Multilayer Information Spillover Network Analysis in Fossil Energy, Metal, and Clean Energy Markets

Xinnan Hong *

School of Nanjing University of Science and Technology, Nanjing 210000, China

* Corresponding Author Email: Hong222@163.com

Abstract. With the accelerating transformation of the global energy structure, the interplay between fossil energy and clean energy markets has become increasingly complex, while critical metal markets further shape the overall risk landscape. To systematically characterize the multidimensional risk transmission among these three markets, this study constructs a multi-layer information spillover network encompassing returns, volatility, and extreme risk. Using daily data from May 1, 2014, to April 30, 2024, and employing the TVP-VAR model and multi-layer network methodology, the research reveals risk spillover mechanisms from both static and dynamic perspectives. The findings indicate: first, significant risk spillover effects exist between energy and metal markets; second, the systemic spillover effects exhibit clear time-varying characteristics, with the volatility dimension being particularly sensitive to shocks from major events; third, the roles of key markets are dimension-dependent: clean energy consistently acts as a net risk transmitter across all three dimensions, while markets such as copper and coal play varying roles under different dimensions, and the safe-haven function of precious metals weakens significantly under extreme conditions. The conclusions of this study provide a basis for regulatory authorities to construct a multidimensional risk monitoring framework and offer insights for investors to implement cross-dimensional risk management strategies.

Keywords: fossil energy, metals, clean energy, multi-layer networks, information spillover.

1. Introduction

The fast escalation of global energy demand and intensified energy consumption have triggered increasingly severe climate and environmental challenges. Against this backdrop, low-carbon and green development have emerged as a worldwide consensus, with countries accelerating their transition from fossil energy to clean energy (Tiwari, 2024; Huang et al., 2025). The International Energy Agency's (IEA) World Energy Outlook 2024 forecasts that the global clean energy generation capacity will rise from the current 4,250 GW to nearly 10,000 GW by 2030, while the demand for critical minerals will double. By 2040, this figure is expected to quadruple, with the market for metals such as copper, lithium, and nickel reaching an estimated value of $770 billion. This transformation not only reshapes the energy market's structure but also profoundly impacts the metal market.

Amid the ongoing energy transition, energy and metal systems have evolved rapidly, forming complex and interconnected cross-market linkages (Chen et al., 2022). The interplay between fossil and clean energy markets is characterized by both complementarity and substitutability (Liang et al., 2015; Yarovaya et al., 2022). Specifically, fossil energy, owing to its inherent stability, provides essential support for the advancement of clean energy (Sohag et al., 2023; Zhu et al., 2025), and the rise of clean energy exerts substitution pressure on the fossil energy market, driving fossil energy enterprises to accelerate their transition toward low-carbon models (Geng et al., 2021; Chen et al., 2024). As fundamental resources underpinning economic development, fossil energy and metal markets exhibit a persistent and interactive relationship (Cagli et al., 2019). The extraction and refining processes of metal are highly reliant on fossil energy inputs (Zhou et al., 2022), while the growing adoption of clean energy technologies has sharply heightened the demand for key metals, further driving the financialization of metal markets (Chen et al., 2022). Such development not only reinforces the coupling of energy and metal markets but also exacerbates the transmission of risks across these markets. For instance, fluctuations in energy prices directly influence the production costs and supply stability of metals, thereby amplifying price volatility in metal markets. A case in point is the solar energy market, where rapid growth has spurred heightened demand for silicon and silver, leading to significant upward pressure on their prices.

Given the close and complex interrelationship between energy and metals, the spillover effects among fossil energy, clean energy, and metal sectors need to be further explored. Although the interactions between energy and metal markets have been extensively examined, most studies focus on the interactions within the energy markets (Zhang et al., 2019; Ren et al., 2025; Xie et al., 2025) or between a single energy and metal market (Gustafsson et al., 2022; Bouri et al., 2023). In other words, the broader network-level interactions among these three markets remain underexplored. By distinguishing between fossil energy and clean energy, we can more clearly discern the complex risk transmission relationships between energy and carbon markets during the societal shift towards low-carbon alternatives. This study, therefore, integrates fossil energy, metal, and clean energy markets into a unified framework to thoroughly analyze the risk interdependencies. Along this line, the first key question this paper focuses on is what distinct roles do these three markets play in the spillover dynamics?

