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Multiscale Spillovers between Clean Energy and Related Metal Markets

Zhihao Zhang*

Nanjing University of Science and Technology ZiJin College, Nanjing 210023, Jiangsu, China

***Corresponding author*: Zhihao Zhang, 18743767805@126.com

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Abstract: The global energy transition has strengthened the linkages between clean energy and metal markets, yet the direction and structure of these linkages may vary across investment horizons and market conditions. This study examines multiscale connectedness between metal futures and global clean energy equity markets using daily data from January 2017 to October 2025. Wavelet coherence, MODWT, and the TVP-VAR-DY framework are employed to identify time–frequency dependence and directional spillovers. The results show clear horizon dependence. The total connectedness index rises from 36.65% at D1 to 58.34% at D4 and 67.19% at D6, indicating stronger medium- and longer-term linkages. Market roles also vary across scales: copper dominates short-term transmission, nickel becomes the main transmitter at the medium-term scale, while tin and copper dominate at the longer-term scale. Cobalt remains a net receiver, while the roles of wind and solar energy markets vary across horizons. The COVID-19 pandemic and the Russia–Ukraine conflict are associated with distinct changes in the identity of key transmitters and receivers. These findings show that cross-market connectedness depends jointly on investment horizon and external-shock conditions, with implications for portfolio allocation, raw-material risk management, and market monitoring.

Keywords: Clean energy; Metal futures; Connectedness; Time–frequency analysis; TVP-VAR-DY

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1. Introduction

The global energy transition has strengthened the dependence of clean energy industries on critical metals and has consequently intensified the linkages between clean energy and metal markets [1]. Metals such as copper, nickel, and tin are essential inputs into renewable energy technologies and related infrastructure. Their price fluctuations can affect production costs, project profitability, and clean energy firms' valuations. At the same time, the expansion of clean energy industries changes expected demand for transition-related metals and may influence their price formation. The relationship between the two market groups is therefore inherently bidirectional.

These linkages may vary across investment horizons. Short-term price movements are more likely to reflect market sentiment, liquidity conditions, and rapidly arriving information, whereas medium- and longer-term dynamics may increasingly incorporate changes in supply conditions, production costs, investment demand, and expectations regarding the energy transition. Major external shocks can further alter these relationships by simultaneously affecting commodity supply, investor expectations, and clean energy valuations. Connectedness between clean energy and metal markets is therefore likely to vary across both time and frequency.

A growing literature has examined these cross-market linkages. Gustafsson et al. document significant relationships between clean energy equities and metals such as copper, nickel, and cobalt, with implications for hedging and diversification [2]. Igeland et al. further show that fluctuations in energy-metal prices have important long-term effects on clean energy assets [3]. From a multiscale perspective, Shao and Zhang find that cross-market relationships vary across time horizons [4], while Ding et al. report significant connectedness between clean energy stock indices and metal markets [5]. Recent studies increasingly emphasize time–frequency heterogeneity. Magzumov and Kumral identify frequency-specific lead–lag relationships using wavelet-based methods [6]. Hou et al. combine wavelet analysis with a time-varying parameter VAR framework [7], while Xu et al. integrate dynamic connectedness models with wavelet coherence [8]. Bi et al. further show that connectedness between clean energy and metal markets is stronger at medium- and longer-term frequencies and can be amplified by major external events [9].

Although these studies have substantially advanced the literature, two issues remain insufficiently explored. First, less attention has been paid to whether the transmitter–receiver roles of individual markets change systematically across short-, medium-, and longer-term horizons. Existing studies generally establish that clean energy and metal markets are dynamically connected, but the direction of transmission may not remain stable across scales. This issue is especially relevant when metal futures are considered together with global segment-specific clean energy equity markets. China plays an important role in global metal production, consumption, and futures trading, while solar and wind equity indices reflect expectations regarding downstream clean energy development.

Second, major external shocks may alter not only the intensity of connectedness but also its internal transmission structure. The COVID-19 pandemic and the Russia–Ukraine conflict provide two distinct episodes for examining this issue. The pandemic generated abrupt disruptions to economic activity, supply chains, and financial markets, whereas the Russia–Ukraine conflict was associated more directly with commodity supply concerns and geopolitical uncertainty. Comparing these episodes can therefore help determine whether crises simply increase market connectedness or also change the identity of dominant transmitters and receivers.

Against this background, this study examines multiscale connectedness between metal futures and global clean energy equity markets. The analysis considers copper, nickel, zinc, and tin futures traded on the Shanghai Futures Exchange, cobalt futures traded on the London Metal Exchange, and global solar and wind energy stock indices. Wavelet coherence is first used to examine time–frequency dependence and lead–lag relationships. MODWT is then employed to decompose market returns across different time scales, followed by the TVP-VAR-DY framework to measure total, directional, and pairwise net spillovers.

This study contributes to the literature in three respects. First, it focuses on how transmitter–receiver roles change across investment horizons rather than treating connectedness as horizon-invariant. Second, it

provides evidence on the interaction between metal futures and global segment-specific clean energy equity markets. Third, it compares how the transmission structure changes during the COVID-19 pandemic and the Russia–Ukraine conflict. The analysis therefore seeks not only to determine whether clean energy and metal markets are connected, but also to identify when, at what horizon, and from which market the dominant transmission originates.

2. Research design

This study first uses wavelet coherence analysis to identify time–frequency dependence and lead–lag relationships between clean energy and metal markets. It then applies MODWT to decompose return series across time scales and uses the TVP-VAR-DY model to measure static, dynamic, and pairwise net spillovers at each scale.

