity Index, and green bonds by the ChinaBond China Green Bond Index. The energy series use a South China Sea crude oil price, a liquefied natural gas price, coking coal futures traded on the Dalian Commodity Exchange, and the CNI New Energy Index.

The sample runs from June 2017 through January 2025. Prices are converted to continuously compounded returns as first log differences. Dates without a common market observation are removed, leaving 1,539 matched daily observations for each series. The identifier Goal is retained in the figures and connectedness tables because it is the source dataset code; it denotes the coking coal futures series throughout the paper.

Financial market uncertainty is constructed from the CSI 300 equity index. A GARCH (1,1) model is fitted to CSI 300 returns, following the standard conditional-variance specification of Bollerslev [21]. Daily changes in the estimated conditional volatility form the uncertainty series used in the descriptive statistics and wavelet analysis. This proxy captures market-implied stress in Chinese equities and should be interpreted as financial market uncertainty rather than a broad measure of economic policy uncertainty. Table 1 summarizes the variables and data sources.

**Table 1. Variables and Data Sources**

| Market            | Code | Construction                                                                                | Source |
|-------------------|------|---------------------------------------------------------------------------------------------|--------|
| Carbon allowances | CET  | First log difference of the arithmetic mean of Hubei and Guangdong allowance closing prices | Wind   |
| Green equities    | CSI  | First log difference of the CSI Green Investment Equity Index                               | CSMAR  |
| Green bonds       | GB   | First log difference of the ChinaBond China Green Bond Index                                | CSMAR  |

|                              |      |                                                                                      |                           |
|------------------------------|------|--------------------------------------------------------------------------------------|---------------------------|
| Crude oil                    | Oil  | First log difference of the South China Sea crude oil price series                   | Wind                      |
| Liquefied natural gas        | Gas  | First log difference of the LNG price series                                         | Wind                      |
| Coking coal futures          | Goal | First log difference of Dalian Commodity Exchange coking coal futures closing prices | Dalian Commodity Exchange |
| New energy equities          | CNI  | First log difference of the CNI New Energy Index                                     | Wind                      |
| Financial market uncertainty | FU   | Daily change in CSI 300 conditional volatility estimated by GARCH (1,1)              | CSMAR                     |

Note. Goal is the original dataset code for the coking coal futures series and is retained to match the figures and reported estimates.

### 3.2 Descriptive Statistics

Table 2 reports the distributional properties of the seven market returns and the change in financial uncertainty. Green equities and financial uncertainty have slightly negative means; the remaining series have positive means. Green bonds have the smallest standard deviation, while financial uncertainty and carbon allowances display the largest standard deviations among the reported series. Skewness and kurtosis reveal substantial departures from Gaussian behavior, particularly for carbon allowances, crude oil, natural gas, and green bonds. The Jarque-Bera test rejects normality for every series at the 1% level. The

augmented Dickey-Fuller statistics reject a unit root at the 1% level, supporting the use of the transformed series in the QVAR system.

### 3.3 Quantile Vector Autoregression and Connectedness

A quantile vector autoregression estimates system dynamics at conditional quantile  $\tau$  rather than only at the conditional mean. This permits direct comparison of the lower tail at  $\tau = 0.05$ , the median at  $\tau = 0.50$ , and the upper tail at  $\tau = 0.95$ . Following the multivariate quantile logic of White et al. [17], the QVAR of order  $p$  is written as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^p \Phi_j(\tau) y_{t-j} + u_t(\tau) \quad (1)$$

Where the vector  $y$  at time  $t$  contains  $k$  stationary transformed variables,  $\mu(\tau)$  is a quantile-specific intercept vector,  $\Phi_j(\tau)$  is a  $k$  by  $k$  coefficient matrix,  $p$  is the lag order, and  $u_t(\tau)$  is the quantile-specific innovation vector. The corresponding infinite moving-average representation is:

$$y_t = \mu(\tau) + \sum_{j=1}^p \Phi_j(\tau) y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \psi_i(\tau) u_{t-i} \quad (2)$$

Table 2. Descriptive Statistics

| Variable | Mean       | SD     | Min     | Median  | Max    | Skew    | Kurtosis | ADF       | JB           |
|----------|------------|--------|---------|---------|--------|---------|----------|-----------|--------------|
| CET      | 2.854e-05  | 0.0198 | -0.2997 | 2e-04   | 0.2567 | -1.1840 | 109.3193 | -20.40*** | 768251.5***  |
| CSI      | -1.450e-05 | 0.0077 | -0.0622 | -1e-04  | 0.0572 | 0.0937  | 7.3202   | -17.50*** | 3448.8***    |
| GB       | 0.000114   | 4e-04  | -0.0033 | 1e-04   | 0.0075 | 4.2062  | 91.7252  | -14.58*** | 545160.7***  |
| Oil      | 7.107e-05  | 0.0165 | -0.4102 | 5e-04   | 0.1306 | -9.4513 | 257.5283 | -17.40*** | 4284200.8*** |
| Gas      | 7.855e-05  | 0.0098 | -0.1718 | -2e-04  | 0.0691 | -3.6979 | 74.3621  | -12.61*** | 358835.3***  |
| Goal     | 1.348e-05  | 0.0118 | -0.0895 | 5e-04   | 0.0505 | -0.6842 | 5.8757   | -18.28*** | 2341.3***    |
| CNI      | 3.704e-05  | 0.0091 | -0.0638 | -4e-04  | 0.0670 | 0.3600  | 6.0252   | -17.31*** | 2368.8***    |
| FU       | -2.645e-05 | 0.0297 | -0.0277 | -0.0100 | 0.2710 | 0.0052  | 3.1815   | -27.48*** | 16693.8***   |

Note. ADF is the augmented Dickey-Fuller statistic and JB is the Jarque-Bera statistic. \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively.  $N = 1,539$ .