Furthermore, in response to catastrophic occurrences such as the COVID-19 pandemic, recent studies have shifted their focus from the return or volatility level to tail risk. While information spillover networks serve as effective tools for quantifying market interconnectedness, most existing networks are single-layered, focusing only on particular types of spillover effects while overlooking the diversity and heterogeneity of information spillovers across markets (Wang et al., 2021; Dai et al., 2023). This raises the second key question: Do the interactions between energy and metal markets exhibit varying degrees of influence under different conditions? Moreover, how does the overall market connectivity evolve under different conditions?

To address these issues, this study constructs a multi-layer information spillover network incorporating return, volatility, and extreme risk spillovers to explore the interconnections among fossil energy, clean energy, and metal markets. Based on the spillover indices derived from the time-varying parameter vector autoregression (TVP-VAR) model, we analyze the static spillover effects, total connectivity, directional spillovers, and net spillover characteristics among these markets. The findings indicate that clean energy, as the dominant net risk transmitter, plays a leading role, with its transmission effect being more pronounced under extreme risks. Fossil energy exhibits strong self-spillover effects, while the metal market displays dual characteristics: precious metals serve as risk absorbers under normal conditions (but their hedging role weakens during crises), whereas industrial metals consistently amplify risk spillover effects.

The remainder of the paper is structured as follows: Section 2 presents the literature review; Section 3 outlines the methodology; Section 4 details the data and empirical results; and Section 5 concludes the analysis.

2. Literature Review

2.1. Research on the interrelationship between fossil energy, metals, and clean energy

Two pivotal aspects of the global energy transition have emerged as key research foci in recent literature (Huang et al., 2025; Lin et al., 2025), namely the connection between energy and metal sectors, and the interaction between the markets for clean and fossil energy. The interconnection of fossil energy, metal, and clean energy markets is deeply intertwined, reflecting the intricate structure of energy systems during the transition era. From one perspective, the metal industry, as a highly energy-intensive sector, exhibits pronounced sensitivity to fossil energy markets, with variations in both natural gas and crude oil prices directly influencing production costs and final product pricing (Wang et al., 2021). From another perspective, the transition to clean energy has created new dependencies on critical metal resources such as aluminum, lithium, and copper, which are vital for renewable energy technologies (Valero et al., 2018). This dual dynamic—linkages between fossil energy and metal sectors, as well as dependence on clean energy and metal sectors—highlights the multifaceted nature of energy-market interdependencies.

Moreover, the connectedness between fossil and clean energy markets has been shaped by the substitutive characteristics of fossil energy sources and the growing role of renewables in the global energy mix. Fossil energy markets, particularly oil and natural gas, exert a significant influence on clean energy markets due to their substitutive nature (Geng et al., 2021; Chen et al., 2024). For instance, rising oil prices can drive up clean energy prices and stimulate their development (Shaen et al., 2020). However, this relationship is not static; it varies under different market conditions, with connections significantly strengthening during extreme conditions and crises (Dawar et al., 2021; Umar et al., 2022). Khalfaoui et al. (2022) further emphasize the asymmetric responses of clean energy markets to shocks from stock and oil markets, which are contingent upon the prevailing market conditions.

The intricate relationship between these markets is further complicated by the pivotal role of critical metals in enabling clean energy technologies. As global decarbonization efforts intensify, the burgeoning demand for key metals has surged. This phenomenon has given rise to a novel form of resource interdependencies between energy and metal markets. Empirical studies reveal intricate interactions within these relationships. Zhu et al. (2025) demonstrate an inverse relationship between metal price increases and clean energy consumption, while Yahya et al. (2020) identify time-varying, asymmetric dependencies that intensify during periods of market turmoil using copula methods. These findings collectively underscore the evolving and interconnected nature of energy, metal, and clean energy markets in the context of the global energy transition.