2.1. Model specification

2.1.1. Wavelet coherence model

Wavelet coherence (WTC) characterizes the relationship between two series in the time–frequency domain. Let the market series be x(t). Its continuous wavelet transform (CWT) can be expressed as:

$$W_x(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt$$

where a and b are the scale and translation parameters, respectively. For market series x(t) and y(t), with wavelet transforms $W_x(a,b)$ and $W_y(a,b)$, respectively, the cross-wavelet transform (XWT) is defined as:

$$W_{xy}(a,b) = W_x(a,b)W^*_y(a,b)$$

where * denotes the complex conjugate. The wavelet coherence coefficient (WTC) can then be expressed as:

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

where S is the time–frequency smoothing operator, and $R^2(a,b)$ ranges from 0 to 1. A larger value indicates stronger dependence between the two markets. The phase difference, used to identify lead–lag relationships, can be expressed as:

$$\varphi_{xy}(a,b) = \tan^{-1}\left(\frac{I\left\{S\left(a^{-1}W_{xy}(a,b)\right)\right\}}{R\left\{S\left(a^{-1}W_{xy}(a,b)\right)\right\}}\right)$$

where $\Im(\cdot)$ and $\Re(\cdot)$ denote the imaginary and real parts, respectively. A phase difference of zero indicates that the metal and clean energy markets co-move at the specified frequency. Specifically, this lead–lag relationship is represented by black arrows pointing in different directions in the wavelet coherence plots.

2.1.2. Maximal overlap discrete wavelet transform (MODWT)

Wavelet decomposition separates an original series into different time scales and distinguishes high-

frequency fluctuations from low-frequency trends. Aydoğdu notes that wavelet analysis is based primarily on father and mother wavelets: the former captures low-frequency and smooth components, whereas the latter captures high-frequency and detail components [10]. They can be expressed as:

$$\phi_{j,k} = 2^{-\frac{1}{2}}\phi\left(\frac{t-2^{jk}}{2^{j}}\right), \int\phi(t)\,dt = 1 \psi_{j,k} = 2^{-\frac{1}{2}}\psi\left(\frac{t-2^{jk}}{2^{j}}\right), \int\psi(t)\,dt = 0$$

where j=1..., J is the scale parameter and k=1..., K is the translation parameter. The father-wavelet smooth coefficients and mother-wavelet detail coefficients are, respectively:

$$S_{j,k} = \int f(t)\,\phi_{j,k}\,dt d_{j,k} = \int f(t)\,\psi_{j,k}\,dt$$

where the mathematical form of f(t) and its simplified expression are:

$$f(t) = \sum_{k} S_{j,k}\phi_{j,k}(t) + \sum_{k} d_{j,k}\psi_{j,k}(t) + \ldots + \sum_{j,k} d_{j,k}\psi_{j,k}(t) + \ldots + \sum_{k} d_{1,k}\psi_{1,k}(t)$$

$$f(t) = S_{J} + D_{J} + D_{J-1} + \ldots + D_{j} + \ldots + D_{1}$$

The orthogonal components are defined as:

$$S_{j} = \sum_{k} S_{j,k}\phi_{j,k}(t)\, D_{j} = \sum_{k} d_{j,k}\psi_{j,k}(t)$$

MODWT imposes relatively few restrictions on sample size and allows flexible decomposition, making it suitable for financial time series. This study uses it to identify differences between clean energy and metal markets across frequencies [11].

First, the filters are specified. For the two market series $X=\{X_t;t=0,\ldots,N-1\}$, each with N observations, the MODWT wavelet and scaling coefficients at the jth decomposition level are:

$$\tilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{(t-l) \bmod N}, t = 0,1,\ldots,N-1$$

where $\{\tilde{h}_{j,l}, l=0,\ldots,L_j\}$ and $\{\tilde{g}_{j,l}, l=0,\ldots,L_j\}$ are the wavelet and scaling filters at level j, respectively, with width $L_j=(2^j-1)(L-1)+1$. $h_{j,l}$ and $g_{j,l}$ satisfy the following conditions:

$$\sum_{l=0}^{L_j-1} \tilde{h}_{j,l} = 0, \sum_{l=0}^{L_j-1} h_{j,l}^{2} = 2^{-j}, \sum_{l=0}^{L_j-1-2n} h_{j,l} h_{j,l+2n} = 0$$

$$\forall n > 0, \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} = 0, \sum_{l=0}^{L_j-1} g_{j,l}^{2} = 2^{-j}, \sum_{l=0}^{L_j-1} g_{j,l} h_{j,l} = 0$$

The MODWT detail and smooth coefficients at level j are, respectively:

$$\tilde{D}_{j,t} = \sum_{l=0}^{L_j-1} h_{j,l} W_{j,t+1}\, S_{j,t} = \sum_{l=0}^{L_j-1} g_{j,l} V_{j,t+1}$$

Because the MODWT coefficients at each scale have the same length as the original series X_t, the clean energy and metal market series can be decomposed as:

$$X_t = D_{1,t} + D_{2,t} + \ldots + D_{J,t} + S_{J,t}$$

2.1.3. TVP-VAR-DY spillover index model

This study adopts the TVP-VAR connectedness framework of Antonakakis et al. [12] and measures time-varying spillovers between clean energy and metal markets using the generalized variance decomposition approach of Diebold and Yilmaz [13].

$$y_t = \phi_{1,t} y_{t-1} + \phi_{2,t} y_{t-2} + \ldots + \phi_{p,t} y_{t-p} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_t)$$

where y_t is an N×1 vector of endogenous variables; ε_t is an N×1 disturbance vector with the time-varying variance–covariance matrix Σt; $\Phi_{i,t}$ is an N×N matrix of time-varying VAR coefficients, i=1..., p; v_t is an N^2×1 disturbance vector; and vec(Φ_t) denotes the vectorization of Φ_t.