Generalized forecast error variance decompositions identify the contribution of shock  $j$  to the  $H$ -step forecast error variance of variable  $i$  without requiring an ordering of the variables. The construction follows Koop et al. [22] and Pesaran and Shin [23]:

$$\psi_{ij}^g(H) = \frac{\sum_{h=0}^{H-1} \sum_{j=1}^k (e_i' \psi_h(\tau) \Sigma(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i' \psi_h(\tau) \Sigma(\tau) \psi_h(\tau)' e_j)} \quad (3)$$

Because generalized variance shares do not necessarily sum to one, each row is normalized:

$$\tilde{\psi}_{ij}^g(H) = \frac{\psi_{ij}^g(H)}{\sum_{j=1}^k \phi_{ij}^g(H)} \quad (4)$$

Directional connectedness transmitted by variable  $i$  to the remaining variables is:

$$C_{i \rightarrow j}^g(H) = \sum_{i,j=1, i \neq j}^k \tilde{\psi}_{ji}^g(H) \quad (5)$$

Directional connectedness received by variable  $i$  from the remaining variables is:

$$C_{i \leftarrow j}^g(H) = \sum_{i,j=1, i \neq j}^k \tilde{\psi}_{ij}^g(H) \quad (6)$$

Net directional connectedness is the difference between transmitted and received spillovers:

$$C_i^g(H) = C_{i \rightarrow j}^g(H) - C_{i \leftarrow j}^g(H) \quad (7)$$

The total connectedness index aggregates the off-diagonal normalized variance shares. Reported values are expressed as percentages:

$$TCI(H) = \frac{\sum_{i,j=1, i \neq j}^k \tilde{\psi}_{ij}^g(H)}{k-1} \quad (8)$$

A positive net value identifies a net transmitter, while a negative value identifies a net receiver. The static tables summarize full-sample averages at each quantile, and the dynamic figures trace the corresponding estimates through time. The

connectedness interpretation follows Diebold and Yilmaz [16].

### 3.4 Frequency Domain Connectedness

The frequency decomposition attributes connectedness to shocks with different persistence. Let the QVAR moving-average representation have a transfer function evaluated at  $\exp(-i\omega)$ . The spectral density at frequency  $\omega$  is:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega h}) \sum_t \Psi'(e^{+i\omega h}) \quad (9)$$

The generalized variance decomposition at each frequency combines the transfer function with the quantile-specific innovation covariance matrix:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))_{jj}^{-1} \left[ \sum_{h=0}^{\infty} (\Psi(\tau)(e^{-i\omega h}) \Sigma(\tau))_{ij} \right]^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h}) \Sigma(\tau) \Psi(\tau)(e^{i\omega h}))_{ij}} \quad (10)$$

The frequency-specific contribution is normalized across shocks:

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^N \theta_{ij}(\omega)} \quad (11)$$

For frequency band  $d = (a, b)$ , where  $a$  and  $b$  lie between  $-\pi$  and  $\pi$  and  $a < b$ , the normalized variance shares are integrated over the band. Directional spillovers transmitted to and received from the system are:

$$TO_i(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(d), \text{ FROM}_i(d) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}(d) \quad (12)$$

Total connectedness within band  $d$  is:

$$TCI(d) = N^{-1} \sum_{i=1}^N TO_i(d) = N^{-1} \sum_{i=1}^N \text{FROM}_i(d) \quad (13)$$

For market  $i$ , net frequency connectedness is  $\text{NET}_i(d) = TO_i(d) - \text{FROM}_i(d)$ . Following Baruník and Křehlík [18], the empirical results separate short-term spillovers of one to five trading days from long-term spillovers exceeding five trading days. The two bands add to the time-domain connectedness measure, subject to numerical approximation.

### 3.5 Wavelet Coherence

Wavelet coherence measures localized co-movement between two series across both calendar time and periodicity. The squared wavelet coherence between total connectedness  $x$  and financial uncertainty  $y$  at scale  $a$  and location  $b$  is defined as in Torrence and Compo [24]:

$$R_{xy}^2(a, b) = \frac{|S(b^{-1}W_{xy}(a, b))|^2}{S(b^{-1}W_x(a, b))^2 S(b^{-1}W_y(a, b))^2} \quad (14)$$

$W_{xy}(a, b)$  is the cross-wavelet transform and  $S$  is a smoothing operator. Coherence ranges from zero to one. Values near one indicate strong localized co-movement, while values near zero indicate weak co-movement. The phase difference is:

$$\phi_{xy} = \arctan \left( \frac{\text{Im} [S(b^{-1}W_{xy}(a, b))]}{\text{Re} [S(b^{-1}W_{xy}(a, b))]} \right), \quad (15)$$

with  $\phi_{xy} \in [-\pi, \pi]$

The phase arrows summarize whether the series move together or in opposite directions and which series leads. Black contours in the coherence figures denote statistically significant regions, while the cone of influence marks areas where edge effects make inference less reliable. Coherence is an association measure and does not by itself establish causality.

## 4. Empirical Results

### 4.1 Static Time Domain Connectedness

Table 3 reports static connectedness at the median, Table 4 reports the lower tail, and Table 5 reports the upper tail. Total connectedness is 21.63% at  $\tau = 0.50$ , compared with 69.06% at  $\tau = 0.05$  and 69.15% at  $\tau = 0.95$ . The similarity of the two tail totals masks differences in bilateral flows and net roles. Mean-state dependence therefore understates the system-wide transmission observed during unusually negative or positive returns.