2.2. Research on information spillover methods

The rapid evolution of methodologies for estimating market interdependencies has significantly enhanced our ability to analyze the complex interconnectedness of energy, metal, and clean energy markets. These advancements can be broadly categorized into three groups: correlation and risk spillover models, such as copula and GARCH models; spillover index frameworks, including the Diebold-Yilmaz (DY) approach and its extensions; and time-varying models, such as TVP-VAR and quantile spillover methods (Liow et al., 2021; Liao et al., 2021). Each category addresses specific aspects of market interdependencies, offering unique insights into risk transmission, volatility dynamics, and evolving relationships.

Among these, copula models have gained prominence for their flexibility in capturing non-normal, asymmetric, and nonlinear distributions, making them particularly suitable for studying extreme risk spillovers. For instance, Ji et al. (2018) utilize copula models to investigate extreme spillover effects in energy markets, revealing asymmetric behaviors under CoVaR and ΔCoVaR conditions. Similarly, Xu et al. (2021) combine a copula with CoVaR to explore asymmetric risk spillovers between domestic and international energy markets, particularly in the context of carbon market risks. Complementing these approaches, GARCH models, especially the BEKK-GARCH variant, have been widely applied to study volatility spillovers. Building on this methodology, Sadorsky et al. (2012) demonstrate significant volatility linkages between the petroleum and clean energy sectors, with their GARCH-based analysis revealing oil futures' hedging efficacy for clean energy investments. Extending this line of research, Lan et al. (2024) investigate China's multi-market dynamics, analyzing volatility transmission among carbon trading, conventional and renewable energy sectors, high-tech industries, and climate policy uncertainty, with a particular focus on the time-varying nature of spillover effects.

Building on these foundations, spillover index frameworks, such as the DY approach, have become a cornerstone in quantifying risk spillovers. The DY method, based on variance decomposition from VAR models, provides a robust metric for measuring interconnectedness (Diebold and Yilmaz, 2009). Ahmad (2017) employs the DY framework to analyze the bidirectional transmission channels between oil sectors and renewable equity markets, with clean energy indices emerging as significant transmitters of return spillovers to hydrocarbon markets. Song et al. (2019) construct a spillover network for multiple markets, demonstrating that fossil fuel price fluctuations, particularly oil, exert a stronger influence on renewable energy prices than investor sentiment. However, traditional DY methods often fail to capture evolving spillover dynamics and potential information loss, prompting the development of more dynamic frameworks.

In response to these limitations, time-varying models, such as TVP-VAR, have emerged as powerful tools for accurately depicting changing market linkages, particularly demonstrating efficacy in modeling dynamic interdependencies (Liow et al., 2021; Liao et al., 2021; Zheng et al., 2024; Zhang et al., 2025). Pham and Nguyen (2022) demonstrate the utility of TVP-VAR in showing green bonds' hedging potential against oil uncertainty, with correlations intensifying during periods of high uncertainty. Similarly, Feng et al. (2023) employ a time-varying spillover model to study the interconnectedness between energy and metal markets, finding that connectivity peaks during crises. Dai et al. (2023) employ TVP-VAR to examine the dynamic spillover effects between fossil energy and the Chinese stock market, concluding that WTI serves as a cost-effective hedging tool. These models not only enhance the accuracy of spillover estimation but also provide more profound insights into the intricate interconnections across hydrocarbon, transition metal, and renewable energy markets.

Despite these advancements, the application of TVP-VAR models has primarily focused on pairwise relationships, such as energy-stock or energy-metal interactions (Feng et al., 2023). While this approach has provided valuable insights into specific market dynamics, it often overlooks the interconnected nature of the global energy transition, where fossil energy, clean energy, and metal markets influence one another simultaneously. Moreover, traditional spillover frameworks, including the DY index, tend to focus on single-layer networks, which may fail to capture the diversity and heterogeneity of information spillovers across markets (Wang et al., 2021). These limitations highlight the need for a more comprehensive framework that can integrate multiple dimensions of market interdependencies, capturing not only dynamic and asymmetric spillover effects but also the systemic interactions among fossil energy, clean energy technologies, and mineral markets. Addressing this gap is essential for enhancing our understanding of the intricate interactions influencing the global energy transition.