To calculate generalized impulse responses and the generalized forecast error variance decomposition, define the N×N lag-polynomial matrix with identity matrix IN as:

$$\Phi(L) = \left[I_N - \Phi_{1,t} L - \ldots - \Phi_{p,t} L^p \right]$$

The TVP-VAR model can be written as $\Phi(L)y_t=\varepsilon_t$. By the Wold theorem, a stationary process can be represented as a TVP-VMA (∞):

$$y_t = \Psi(L)\varepsilon_t \Phi(L) = [\Psi(L)]^{-1}$$

The infinite-order lag-polynomial matrix Ψ(L) is approximated by Ψ_h (h=1..., H). The GFEVD measures the contribution of a shock in market j to the H-step-ahead forecast error variance of market i and can be expressed as:

$$\theta_{ij,t}(H) = \frac{(\Sigma_t)_{jj}^{-1} \sum_{h=0}^{H} \left((\Psi_h \Sigma_t)_{ij,t} \right)^2}{\sum_{h=0}^{H} (\Psi_h \Sigma_t \Psi_h')_{ii}} \quad \tilde{\theta}_{ij,t}(H) = \frac{\theta_{ij,t}(H)}{\sum_{k=1}^{N} \theta_{ij,t}(H)}$$

where $\theta_{ij,t}(H)$ satisfies:

$$\sum_{i=1}^{N} \theta_{ij,t}(H) = 1 \sum_{j=1}^{N} \sum_{i=1}^{N} \theta_{ij,t}(H) = N$$

For each decomposed scale, the directional connectedness measures are defined as follows:

$$\mathrm{FROM}_{i,t}(H) = \frac{\sum_{j=1 j \neq i}^{N} \theta_{ij,t}(H)}{\sum_{j=1}^{N} \theta_{ij,t}(H))} \times 100 \quad TO_{i,t}(H) = \frac{\sum_{j=1 j \neq i}^{N} \theta_{ji,t}(H)}{\sum_{j=1}^{N} \theta_{ji,t}(H)} \times 100$$

The net spillover index for market i (net total directional connectedness, NET) is therefore:

$$NET_{i,t}(H) = TO_{i,t}(H) - FROM_{i,t}(H)$$

When NET>0, market i is a net transmitter; when NET<0, it is a net receiver.

The total connectedness index measures system-wide connectedness:

$$TCI_t(H) = N^{-1} \sum_{i=1}^{N} TO_{i,t}(H) = N^{-1} \sum_{i=1}^{N} FROM_{i,t}(H)$$

A larger TCI indicates stronger spillovers among markets in the system.

2.2. Variables and data

Copper, nickel, zinc, tin, and cobalt are important raw materials for clean energy technologies such as

photovoltaics, wind power, and electric-vehicle batteries. Changes in their supply, demand, and prices can affect the cost and construction schedules of clean energy projects. Based on raw-material relevance and data availability, this study examines these five metals and two clean energy indices. The metal-market data comprise daily closing prices for copper, nickel, zinc, and tin futures traded on the Shanghai Futures Exchange and cobalt futures traded on the London Metal Exchange. The clean energy markets are represented by the MAC Global Solar Energy Stock Index (SEI) and the ISE Global Wind Energy Index (WEI). The sample runs from January 4, 2017, to October 29, 2025, and contains 2,008 common trading days. The data are obtained from the Wind and Bloomberg databases.

Table 1. Variable selection

Variable	Description	Frequency	Exchange/Ticker
Copper	Copper futures prices on the Shanghai Futures Exchange	Daily	SHFE
Nickel	Nickel futures prices on the Shanghai Futures Exchange	Daily	SHFE
Zinc	Zinc futures prices on the Shanghai Futures Exchange	Daily	SHFE
Tin	Tin futures prices on the Shanghai Futures Exchange	Daily	SHFE
Cobalt	Cobalt futures prices on the London Metal Exchange	Daily	LME
Solar Energy	MAC Global Solar Energy Stock Index	Daily	SUNIDX
Wind Energy	ISE Global Wind Energy Stock Index	Daily	NASDAQGWE

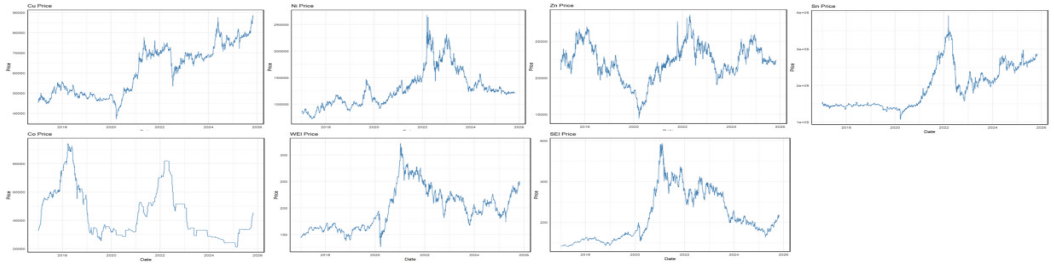


Figure 1. Price series for metal and clean energy markets.

Figure 1 shows that market prices underwent distinct phases of volatility over the sample period. Volatility was relatively high during 2018–2020 and 2021–2022. Copper prices generally rose after 2020; nickel and tin surged and then retreated during 2021–2022; zinc fluctuated within a range; cobalt generally declined after 2018; and the wind energy index remained high but volatile after sharp fluctuations in 2021.