**Table 3. Static QVAR Connectedness at the Median Quantile ( $\tau = 0.50$ )**

|          | CET    | CSI    | GB    | Oil   | Gas    | Goal  | CNI    | FROM   |
|----------|--------|--------|-------|-------|--------|-------|--------|--------|
| CET      | 98.13  | 0.06   | 0.20  | 0.10  | 1.39   | 0.08  | 0.05   | 1.87   |
| CSI      | 0.23   | 50.48  | 2.16  | 3.82  | 0.41   | 0.93  | 41.97  | 49.52  |
| GB       | 0.52   | 3.61   | 79.33 | 11.38 | 1.65   | 0.55  | 2.96   | 20.67  |
| Oil      | 0.24   | 5.75   | 11.12 | 78.16 | 0.26   | 0.35  | 4.11   | 21.84  |
| Gas      | 1.30   | 0.13   | 1.97  | 0.27  | 95.95  | 0.23  | 0.15   | 4.05   |
| Goal     | 0.36   | 1.72   | 0.37  | 0.60  | 0.34   | 95.06 | 1.54   | 4.94   |
| CNI      | 0.13   | 42.64  | 1.75  | 2.69  | 0.44   | 0.86  | 51.49  | 48.51  |
| TO       | 2.79   | 53.90  | 17.58 | 18.86 | 4.49   | 3.00  | 50.77  | 151.39 |
| Inc. own | 100.92 | 104.38 | 96.91 | 97.02 | 100.44 | 98.06 | 102.26 | TCI    |
| NET      | 0.92   | 4.38   | -3.09 | -2.98 | 0.44   | -1.94 | 2.26   | 21.63  |

Note. Rows show forecast error variance shares received by the row variable from column-variable shocks. TO is directional connectedness transmitted to other markets; FROM is directional connectedness received from other markets; NET = TO - FROM; and TCI is total connectedness.

Positive NET values indicate net transmitters.

**Table 4. Static QVAR Connectedness at the Lower Tail ( $\tau = 0.05$ )**

|          | CET    | CSI    | GB     | Oil   | Gas    | Goal   | CNI    | FROM   |
|----------|--------|--------|--------|-------|--------|--------|--------|--------|
| CET      | 36.90  | 11.87  | 10.93  | 8.98  | 6.85   | 12.62  | 11.84  | 63.10  |
| CSI      | 8.56   | 25.10  | 8.60   | 12.26 | 9.01   | 13.19  | 23.27  | 74.90  |
| GB       | 10.26  | 12.09  | 36.65  | 6.36  | 8.48   | 14.29  | 11.86  | 63.35  |
| Oil      | 7.70   | 16.09  | 5.67   | 32.54 | 9.24   | 13.22  | 15.53  | 67.46  |
| Gas      | 8.42   | 13.65  | 8.93   | 10.51 | 31.04  | 14.14  | 13.31  | 68.96  |
| Goal     | 8.25   | 15.11  | 10.65  | 12.20 | 9.77   | 28.86  | 15.16  | 71.14  |
| CNI      | 8.05   | 23.59  | 8.40   | 11.95 | 8.89   | 13.62  | 25.51  | 74.49  |
| TO       | 51.24  | 92.41  | 53.19  | 62.26 | 52.25  | 81.08  | 90.97  | 483.40 |
| Inc. own | 88.14  | 117.51 | 89.84  | 94.81 | 83.28  | 109.94 | 116.48 | TCI    |
| NET      | -11.86 | 17.51  | -10.16 | -5.19 | -16.72 | 9.94   | 16.48  | 69.06  |

Note. Entries are percentages. TO, FROM, NET, and TCI are defined in Table 3; positive NET values indicate net transmitters.

At the median, CSI and CNI are the largest net transmitters, with net values of 4.38 and 2.26. CET and Gas are small net transmitters, while GB, Oil, and Goal are receivers. The largest bilateral relationship is between green equities and new energy equities: 41.97% of the CSI forecast variance is associated with CNI shocks, and 42.64% of the CNI forecast variance is associated with CSI shocks. This concentration indicates a strong common repricing channel between environmentally screened equities and the new energy sector.

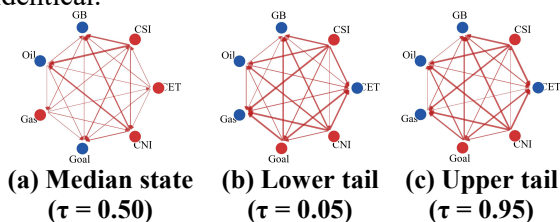
In the lower tail, CSI, Goal, and CNI become the system's principal transmitters, with net values of 17.51, 9.94, and 16.48. In the upper tail, the same three markets remain transmitters, with net values of 18.06, 9.98, and 18.72. Carbon allowances, green bonds, crude oil, and natural gas are net receivers in both tails. The shift of coking coal from a receiver at the median to a transmitter in the tails is economically important because it indicates that extreme energy-price movements can reshape the direction of risk propagation.

**Table 5. Static QVAR Connectedness at the Upper Tail ( $\tau = 0.95$ )**

|          | CET    | CSI    | GB     | Oil    | Gas    | Goal   | CNI    | FROM   |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|
| CET      | 37.22  | 12.46  | 10.93  | 7.43   | 7.23   | 12.32  | 12.41  | 62.78  |
| CSI      | 7.77   | 25.05  | 8.74   | 11.60  | 9.39   | 14.15  | 23.29  | 74.95  |
| GB       | 9.02   | 12.89  | 33.52  | 5.64   | 10.65  | 14.64  | 13.64  | 66.48  |
| Oil      | 6.47   | 16.00  | 5.24   | 34.45  | 9.82   | 12.49  | 15.53  | 65.55  |
| Gas      | 7.40   | 13.27  | 9.48   | 9.64   | 32.83  | 13.50  | 13.88  | 67.17  |
| Goal     | 8.92   | 15.30  | 11.47  | 9.76   | 10.31  | 28.58  | 15.66  | 71.42  |
| CNI      | 8.06   | 23.09  | 9.55   | 11.15  | 9.53   | 14.31  | 24.32  | 75.68  |
| TO       | 47.66  | 93.01  | 55.41  | 55.23  | 56.93  | 81.40  | 94.41  | 484.04 |
| Inc. own | 84.87  | 118.06 | 88.93  | 89.68  | 89.76  | 109.98 | 118.72 | TCI    |
| NET      | -15.13 | 18.06  | -11.07 | -10.32 | -10.24 | 9.98   | 18.72  | 69.15  |

Note. Entries are percentages. TO, FROM, NET, and TCI are defined in Table 3; positive NET values indicate net transmitters.

Figure 1 confirms that tail connectedness reflects more than a uniform increase in all links. Network density and node roles change across quantiles. In particular, the direction of the CSI-CNI relationship differs between the lower and upper tails, and crude oil receives stronger net spillovers in the lower tail than in the upper tail. Tail asymmetry is therefore visible in bilateral direction even though the two tail TCIs are nearly identical.