2.3. Literature Review

Through a systematic review of relevant literature at home and abroad, it can be found that the academic community has accumulated rich achievements in the fields of energy and metal market linkage, information spillover methods, etc., laying a solid theoretical foundation and methodological support for this study. However, there is still room for improvement in the following areas:

Firstly, in terms of research subjects, most existing literature focuses on analyzing the bilateral relationship between two types of markets, or simply comparing clean energy with fossil energy. There is little literature that systematically analyzes fossil energy, metals, and clean energy as a whole. Based on this, this article incorporates the above three types of markets into a unified analysis framework to better understand the complex interrelationships between markets in the context of energy transition.

Second, in terms of research dimensions, existing studies mostly focus on spillover effect analysis at the return and volatility levels, with relatively insufficient attention paid to the extreme risk dimension. In response to this limitation, this article comprehensively reveals the multidimensionality of the risk transmission mechanism between the energy and metal markets by constructing spillover networks in three dimensions: return, volatility, and extreme risk.

3. Methodology

This paper proposes an information spillover network comprising return spillover, volatility spillover, and extreme risk spillover layers. We first define return, volatility, and extreme risk, then introduce the DY spillover index method based on the TVP-VAR model to explore the relationship among the metal-clean energy-fossil energy system.

3.1. Definitions of return, volatility, and extreme risk

To comprehensively analyze the risk characteristics of the fossil energy, metals, and clean energy markets, we define three dimensions: return, volatility, and extreme risk. The return is used to measure the average performance of markets, volatility reflects the market's fluctuation amplitude and uncertainty, while extreme risk is used to assess the market's risk level and potential losses during extreme events.

To measure return, we select the closing price data of various market indicators to measure their return performance. For each market *i*, the daily return is defined as:

$$R_{it}=\ln(p_{it}/p_{it-1}) \tag{1}$$

where p_{it} represents the closing price of market *i* on day *t*.

Following Dong et al. (2024), we employ GARCH modeling to derive volatility series from return data. The technical implementation involves:

First, establishing an *N*-variable VAR(*P*) system satisfying covariance stationarity:

$$x_t = \sum_{i=1}^{P} \Phi_i x_{t-1} + \varepsilon_t \tag{2}$$

where $\varepsilon \sim (0, \sum)$ represents independently and identically distributed disturbances.

Second, decomposing into a moving average representation:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{3}$$

With coefficient matrices recursively defined:

$$A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_P A_{i-P} \tag{4}$$

where A_0 as the $N\times N$ identity matrix and with $A_i=0$ for $i<0$.

In terms of characterizing extreme risk, we adopt the Conditional Autoregressive Value at Risk (CAViaR) model proposed by Engle and Manganelli (2004). The key idea of this model is to directly calculate Value at Risk (VaR) using an autoregressive approach, without estimating the shape and parameters of the return distribution. This method is particularly suitable for handling thick-tailed data in financial markets, as it can more accurately capture the impact of extreme market movements on risk value. The general CAViaR model can be expressed as:

$$\mathrm{VaR}_{it}(\varphi_i) = \varphi_{i0} + \sum_{j=1}^{q} \varphi_{ij}\,\mathrm{VaR}_{it-j}(\varphi_i) + \sum_{j=1}^{r} \varphi_{i(q+j)}\,L(R_{it-j}) \tag{5}$$

where VaR_{it} represents the VaR for market *i* on day *t*, and L is a function of a finite number of lagged observations. The autoregressive component allows the VaR to change smoothly over time. Specifically, following Hong et al. (2009), we use the asymmetric slope model of CAViaR for VAR calculations, which is given by:

$$\mathrm{VaR}_{it}(\varphi_i) = \varphi_{i0} + \varphi_{i1}\mathrm{VaR}_{it-1}(\varphi_i) + \varphi_{i2}(r_{it-1})^{+} + \varphi_{i3}(r_{it-1})^{-} \tag{6}$$

where $(r_{it-1})^{+}$=max（r_{it-1},0）, $(r_{it-1})^{-}$=min（r_{it-1},0）, φ_{i2} and φ_{i3} represent the impact of positive and negative return on VaR, VaR_{it} represent the risk value at the 5% level.