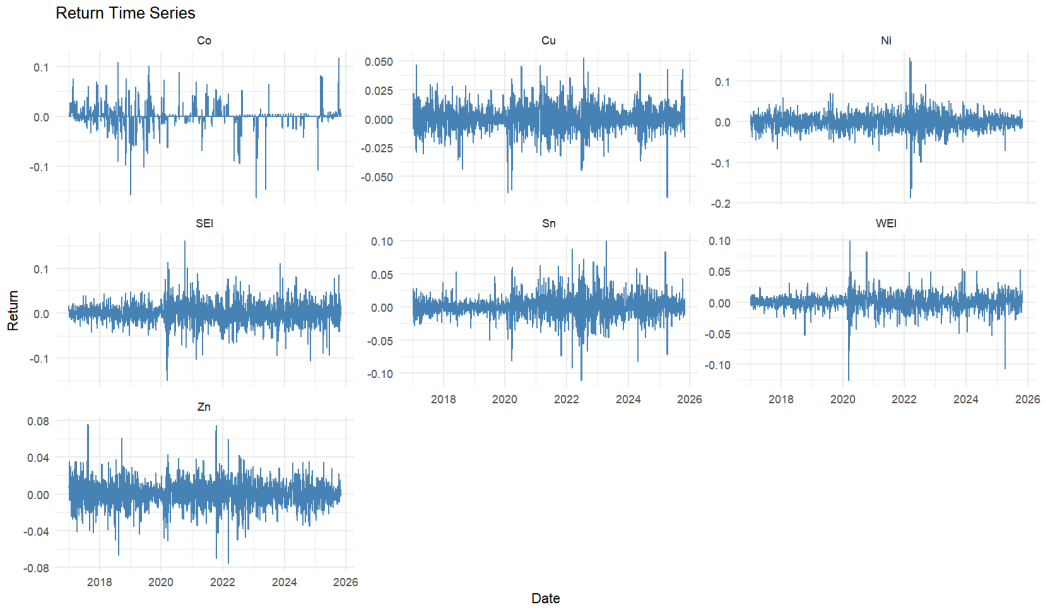


Figure 2. Return series for metal and clean energy markets.

Daily returns are obtained by taking log differences of the price series (**Figure 2**). All markets exhibit pronounced volatility clustering, especially during 2018–2020, 2021–2022, and the period since 2024, indicating that macroeconomic shocks, geopolitical events, and developments in the clean energy industry can substantially affect market returns.

2.3. Descriptive statistics

Table 2 shows that mean daily returns are close to zero in all markets and that the return series are generally leptokurtic and heavy-tailed. The J-B test rejects the null hypothesis of normality, while the ADF test rejects the null hypothesis of a unit root at the 1% significance level, indicating that all return series are stationary.

Table 2. Descriptive statistics for metal and clean energy market returns

	Minimum	Maximum	Mean	Median	Standard Deviation	Skewness	Kurtosis	ADF Statistic	J-B Statistic
Cu	-0.07	0.05	0.00033	0.00027	0.01	-0.26	4.21	-12.69***	1510.6***
Ni	-0.19	0.16	0.00017	0.00067	0.02	-0.19	10.79	-13.11***	9765.3***
Zn	-0.08	0.08	0.00003	0.00000	0.01	-0.03	3.37	-13.36***	955.89***
Sn	-0.11	0.10	0.00032	0.00021	0.02	-0.16	6.47	-12.69***	3524.7***
Co	-0.16	0.12	0.00016	0.00000	0.02	-1.30	25.48	-9.49***	54998***
WEI	-0.13	0.10	0.00028	0.00062	0.01	-0.66	12.41	-12.23***	13047***
SEI	-0.15	0.16	0.00052	0.00010	0.02	-0.10	5.13	-11.88***	2214.2***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The J-B statistic is the Jarque–Bera statistic used to test whether a series follows a normal distribution; its null hypothesis is normality. The null hypothesis of the ADF statistic is that the autoregressive representation of the series contains a unit root, meaning that the series is nonstationary.

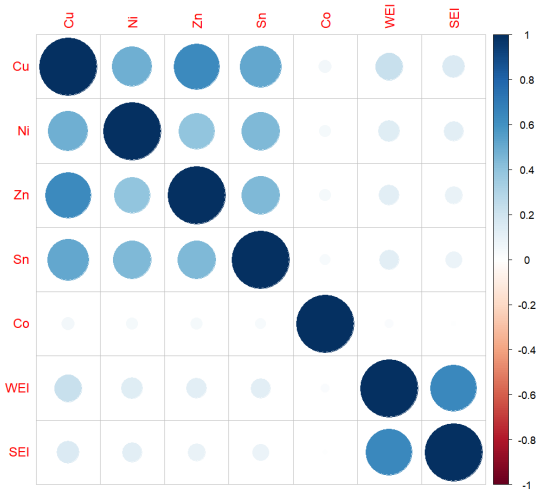


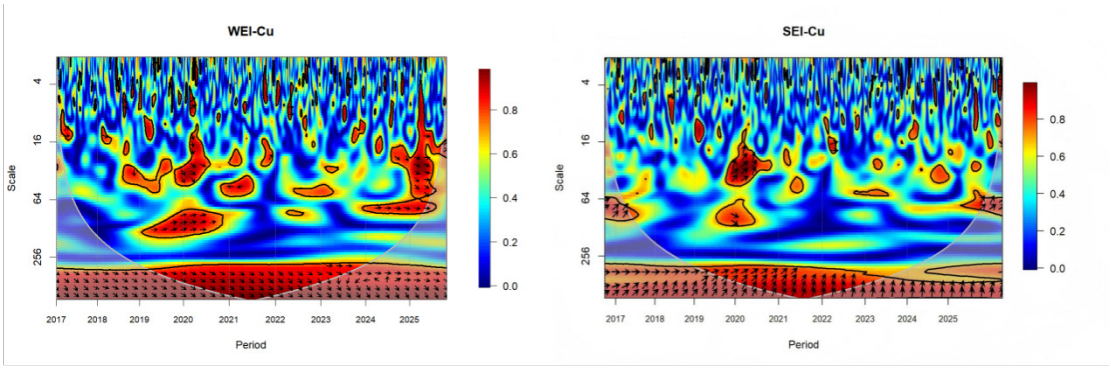
Figure 3. Pearson correlation heatmap.

Figure 3 shows moderate positive correlations among Cu, Ni, Zn, and Sn, whereas Co is weakly correlated with the other metals and the clean energy indices. WEI and SEI are highly positively correlated. The two market groups are weakly positively correlated overall, suggesting limited short-term price connectedness.

3. Empirical results

3.1. Wavelet coherence analysis

Figure 4 reports the wavelet coherence results. The horizontal axis represents sample time, and the vertical axis represents frequency bands. Black contours mark regions significant at the 5% level [14], and regions outside the cone of influence (COI) are not interpreted [15]. Warm colors indicate stronger correlation and cool colors weaker correlation; arrow directions identify the sign of the correlation and lead–lag relationships. Because the continuous wavelet transform is subject to boundary effects, results near both ends of the sample should be interpreted with caution.