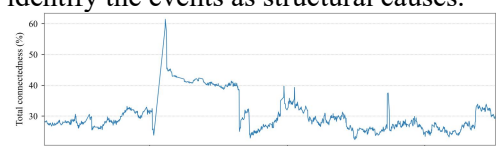
**Figure 1. Static Spillover Networks across Quantiles**

Note. Panels show  $\tau = 0.50$ ,  $\tau = 0.05$ , and  $\tau = 0.95$ . Red nodes indicate net transmitters and blue nodes indicate net receivers. Arrows point toward the net receiving market, and line width reflects bilateral net spillover intensity. Goal denotes coking coal futures.

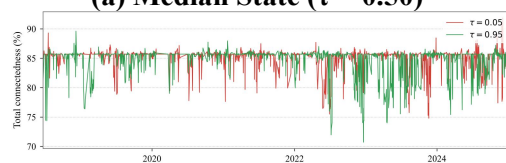
#### 4.2 Dynamic Time Domain Connectedness

Figure 2 traces total connectedness through time. Median connectedness remains below tail connectedness throughout the sample. The median series shows a pronounced increase around the onset of the COVID-19 pandemic and further abrupt changes around 2022. These dates coincide with widespread market disruption and the energy and geopolitical shock associated with the Russia-Ukraine war. The timing is descriptive; the connectedness estimates alone do

not identify the events as structural causes.



(a) Median State ( $\tau = 0.50$ )



(b) Lower- and Upper-Tail States ( $\tau = 0.05$  and  $\tau = 0.95$ )

**Figure 2. Dynamic Total Connectedness Across market States**

Note. Panel a reports  $\tau = 0.50$ . Panel b reports  $\tau = 0.05$  and  $\tau = 0.95$ . The vertical scale differs across panels.

The lower- and upper-tail series remain at elevated levels but display different short-lived

declines and spikes. Their nonparallel movements provide further evidence of tail asymmetry. A single average connectedness measure would miss both the persistent gap between central and tail states and the differences between negative and positive extremes.

#### 4.3 Static Frequency Domain Connectedness

Tables 6 and 7 report short- and long-term connectedness at the median, Tables 8 and 9 report the corresponding lower-tail results, and Tables 10 and 11 report the upper-tail results. Short horizons cover one to five trading days, and long horizons exceed five trading days. In every market state, short-term connectedness is substantially larger than long-term connectedness. The result is consistent with rapid information processing and portfolio adjustment, although the persistence and direction of individual market roles vary by quantile.

**Table 6. Short-Term Connectedness at the Median Quantile ( $\tau = 0.50$ )**

|          | CET   | CSI   | GB    | Oil   | Gas   | Goal  | CNI   | FROM   |
|----------|-------|-------|-------|-------|-------|-------|-------|--------|
| CET      | 87.14 | 0.05  | 0.17  | 0.09  | 1.18  | 0.06  | 0.04  | 1.61   |
| CSI      | 0.11  | 40.03 | 1.68  | 3.14  | 0.40  | 0.77  | 32.83 | 38.93  |
| GB       | 0.37  | 2.33  | 50.70 | 7.42  | 1.18  | 0.19  | 1.85  | 13.33  |
| Oil      | 0.19  | 4.19  | 9.00  | 64.20 | 0.23  | 0.28  | 2.94  | 16.83  |
| Gas      | 0.84  | 0.08  | 1.28  | 0.19  | 59.69 | 0.19  | 0.11  | 2.68   |
| Goal     | 0.29  | 1.58  | 0.33  | 0.44  | 0.33  | 79.59 | 1.35  | 4.34   |
| CNI      | 0.08  | 35.16 | 1.42  | 2.29  | 0.40  | 0.69  | 42.03 | 40.05  |
| TO       | 1.88  | 43.40 | 13.89 | 13.56 | 3.72  | 2.18  | 39.12 | 117.76 |
| Inc. own | 89.02 | 83.44 | 64.58 | 77.76 | 63.41 | 81.77 | 81.15 | TCI    |
| NET      | 0.27  | 4.48  | 0.56  | -3.26 | 1.04  | -2.16 | -0.93 | 16.82  |

Note. Entries are percentages. TO, FROM, NET, and TCI are defined in Table 3; positive NET values indicate net transmitters.

**Table 7. Long-Term Connectedness at the Median Quantile ( $\tau = 0.50$ )**

|          | CET   | CSI   | GB    | Oil   | Gas   | Goal  | CNI   | FROM  |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|
| CET      | 10.99 | 0.00  | 0.03  | 0.00  | 0.21  | 0.02  | 0.00  | 0.26  |
| CSI      | 0.12  | 10.45 | 0.48  | 0.68  | 0.01  | 0.16  | 9.14  | 10.59 |
| GB       | 0.15  | 1.28  | 28.64 | 3.96  | 0.47  | 0.36  | 1.11  | 7.34  |
| Oil      | 0.05  | 1.56  | 2.13  | 13.96 | 0.03  | 0.07  | 1.17  | 5.01  |
| Gas      | 0.46  | 0.04  | 0.69  | 0.09  | 36.26 | 0.04  | 0.04  | 1.37  |
| Goal     | 0.07  | 0.14  | 0.04  | 0.16  | 0.01  | 15.47 | 0.19  | 0.60  |
| CNI      | 0.05  | 7.48  | 0.33  | 0.40  | 0.04  | 0.16  | 9.46  | 8.46  |
| TO       | 0.91  | 10.50 | 3.69  | 5.29  | 0.77  | 0.82  | 11.65 | 33.63 |
| Inc. own | 11.90 | 20.95 | 32.33 | 19.26 | 37.03 | 16.29 | 21.12 | TCI   |
| NET      | 0.65  | -0.09 | -3.65 | 0.28  | -0.59 | 0.22  | 3.19  | 4.80  |

Note. TO, FROM, NET, and TCI are defined as in Table 3. Short- and long-term components sum to the corresponding time-domain connectedness, subject to numerical approximation

As shown in Tables 6 and 7, at the median, short-term TCI is 16.82%, compared with 4.80% at longer horizons. CSI is the largest short-term net transmitter at 4.48, while CNI is the largest long-term net transmitter at 3.19. Oil changes from a short-term receiver to a small long-term

transmitter, and CNI changes from a short-term receiver to a long-term transmitter. The direction of risk propagation therefore depends on the holding horizon even under typical market conditions.