3.2. TVP-VAR-DY

We measure the information spillover effects among markets based on the TVP-VAR model, which is proposed by Antonakakis and Gabauer (2017) and is a highly favored tool for financial studies (Deng et al., 2024; He et al., 2025). Compared to similar methods such as wavelet analysis, it has significant advantages in allowing for flexible specification of the rolling window size. The *P*-order TVP-VAR model can be constructed as:

$$z_t = B_1 z_{t-1} + B_2 z_{t-2} + \cdots + B_P z_{t-p} + u_t \qquad u_t \sim N(0, S_t) \tag{7}$$

$$\mathrm{vec}(B_t) = \mathrm{vec}(B_{t-1}) + v_t \qquad v_t \sim N(0, R_t) \tag{8}$$

where $k \times k$ matrices B_t and S_t represent the time-varying VAR coefficients and the variance-covariance matrix, $vec(B_t)$ and v_t are $k^2 \times 1$ vectors, and R_t is a $k^2 \times k^2$ matrix.

To estimate the connectivity process using the Generalized Forecast Error Variance Decomposition (GFEVD) and Generalized Impulse Response Function (GIRF) proposed by Diebold and Yilmaz (2014), we employ the Kalman filter with a forgetting factor. This approach allows for the estimation of the time-varying parameters and time-varying variance-covariance matrix in the model. Following Wold's theorem, we transform the TVP-VAR into its Vector Moving Average (VMA) representation, which is expressed as follows:

$$z_t = \sum_{i=1}^{P} B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j} \tag{9}$$

After normalizing the unscaled GFEVD, row-wise summation return unity. Thus, $\widehat{\Psi}^{g}_{ij,t}(H)$ can explain the normalized variance contribution from j to i. This quantifies the directional pairwise spillover intensity:

$$\Psi^{g}_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota_i' A_t S_t \iota_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i A_t S_t A_t' \iota_i)}, \widehat{\Psi}^{g}_{ij,t}(H) = \frac{\Psi^{g}_{ij,t}(H)}{\sum_{j=1}^{k} \Phi^{g}_{ij,t}(H)} \tag{10}$$

where, $\sum_{j=1}^{k} \widehat{\Psi}^{g}_{ij,t}(H)=1$, $\sum_{i,j=1}^{k} \widehat{\Psi}^{g}_{ij,t}(H)=k$, H is the forecast horizon, ι_i represents the selection vector, with its i-th element set to 1 and all others to 0.

The shock from variable i to other variables j (TO) can be expressed as:

$$C^{g}_{i \to j,t}(H) = \sum_{j=1, i \neq j}^{k} \widehat{\Psi}^{g}_{ji,t}(H) \tag{11}$$

Similarly, the shock from other variables j to i (FROM) can be represented as:

$$C^{g}_{i \leftarrow j,t}(H) = \sum_{j=1, i \neq j}^{k} \widehat{\Psi}^{g}_{ij,t}(H) \tag{12}$$

The net spillover effect is computed by subtracting incoming spillovers from outgoing spillovers for a given variable, expressed mathematically as:

$$C^{g}_{i,t}(H) = C^{g}_{i \to j,t}(H) - C^{g}_{i \leftarrow j,t}(H) \tag{13}$$

The market interconnectedness is determined by the Total Connectedness Index (TCI), which measures the extent to which spillover effects between energy and metals impact the overall system. The TCI can be calculated as:

$$C^{g}_{t}(H) = \frac{\sum_{i,j=1, i \neq j}^{k} \widehat{\Psi}^{g}_{ij,t}(H)}{\sum_{i,k=1}^{k} \widehat{\Psi}^{g}_{ij,t}(H)} = \frac{\sum_{i,j=1, i \neq j}^{k} \widehat{\Psi}^{g}_{ij,t}(H)}{k} \tag{14}$$

4. Data and Empirical Findings

4.1. Data

To determine the time-frequency risk spillover effects on return, volatility, and extreme risk between fossil energy, metals, and clean energy markets, we utilize WTI crude oil futures (oil), natural gas futures (gas), and Rotterdam coal futures (coal) from the London International Petroleum Exchange (IPE), along with COMEX gold futures (gold), COMEX silver futures (silver), LME copper futures (copper), LME aluminum futures (aluminum), LME zinc futures (zinc), LME nickel futures (nickel), LME tin futures (Tin), LME lead futures (Lead), and three indicators representing the clean energy market: iShares Global Wind Energy (Wind), Invesco Solar ETF (Solar), and iShares Global Clean Energy (Clean). We selected daily closing price data from May 1, 2014, to April 30, 2024. Due to the impacts of the COVID-19 pandemic and the Russia-Ukraine conflict, outliers occurred in the oil and nickel markets on April 20, 2020, April 21, 2020, and March 7, 2022, respectively. To avoid influencing the results, these three days' outliers were specifically excluded.