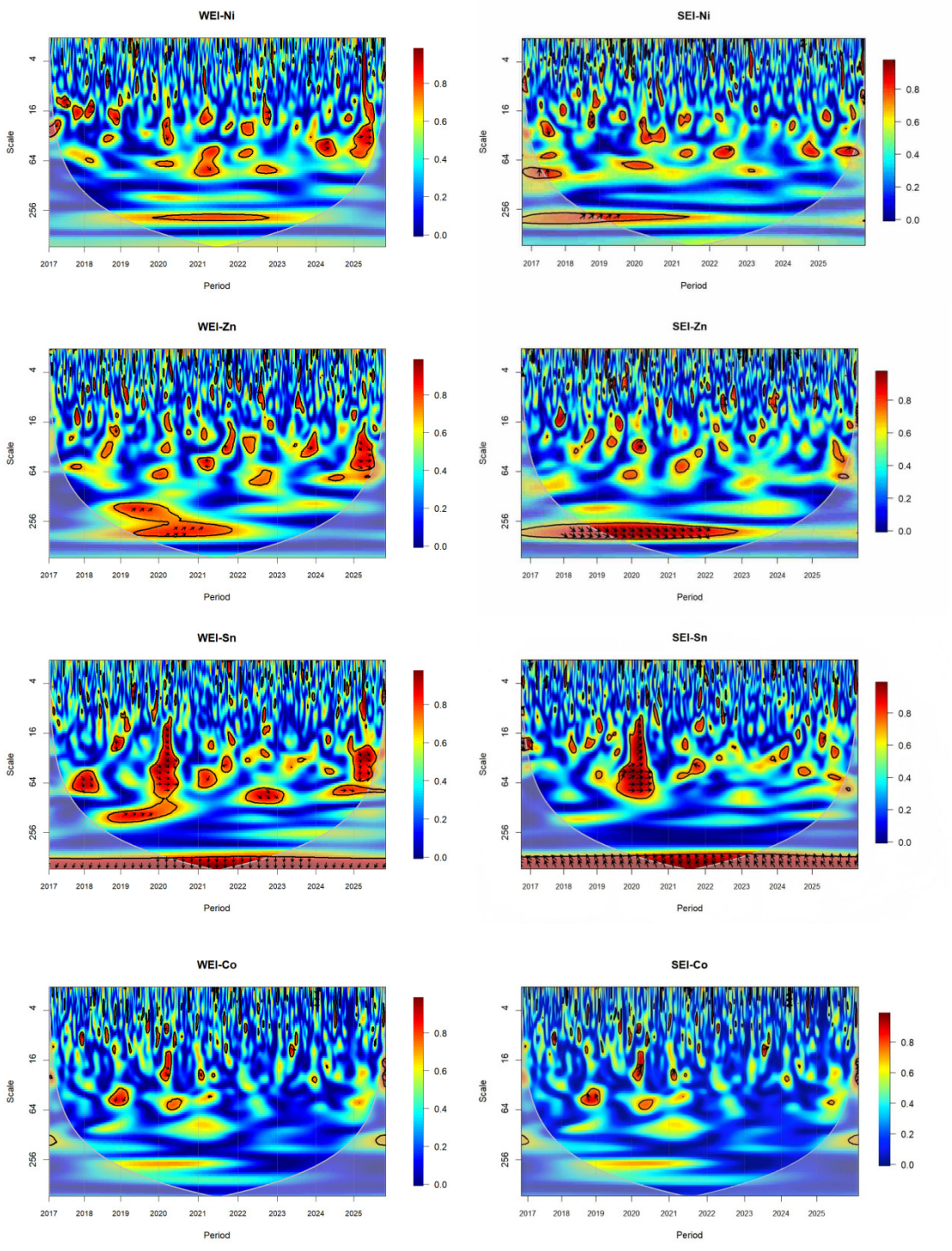


Figure 4. Wavelet coherence plots.

Figure 4 shows that correlations between metal and clean energy markets vary markedly across time and frequency. In most valid regions, arrows point to the right, indicating that positive co-movement predominates, although lead–lag relationships differ across metals. Over time, numerous regions of high coherence appear between each metal and WEI or SEI during 2019–2022, corresponding to events such as the COVID-19 pandemic and the Russia–Ukraine conflict. Across frequencies, correlations are generally weaker at high frequencies,

whereas regions of high coherence become more prevalent at medium and low frequencies, indicating stronger medium- and long-term than short-term connectedness. At long-term scales, correlations between each metal and the two clean energy indices strengthen further. Cu tends to lead or move synchronously with WEI and SEI, whereas Co displays more dispersed phase directions. These results point to heterogeneous cross-market transmission patterns across metals: weak short-term correlations suggest greater potential for diversification, while stronger medium- and long-term cross-market connectedness warrants closer attention.

3.2. Multiscale decomposition results

The original series are decomposed into D1–D6 and S6, corresponding to 2–4, 4–8, 8–16, 16–32, 32–64, 64–128, and 128 trading days or more, respectively. Following Liu et al. and Kumah and Mensah, D1, D4, and D6 are selected to represent the short-, medium-, and long-term scales, respectively [16,17].