**Table 8. Short-Term Connectedness at the Lower Tail ( $\tau = 0.05$ )**

|     | CET   | CSI   | GB    | Oil   | Gas  | Goal  | CNI   | FROM  |
|-----|-------|-------|-------|-------|------|-------|-------|-------|
| CET | 33.11 | 10.43 | 9.88  | 7.83  | 6.16 | 11.35 | 10.35 | 56.00 |
| CSI | 8.08  | 21.55 | 7.92  | 10.80 | 7.54 | 11.75 | 20.09 | 66.18 |
| GB  | 8.47  | 9.80  | 27.79 | 4.93  | 6.47 | 11.51 | 9.69  | 50.89 |
| Oil | 5.66  | 12.29 | 4.55  | 24.13 | 6.83 | 9.96  | 11.38 | 50.67 |

|          |        |       |       |       |       |       |       |        |
|----------|--------|-------|-------|-------|-------|-------|-------|--------|
| Gas      | 4.03   | 6.04  | 4.49  | 5.10  | 16.89 | 6.50  | 6.54  | 32.69  |
| Goal     | 5.58   | 11.20 | 7.76  | 8.36  | 7.30  | 21.50 | 11.04 | 51.24  |
| CNI      | 7.63   | 20.94 | 7.77  | 10.87 | 8.08  | 12.67 | 22.51 | 67.96  |
| TO       | 39.45  | 70.71 | 42.37 | 47.89 | 42.39 | 63.74 | 69.10 | 375.63 |
| Inc. own | 72.56  | 92.25 | 70.15 | 72.02 | 59.27 | 85.24 | 91.60 | TCI    |
| NET      | -16.55 | 4.52  | -8.52 | -2.78 | 9.69  | 12.50 | 1.14  | 53.66  |

Note. Entries are percentages. TO, FROM, NET, and TCI are defined in Table 3; positive NET values indicate net transmitters.

**Table 9. Long-Term Connectedness at the Lower Tail ( $\tau = 0.05$ )**

|          | CET   | CSI   | GB    | Oil   | Gas    | Goal  | CNI   | FROM   |
|----------|-------|-------|-------|-------|--------|-------|-------|--------|
| CET      | 3.79  | 1.44  | 1.05  | 1.15  | 0.69   | 1.27  | 1.49  | 7.10   |
| CSI      | 0.48  | 3.55  | 0.68  | 1.47  | 1.47   | 1.44  | 3.18  | 8.72   |
| GB       | 1.79  | 2.29  | 8.87  | 1.43  | 2.00   | 2.78  | 2.17  | 12.46  |
| Oil      | 2.04  | 3.80  | 1.13  | 8.41  | 2.41   | 3.25  | 4.15  | 16.79  |
| Gas      | 4.39  | 7.61  | 4.44  | 5.41  | 14.15  | 7.64  | 6.77  | 36.27  |
| Goal     | 2.67  | 3.91  | 2.89  | 3.84  | 2.47   | 7.36  | 4.12  | 19.90  |
| CNI      | 0.42  | 2.65  | 0.63  | 1.08  | 0.81   | 0.96  | 3.00  | 6.54   |
| TO       | 11.79 | 21.71 | 10.82 | 14.38 | 9.86   | 17.34 | 21.87 | 107.77 |
| Inc. own | 15.59 | 25.26 | 19.69 | 22.79 | 24.01  | 24.70 | 24.87 | TCI    |
| NET      | 4.69  | 12.99 | -1.64 | -2.41 | -26.41 | -2.56 | 15.34 | 15.40  |

Note. TO, FROM, NET, and TCI are defined as in Table 3. Short- and long-term components sum to the corresponding time-domain connectedness, subject to numerical approximation.

**Table 10. Short-Term Connectedness at the Upper Tail ( $\tau = 0.95$ )**

|          | CET    | CSI   | GB    | Oil    | Gas   | Goal  | CNI   | FROM   |
|----------|--------|-------|-------|--------|-------|-------|-------|--------|
| CET      | 34.50  | 11.92 | 10.36 | 7.13   | 6.92  | 11.62 | 11.82 | 59.77  |
| CSI      | 6.90   | 22.02 | 7.91  | 10.48  | 8.52  | 12.72 | 20.33 | 66.86  |
| GB       | 5.87   | 7.17  | 19.52 | 2.45   | 5.37  | 8.55  | 7.49  | 36.89  |
| Oil      | 5.71   | 13.34 | 4.36  | 29.59  | 8.43  | 10.41 | 12.95 | 55.20  |
| Gas      | 4.17   | 8.06  | 6.07  | 6.02   | 18.95 | 8.27  | 8.43  | 41.02  |
| Goal     | 7.37   | 12.61 | 9.91  | 8.02   | 8.71  | 23.46 | 12.83 | 59.44  |
| CNI      | 7.45   | 20.85 | 8.94  | 10.27  | 8.87  | 13.15 | 21.77 | 69.53  |
| TO       | 37.47  | 73.96 | 47.55 | 44.37  | 46.82 | 64.72 | 73.85 | 388.73 |
| Inc. own | 71.96  | 95.98 | 67.06 | 73.96  | 65.77 | 88.17 | 95.63 | TCI    |
| NET      | -22.31 | 7.10  | 10.65 | -10.83 | 5.80  | 5.27  | 4.32  | 55.53  |

Note. Entries are percentages. TO, FROM, NET, and TCI are defined in Table 3; positive NET values indicate net transmitters.