Data for the metals market was sourced from iFind, while data for clean energy and fossil energy markets were sourced from Investing.com (https://cn.investing.com/).

4.2. Empirical findings

4.2.1 Static spillover effects

To enhance our understanding of time-frequency spillover effects within the fossil energy-metals-clean energy relationship, we measure market connectivity across three dimensions: return, volatility, and extreme risk. In this study, the lag order of the TVP-VAR model was determined to be 3 based on the SIC criterion.

Table 1. Static spillover effect of return

	oil	gas	coal	wind	solar	clean	gold	silver	copper	aluminum	zinc	nickel	tin	lead	FROM
oil	53.5	3.7	2.4	2.8	3.4	3.1	2.8	3.7	6.8	4.5	3.4	3.5	3.2	3.3	46.5
gas	3.6	22.0	4.5	4.7	2.6	4.1	5.6	3.8	10.7	5.5	8.2	10.1	9.6	5.1	78.0
coal	2.5	3.3	61.4	2.7	4.5	4.7	1.8	3.4	3.2	1.0	1.3	0.2	0.4	0.8	38.6
wind	0.2	0.2	1.5	52.1	15.2	20.1	1.2	3.8	2.1	1.0	1.3	0.2	0.4	0.8	47.9
solar	4.2	2.7	4.3	11.5	26.7	25.3	2.1	4.7	3.1	1.5	2.4	4.4	3.0	4.0	73.3
clean	3.8	3.0	4.0	12.8	26.0	27.3	2.3	4.0	3.2	1.2	2.0	4.3	2.7	3.4	72.7
gold	7.3	4.4	5.9	13.6	4.8	6.1	22.7	11.5	2.5	1.1	4.6	7.4	3.7	4.6	77.3
silver	9.2	5.5	4.9	8.9	3.4	4.2	10.7	21.6	6.5	1.9	8.3	6.0	3.2	5.5	78.4
copper	2.7	4.0	4.7	9.7	4.5	5.0	2.3	7.3	23.8	7.8	9.0	7.6	4.9	6.8	76.2
aluminum	4.3	2.4	3.6	11.4	3.1	4.0	4.6	4.6	9.0	24.2	9.7	9.6	6.6	2.9	75.8
zinc	5.1	4.0	2.2	11.0	5.4	6.0	3.3	5.7	9.0	5.7	22.8	6.2	4.9	8.6	77.2
nickel	1.0	4.4	3.4	7.2	4.1	4.4	5.1	4.8	9.0	6.1	6.9	26.2	11.7	5.8	73.8
tin	6.1	5.8	4.4	9.9	2.4	4.5	4.3	6.3	8.7	4.2	5.8	10.7	24.3	2.7	75.7
lead	1.7	3.0	6.9	8.2	5.3	5.8	4.4	5.0	8.7	3.9	9.4	6.6	4.2	26.8	73.2
TO	51.5	46.4	52.7	114.5	84.6	97.3	50.4	68.6	82.6	45.4	74.3	80.0	59.9	56.2	TCI
NET	5.0	-31.6	14.1	66.6	11.3	24.6	-26.9	-9.8	6.4	-30.4	-2.9	6.3	-15.8	-17.0	68.9