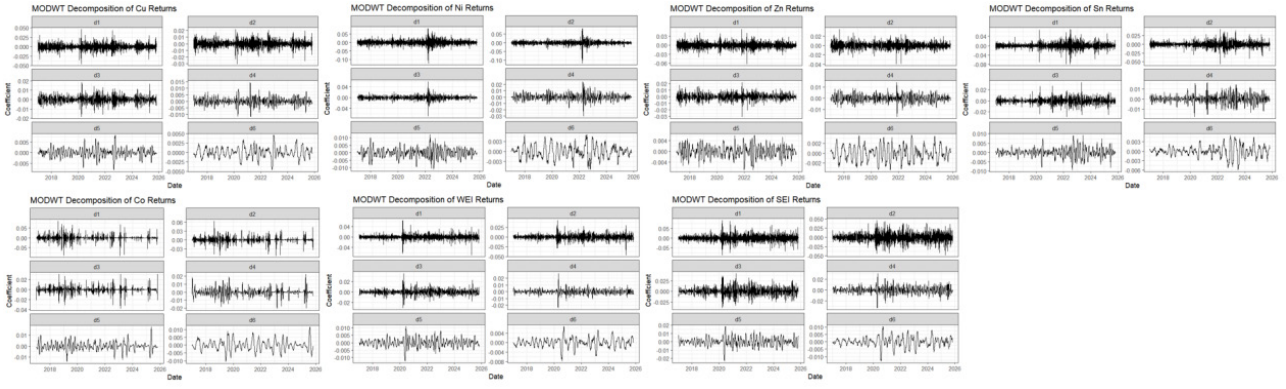


Figure 5. Maximal overlap discrete wavelet transform of return series for the metal and clean energy markets.

Figure 5 shows that market fluctuations gradually moderate as the time scale increases. D1–D2 capture relatively high-frequency movements, while D3–D4 and D5–D6 represent progressively lower-frequency components associated with medium- and longer-horizon market dynamics.

3.3. Static spillover effects

Tables 3–5 report the static spillover results at the D1, D4, and D6 scales, respectively. The diagonal elements show each market's contribution to its own forecast error variance, whereas the off-diagonal elements measure cross-market connectedness. TO and FROM denote outward and inward spillovers, respectively, and NET = TO − FROM. NET > 0 identifies a net transmitter, whereas NET < 0 identifies a net receiver.

Table 3. Connectedness table at the D1 scale

Panel	Market	Cu	Ni	Zn	Sn	Co	WEI	SEI	FROM
	Cu	48.61	13.31	19.27	11.82	1.37	2.88	2.73	51.39
	Ni	16.43	57.75	10.31	10.86	1.17	1.85	1.64	42.25
	Zn	21.28	10	51.91	11.45	1.27	2.33	1.76	48.09
	Sn	14.63	10.18	11.46	58.68	1.06	2.43	1.55	41.32
Panel A: D1	Co	1.37	1.34	1.39	1.27	90.04	2.36	2.22	9.96
	WEI	4.2	2.19	2.27	2.55	1.35	68.76	18.68	31.24
	SEI	3.22	1.7	1.54	1.89	0.84	23.09	67.73	32.27
	TO	61.12	38.73	46.24	39.84	7.06	34.95	28.58	256.52
	NET	9.74	-3.52	-1.84	-1.48	-2.9	3.71	-3.7	TCI/36.65

D1 corresponds to 2–4 trading days. Cobalt and the two clean energy indices have relatively large own-market variance shares, whereas copper, nickel, zinc, and tin are more closely connected to the other markets in the system. Copper is the largest shock transmitter. Wind energy and copper have positive NET values, while nickel and solar energy are mainly net receivers.

Table 4. Connectedness Table at the D4 Scale

Panel	Market	Cu	Ni	Zn	Sn	Co	WEI	SEI	FROM
	Cu	34.23	15.67	14.42	11.7	5.63	10.56	7.79	65.77
	Ni	14.28	45.07	9.85	11.96	4.66	7.15	7.03	54.93
	Zn	17.81	13.53	37.81	11.49	4.91	9.02	5.44	62.19
	Sn	14.07	14.6	9.96	38.26	6.91	7.87	8.33	61.74
Panel B: D4	Co	6.61	11.32	6.87	9.37	51.88	7.63	6.32	48.12
	WEI	7.82	7.44	5.15	8.74	7	44.25	19.6	55.75
	SEI	7.65	8.02	5.29	9.44	7.01	22.45	40.14	59.86
	TO	68.24	70.59	51.54	62.7	36.12	64.68	54.51	408.37
	NET	2.47	15.66	-10.66	0.96	-12	8.93	-5.35	TCI/58.34

D4 corresponds to 16–32 trading days. Compared with D1, own-market variance shares generally decline and system-wide connectedness increases markedly; cobalt's own-market share falls from 90.04% to 51.88%. Nickel replaces copper as the largest net shock transmitter (15.66%), while copper's NET declines to 2.47%. Cross-market spillovers between the clean energy indices and metal markets also strengthen, and the TCI rises from 36.65% to 58.34%.

Table 5. Connectedness table at the D6 scale

Panel	Market	Cu	Ni	Zn	Sn	Co	WEI	SEI	FROM
	Cu	31.92	11.11	15.26	20.09	5.53	8.35	7.74	68.08
	Ni	13.46	34.08	11.91	14.19	6.03	9.99	10.34	65.92
	Zn	18.89	12	33.26	14.79	4.44	9.11	7.51	66.74
	Sn	14.07	13.15	11.71	37.82	4.63	10.86	7.76	62.18
Panel C: D6	Co	11.96	12	11.59	14.8	28.21	8.98	12.45	71.79
	WEI	10.72	12.74	9.73	14.05	6.29	30.08	16.39	69.92
	SEI	10.07	9.69	10.07	11.32	6.34	18.21	34.3	65.7
	TO	79.16	70.7	70.28	89.24	33.26	65.51	62.18	470.33
	NET	11.08	4.78	3.54	27.06	-38.53	-4.41	-3.51	TCI/67.19

D6 corresponds to 64–128 trading days. System-wide connectedness rises further, with the TCI reaching 67.19%. Tin (27.06%) and copper (11.08%) are the main net transmitters, whereas wind energy (−4.41%), solar energy (−3.51%), and cobalt (−38.53%) are net receivers, indicating a stronger transmission role of metal markets at the longer-term scale. This result is also consistent with Ghosh et al. [18], who find stronger connectedness among energy-transition metals under extreme conditions.

Overall, the TCI for the two market groups ranges from 36.65% to 67.19%, indicating substantial cross-market transmission. These values are similar to those reported by Restrepo et al., further suggesting that market connectedness is widespread in the context of the energy transition [19].