**Table 11. Long-Term Connectedness at The upper Tail ( $\tau = 0.95$ )**

|          | CET   | CSI   | GB     | Oil   | Gas    | Goal  | CNI   | FROM  |
|----------|-------|-------|--------|-------|--------|-------|-------|-------|
| CET      | 2.72  | 0.54  | 0.57   | 0.30  | 0.30   | 0.70  | 0.59  | 3.01  |
| CSI      | 0.87  | 3.03  | 0.83   | 1.12  | 0.87   | 1.43  | 2.96  | 8.09  |
| GB       | 3.15  | 5.71  | 14.00  | 3.20  | 5.28   | 6.09  | 6.15  | 29.59 |
| Oil      | 0.76  | 2.66  | 0.88   | 4.86  | 1.40   | 2.08  | 2.57  | 10.35 |
| Gas      | 3.23  | 5.21  | 3.41   | 3.62  | 13.88  | 5.23  | 5.45  | 26.15 |
| Goal     | 1.55  | 2.69  | 1.55   | 1.75  | 1.60   | 5.12  | 2.83  | 11.98 |
| CNI      | 0.61  | 2.24  | 0.61   | 0.87  | 0.66   | 1.15  | 2.54  | 6.15  |
| TO       | 10.19 | 19.05 | 7.86   | 10.86 | 10.11  | 16.69 | 20.55 | 95.31 |
| Inc. own | 12.91 | 22.08 | 21.86  | 15.72 | 23.98  | 21.81 | 23.09 | TCI   |
| NET      | 7.18  | 10.97 | -21.73 | 0.51  | -16.04 | 4.71  | 14.40 | 13.62 |

Note. TO, FROM, NET, and TCI are defined as in Table 3. Short- and long-term components sum to the corresponding time-domain connectedness, subject to numerical approximation.

As shown in Tables 8 and 9, at the lower tail, short-term and long-term TCIs are 53.66% and 15.40%. Short-term transmission is led by Goal, Gas, CSI, and CNI. At longer horizons, CSI and CNI are the largest transmitters, while Gas becomes a pronounced receiver with a net value of -26.41. Goal also changes from a short-term

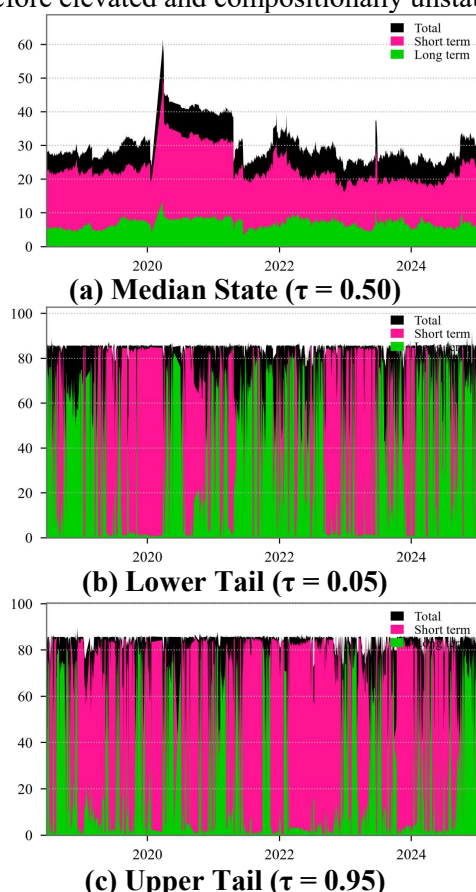
transmitter to a long-term receiver. These reversals show why a time-domain net value can conceal economically different short- and long-horizon roles.

As shown in Tables 10 and 11, at the upper tail, short-term TCI reaches 55.53% and long-term TCI is 13.62%. Green bonds are a major short-

term transmitter with a net value of 10.65 but the largest long-term receiver with a net value of -21.73. CNI is the largest long-term transmitter, followed by CSI and CET. The green bond reversal is specific to the upper tail and is consistent with rapid repricing in fixed-income green assets followed by longer-horizon absorption of shocks from the rest of the system.

#### 4.4 Dynamic Frequency Domain Connectedness

Figure 3 reports the dynamic decomposition of total connectedness. At the median, the short-term component dominates and accounts for most of the large increase around early 2020. The long-term component remains smaller but changes around the same episodes, indicating that some shocks persist beyond the initial high-frequency transmission. In the two tails, total connectedness remains high while the short- and long-term contributions change rapidly. Tail dependence is therefore elevated and compositionally unstable.

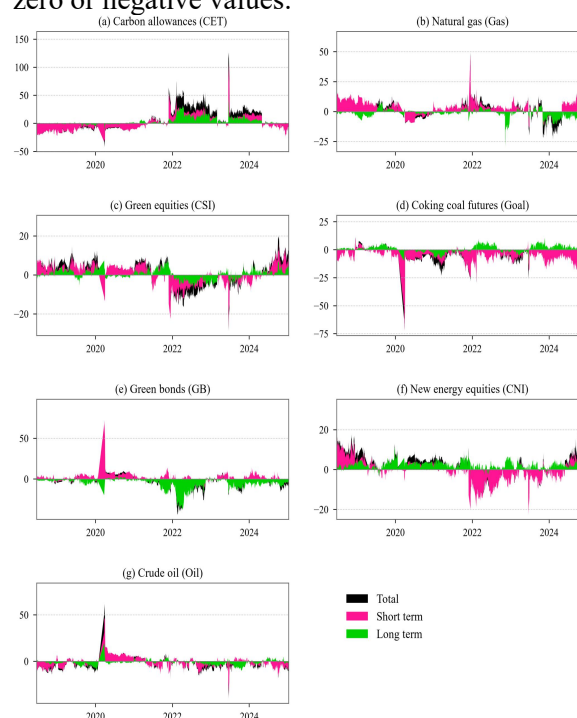


**Figure 3. Dynamic Total Connectedness by Frequency Band**

Note. Panels show  $\tau = 0.50$ ,  $\tau = 0.05$ , and  $\tau = 0.95$ . Short term denotes 1 to 5 trading days and long term denotes more than 5 trading days.