3.4. Dynamic connectedness and role switching

Full-sample connectedness measures provide information on the average transmission structure but may conceal substantial changes in market interactions over time. To examine whether the intensity and direction of connectedness vary across market conditions, Figure 6 presents the dynamic total connectedness indices at the D1, D4, and D6 scales.

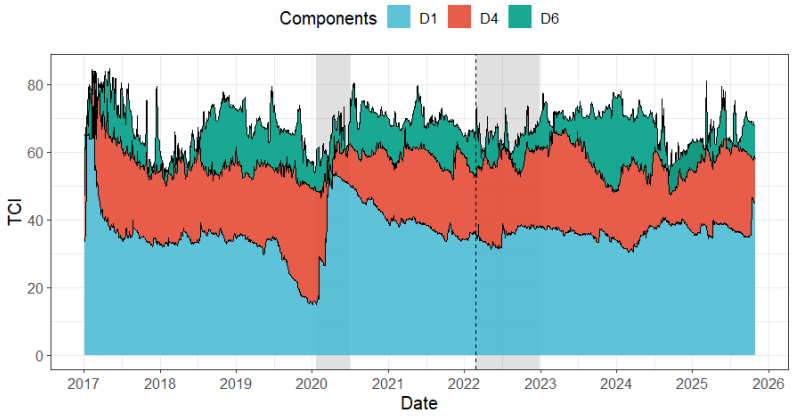


Figure 6. Dynamic total connectedness index.Note: According to the AIC, the optimal lag order for the TVP-VAR model is 1, and the forecast error variance decomposition horizon is 100. The shaded areas denote the initial phase of the COVID-19 outbreak from January to June 2020 and the selected Russia–Ukraine conflict period from February 2022 to December 2023, respectively.

Figure 6 shows pronounced differences in the temporal behavior of connectedness across investment horizons. The D1 total connectedness index is close to 80% in early 2017 and subsequently declines with considerable fluctuations. It falls below 15% between 2019 and early 2020, whereas the D4 and D6 indices remain comparatively stable. Following the outbreak of COVID-19, short-term connectedness rises rapidly into the 35%–65% range, indicating a sharp increase in high-frequency cross-market interactions. Connectedness across the three scales gradually converges after 2020, while the D1 index declines again in mid-to-late 2022. Overall, short-term connectedness responds more sharply to changing market conditions, whereas medium- and longer-term connectedness is comparatively persistent. This pattern suggests that the strength of cross-market transmission depends not only on time but also on the horizon over which market shocks are evaluated.

Changes in total connectedness, however, do not fully reveal how the internal transmission structure evolves. **Figure 7** therefore presents the dynamic net spillover indices of individual markets at the three representative scales. The results indicate substantial horizon-dependent role switching. Copper and nickel frequently act as net transmitters, particularly after 2020, although their relative importance differs across scales and periods. The transmission roles of zinc and tin are more sensitive to the investment horizon, while cobalt remains a net receiver during most of the sample. Within the clean energy markets, wind energy is mainly a net receiver before 2020 but becomes a net transmitter during a number of subsequent periods, whereas solar energy is predominantly a net receiver. These patterns show that the classification of a market as a transmitter or receiver is not invariant over time or frequency.

The comparison of major external shocks further illustrates this structural instability. During the COVID-19 pandemic, short-term net spillovers change abruptly, followed by a more gradual adjustment at the medium- and longer-term scales. During the Russia–Ukraine conflict, several metal markets exhibit larger

changes in their net transmission positions, particularly at the D6 scale. The two episodes therefore differ not only in spillover intensity but also in the identity and relative importance of the markets transmitting shocks.

More specifically, at the D1 scale, zinc emerges as the principal spillover center during the COVID-19 pandemic, whereas copper assumes this role during the Russia–Ukraine conflict. At D4, clean energy markets make a relatively larger contribution to transmission during the pandemic, while cobalt exhibits a stronger transmitter role during the conflict. At D6, the clean energy markets remain net receivers overall, whereas nickel becomes an important long-horizon net transmitter during the Russia–Ukraine conflict. These changes suggest that major external shocks do not simply raise or lower system-wide connectedness; they can also reconfigure the direction of transmission and the roles played by individual markets.

Taken together, the dynamic results reinforce the multiscale evidence reported above. Short-term connectedness is more responsive to abrupt market disturbances, whereas transmission roles at medium- and longer-term horizons display greater persistence but can still be substantially reshaped by major shocks. Accordingly, identifying the dominant market in the clean energy–metal system requires consideration of both the investment horizon and the prevailing market environment.