#### 4.5 Dynamic Net Connectedness

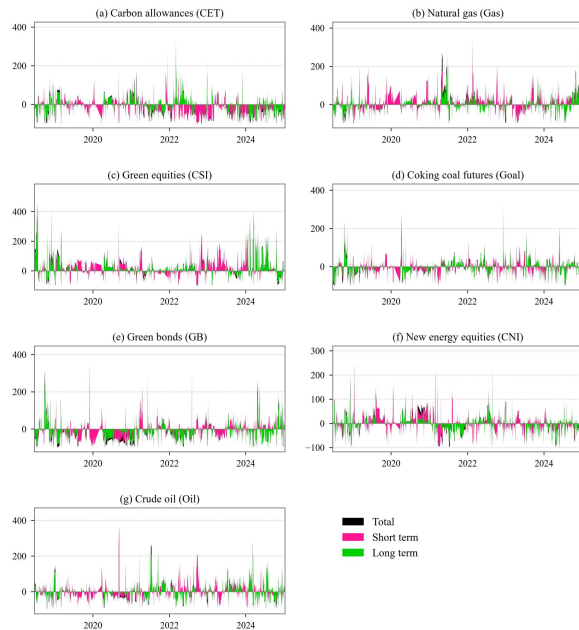
The market-level decompositions in Figures 4 through 6 show that net roles are not permanent. At the median, CSI and CNI frequently transmit short-term shocks, while Goal more often receives them. Green bonds record a marked positive episode around early 2020 and become a receiver during much of the period around 2022. CET moves from predominantly negative net connectedness in the earlier sample toward more positive values after the national carbon market began operating, although it later returns toward zero or negative values.



**Figure 4. Dynamic Net Connectedness at the Median Quantile**

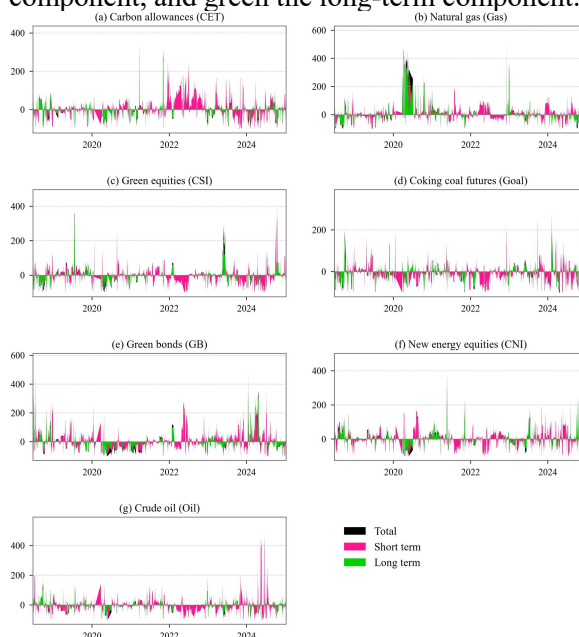
Note. Black denotes total net connectedness, magenta the short-term component, and green the long-term component. Goal denotes coking coal futures.

Figure 5 presents dynamic net connectedness at the lower-tail quantile ( $\tau = 0.05$ ), while Figure 6 presents the corresponding results at the upper-tail quantile ( $\tau = 0.95$ ). Compared with the median-state results in Figure 4, both figures show more frequent sign changes and larger fluctuations in net connectedness. This instability is consistent with the high tail TCIs. It also means that a market classified as a transmitter in the static table can act as a receiver during particular episodes. Dynamic monitoring is therefore necessary whenever portfolio exposures or policy interventions are sensitive to the direction of transmission.



**Figure 5. Dynamic Net Connectedness at the Lower Tail**

Note. The quantile is  $\tau = 0.05$ . Black denotes total net connectedness, magenta the short-term component, and green the long-term component.



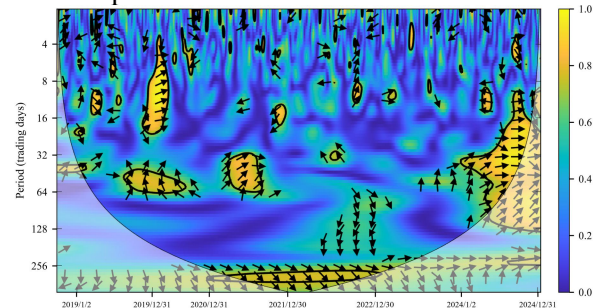
**Figure 6. Dynamic Net Connectedness at the Upper Tail**

Note. The quantile is  $\tau = 0.95$ . Black denotes total net connectedness, magenta the short-term component, and green the long-term component.

#### 4.6 Connectedness and Financial Market Uncertainty

Figures 7 through 9 report wavelet coherence between total connectedness and financial market uncertainty. The color scale ranges from low coherence in blue to high coherence in yellow.

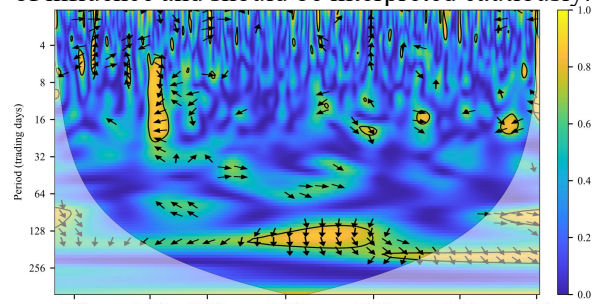
Significant regions appear as black contours. The results are heterogeneous across quantiles, dates, and periodicities, which indicates that the relationship cannot be summarized by a single full-sample correlation.



**Figure 7. Wavelet Coherence at the Median Quantile**

Note. The connectedness series is TCI at  $\tau = 0.50$ . The cone of influence identifies regions more affected by edge effects.

At the median, significant short- and medium-period coherence appears around the onset of the COVID-19 pandemic, particularly over approximately 16 to 64 trading days. Other significant clusters occur later in the sample, including at longer periodicities. Some of the longest-period regions lie near or outside the cone of influence and should be interpreted cautiously.