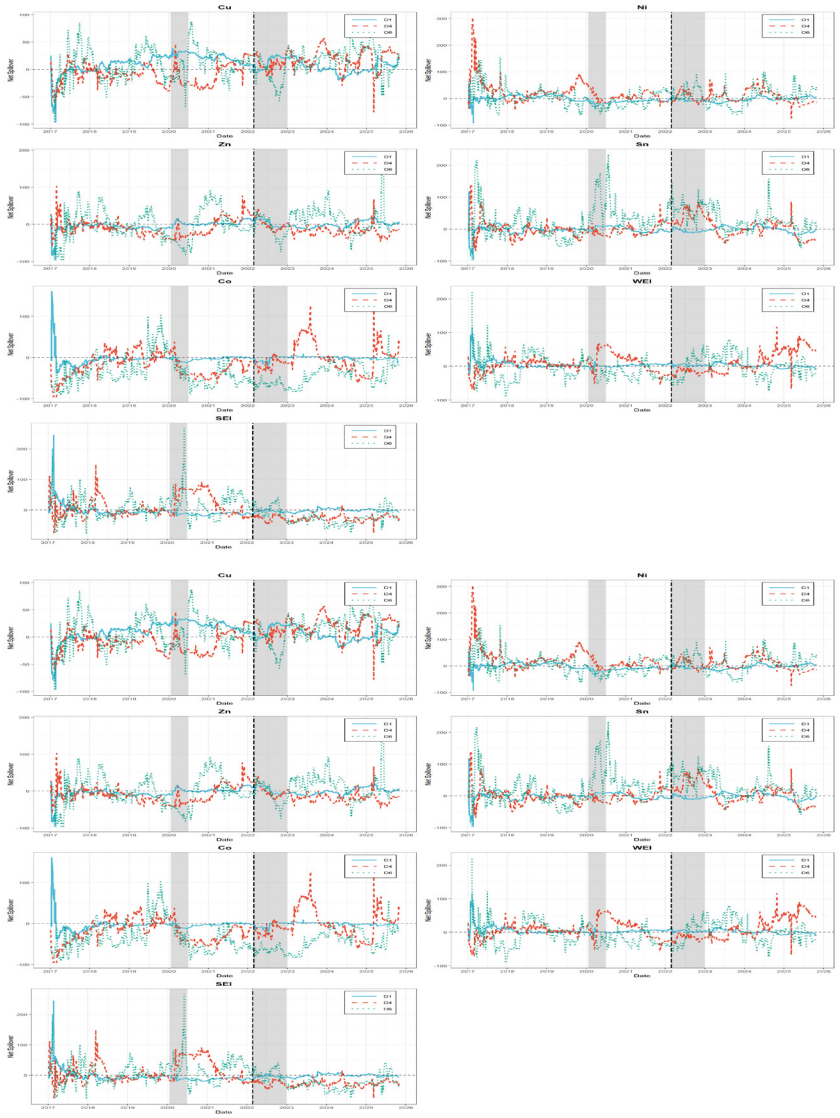


Figure 7. Dynamic net spillover indices for individual markets.

3.5. Net spillover networks

To identify specific transmission channels, pairwise net spillover networks are constructed at different time scales, as shown in Figure 8. Network linkages generally strengthen as the time scale increases, and the metal markets gradually shift from net receivers to net transmitters relative to the clean energy markets. This time-varying pattern is consistent with the related findings of Zhu et al. [20].

At D1, spillovers are strong between solar and wind energy and between copper and nickel. Copper is the main net transmitter, while cobalt is the main net receiver, consistent with Li et al. [21] and Su et al. [22]. At D4, the cobalt–nickel linkage is the strongest, nickel's role as a net transmitter strengthens, and the relative role of the clean energy markets weakens. At D6, within-metal spillovers strengthen further, the cobalt–tin linkage is the strongest, and the overall direction of cross-market transmission runs from the metal markets to the clean energy markets.

Cobalt remains a net receiver over the long term, possibly because of the high concentration of its resource base and its low supply elasticity. As demand for new energy expands, shocks from downstream energy-storage and electric-vehicle markets may therefore be transmitted more readily to the cobalt market. Watari et al. also note that the development of new energy markets can substantially alter demand for critical metals and their price-formation mechanisms [23].

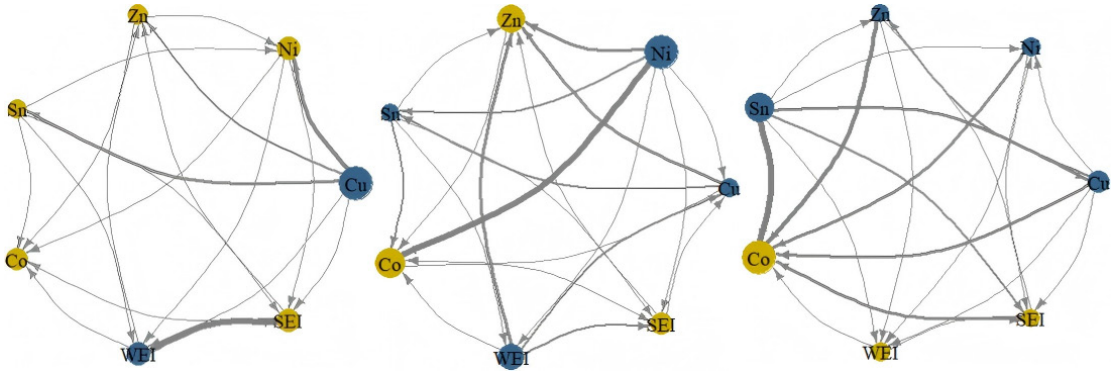


Figure 8. Pairwise directional net spillover networks.Note: Line width indicates the strength of net spillovers between two markets, node size represents a market's overall role as a net transmitter or net receiver, and arrows point from net transmitters to net receivers.

4. Conclusions and implications

4.1. Main conclusions

This study examines multiscale connectedness between metal futures and global clean energy equity markets using wavelet coherence, MODWT, and the TVP-VAR-DY framework.

First, connectedness shows clear horizon dependence. The total connectedness index increases from 36.65% at D1 to 58.34% at D4 and 67.19% at D6, indicating stronger medium- and longer-term linkages.

Second, market roles change across horizons. Copper is the main net transmitter at D1, nickel dominates at D4, while tin and copper become the main transmitters at D6. Cobalt remains a net receiver across all three scales, while wind and solar energy markets generally play weaker transmission roles at longer horizons.

Third, the transmission structure differs across major external shock periods. The COVID-19 pandemic and the Russia–Ukraine conflict are associated with different dominant transmitters across scales, showing

that market leadership depends on both investment horizon and external conditions.

Overall, the results suggest that the clean energy–metal transmission structure is neither time-invariant nor horizon-invariant.

4.2. Implications

The results provide several practical implications. First, investors should consider horizon-dependent connectedness when allocating clean energy and metal assets. Weaker short-term linkages may provide greater diversification benefits, while stronger medium- and longer-term connectedness may reduce such benefits.

Second, clean energy firms should incorporate changing metal-market transmission roles into procurement and risk management. Short-term inventory flexibility can help absorb temporary shocks, while longer-term supply diversification may reduce exposure to persistent metal-market disturbances.

Third, regulators should monitor both total connectedness and changes in directional transmission. Major shocks may alter not only system-wide connectedness but also the identity of key transmitters. Strengthening supply-chain resilience and cross-market information sharing may therefore help reduce persistent spillover risks.

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