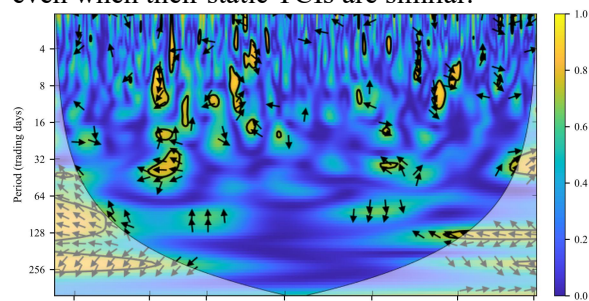
**Figure 8. Wavelet Coherence at the Lower Tail**

Note. The connectedness series is TCI at  $\tau = 0.05$ . The cone of influence identifies regions more affected by edge effects.

Lower-tail coherence is strong at short periodicities around early 2020 and becomes more prominent at approximately 128 trading days during 2021-2022. This pattern suggests that uncertainty was associated first with rapid downside transmission and later with more persistent lower-tail connectedness. The timing overlaps the pandemic and, at the longer band, the period surrounding the Russia-Ukraine war.

Upper-tail coherence is concentrated in smaller clusters, with notable short- to medium-period regions around 2019-2020 and isolated longer-period regions later in the sample. Compared with

the lower tail, the evidence of broad, persistent coherence around 2022 is weaker. The contrast shows that financial uncertainty is associated differently with negative and positive extremes even when their static TCIs are similar.



**Figure 9. Wavelet Coherence at the Upper Tail**

Note. The connectedness series is TCI at  $\tau = 0.95$ . The cone of influence identifies regions more affected by edge effects.

## 5. Discussion

### 5.1 Market State and Transmission Roles

The difference between median and tail connectedness is the central empirical result. The TCI increases by more than 47 percentage points from the median to either tail. This finding is consistent with quantile-network evidence that dependence strengthens away from the center of the return distribution [13,14]. It also adds a market-composition result: stronger tail connectedness is accompanied by changes in which assets transmit shocks.

Green equities and new energy equities are recurrent transmitters because both respond quickly to discount-rate changes, expectations about transition policy, and valuations of clean-technology firms. Their strong bilateral shares also imply that treating the two indexes as separate diversification positions may overstate effective diversification. Coking coal has a different pattern. It is a receiver at the median but a transmitter in both tails, suggesting that extreme movements in a key fossil-energy input can become system-wide information shocks.

Carbon allowances and green bonds are generally net receivers in the tail time-domain tables, but their frequency profiles are more nuanced. Green bonds become an important short-term transmitter in the upper tail and a strong long-term receiver. Carbon allowances become a long-term transmitter in the upper tail. These results are compatible with the broader evidence that green bonds and carbon-related assets occupy changing

positions within financial and energy systems rather than serving as unconditional hedges [7,15].

### 5.2 Horizon Specific Risk

Short-horizon transmission accounts for most connectedness at every quantile. The median short-term TCI is more than three times the long-term value, and the tail short-term TCIs are approximately four times their long-term counterparts. This result agrees with the economic interpretation of high-frequency connectedness as rapid market processing of common or transmitted shocks [18] and with evidence from green and traditional energy markets [9].

The long-term component remains relevant because market roles can reverse across horizons. A risk manager who observes only the time-domain net measure may overlook the fact that a market transmits shocks immediately but absorbs them over longer periods. Green bonds in the upper tail and natural gas in the lower tail provide the clearest examples. Horizon-specific exposure limits and hedges should therefore be based on the relevant holding period rather than a single aggregate network.

### 5.3 Implications of Financial Uncertainty

Wavelet coherence shows that financial uncertainty does not have a stable association with connectedness. The relationship appears in bounded intervals and at different periodicities across quantiles. Shorter-period coherence around the COVID-19 outbreak is consistent with rapid risk repricing during the broad financial disruption documented by Zhang et al. [20]. The lower-tail shift toward longer-period coherence around 2021-2022 is consistent with more persistent adjustment during a period that combined pandemic effects, energy-price pressure, and geopolitical risk.

For regulators, the findings support monitoring dashboards that distinguish typical from tail states and decompose spillovers by horizon. A high tail TCI combined with a change in net transmitters may warrant closer attention to liquidity, margin, and cross-market concentration. For investors, the results imply that diversification weights calibrated on median dependence can fail during extreme returns. Green equities and new energy equities should be stress-tested as a closely connected block, while coal, green bonds, and carbon allowances require state- and horizon-

specific treatment.

#### 5.4 Limitations

The analysis has several limitations. The market proxies do not cover every segment of China's green finance and energy systems, and the carbon series combines two pilot markets rather than the full national market history. The uncertainty proxy is derived from CSI 300 conditional volatility and therefore captures financial market stress, not all dimensions of macroeconomic or policy uncertainty. Asynchronous trading calendars and market-specific liquidity may also affect daily spillover estimates.

The five-day boundary provides a clear short-versus-long comparison but is not unique. Alternative frequency bands, forecast horizons, lag orders, and rolling-window choices could change estimated magnitudes. Wavelet coherence identifies localized association and phase but does not establish causal transmission. Future work could compare alternative uncertainty measures, test sensitivity to frequency partitions, incorporate additional green instruments and energy commodities, and evaluate structural changes following the launch and expansion of the national carbon market.

#### 6. Conclusion

This study combines quantile, time-domain, frequency-domain, and wavelet methods to examine spillovers between China's green finance and energy markets. The evidence shows that connectedness is strongly state dependent: total connectedness is about 21.6% at the median and about 69% in both tails. The near equality of the two tail totals does not imply symmetry because bilateral directions and net market roles differ between lower- and upper-tail states.

Most transmission occurs within one to five trading days. Green equities and new energy equities are recurrent sources of spillovers, and coking coal becomes a transmitter in extreme states. Green bonds display a particularly strong horizon reversal in the upper tail, moving from a short-term transmitter to a long-term receiver. Dynamic estimates show that these classifications vary through time, especially around periods of market disruption.

Financial market uncertainty is associated with total connectedness only at particular dates and periodicities. Shorter-period coherence is prominent around the COVID-19 shock, while lower-tail coherence extends to longer

periodicities around 2021-2022. Risk assessment should therefore combine state, horizon, and time information. Policies and portfolios based only on average connectedness may understate short-lived but system-wide transmission during extreme market conditions.

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