Table 2. Static spillover effect of volatility

	oil	gas	coal	wind	solar	clean	gold	silver	copper	aluminum	zinc	nickel	tin	lead	FROM
oil	27.9	1.6	7.8	28.6	4.5	8.2	2.4	5.1	1.0	0.3	0.3	1.5	9.8	1.1	72.1
gas	2.9	57.0	0.2	16.1	3.7	5.2	1.0	1.9	3.3	1.3	0.6	1.3	4.4	1.1	43.0
coal	12.6	7.2	70.4	0.7	0.6	0.7	0.3	1.0	0.6	0.5	0.1	0.4	4.7	0.0	29.6
wind	1.4	0.1	0.6	54.2	11.1	14.7	2.3	9.2	1.6	1.2	0.7	0.1	2.0	0.7	45.8
solar	6.6	0.4	0.5	13.8	36.7	30.0	1.2	2.7	0.3	0.8	5.8	0.3	0.9	0.0	63.3
clean	6.1	0.5	0.7	16.7	28.8	32.4	1.4	3.2	0.2	0.6	8.8	0.1	0.2	0.2	67.6
gold	3.6	4.4	3.0	1.3	1.2	2.2	46.0	13.8	0.7	7.5	1.9	11.9	1.1	1.5	54.0
silver	8.5	2.3	0.2	8.5	5.2	4.0	18.7	26.7	3.4	7.2	1.2	8.3	2.9	3.0	73.3
copper	3.4	0.8	2.8	3.5	2.0	4.5	2.7	4.8	42.8	7.9	3.4	1.3	12.4	7.7	57.2
aluminum	3.0	1.5	8.3	2.3	2.9	3.3	6.6	1.0	3.8	49.7	9.4	3.5	3.1	1.7	50.3
zinc	0.8	0.2	2.8	1.0	0.5	1.2	5.4	2.4	3.4	5.3	55.8	2.7	5.4	13.1	44.2
nickel	2.6	0.3	3.6	1.1	0.5	1.1	0.2	0.8	2.7	2.8	2.5	73.3	7.5	0.8	26.7
tin	1.3	2.1	2.0	0.3	0.6	0.9	1.5	3.1	4.7	15.6	0.5	2.0	64.4	0.9	35.6
lead	2.3	0.4	5.1	0.5	1.3	2.2	11.8	3.1	2.1	1.8	7.4	2.3	12.5	47.3	52.7
TO	55.1	21.8	37.6	94.5	63.0	78.1	55.3	52.1	27.9	52.9	42.8	35.8	66.8	31.8	TCI
NET	-17.0	-21.2	8.0	48.7	-0.3	10.5	1.2	-21.2	-29.3	2.5	-1.4	9.1	31.2	-20.9	51.1

Table 3. Static spillover effect of extreme risk

	oil	gas	coal	wind	solar	clean	gold	silver	copper	aluminum	zinc	nickel	tin	lead	FROM
oil	43.9	3.7	2.3	2.9	5.6	5.1	1.9	4.0	9.3	2.2	1.5	4.3	6.9	6.5	56.1
gas	9.1	36.1	3.0	4.7	3.8	2.8	5.0	5.1	5.4	9.5	2.9	4.2	4.7	3.7	63.9
coal	3.7	16.6	30.7	5.7	2.9	3.2	3.8	5.6	6.7	2.8	4.6	4.9	2.4	6.4	69.3
wind	0.1	1.0	0.1	81.0	2.5	8.1	0.4	0.2	3.8	0.1	0.8	0.3	1.1	0.6	19.0
solar	4.0	3.5	2.6	3.4	29.2	24.3	6.5	4.4	1.6	3.3	5.7	4.0	3.9	3.6	70.8
clean	3.7	1.3	1.9	5.2	28.5	34.2	4.7	2.5	1.7	1.6	3.0	5.0	4.5	2.0	65.8
gold	2.3	5.8	0.4	6.6	1.4	2.4	42.4	11.3	7.7	3.1	3.2	1.0	9.3	3.1	57.6
silver	3.8	6.7	1.0	2.4	3.5	3.0	13.0	35.8	8.3	1.9	7.4	1.4	4.0	7.9	64.2
copper	5.1	8.4	1.4	4.7	1.3	1.2	5.3	6.9	40.4	1.7	5.5	7.2	7.7	3.4	59.6
aluminum	4.9	5.5	2.1	1.8	6.4	6.1	1.8	3.3	7.4	33.0	4.7	6.9	7.5	8.5	67.0
zinc	3.1	7.5	0.7	5.4	2.1	3.0	5.0	3.9	5.1	4..1	42.2	4.6	7.0	6.2	57.8
nickel	12.6	3.9	3.2	3.5	3.4	3.9	3.9	6.0	5.1	2.7	2.7	36.6	8.7	3.8	63.4
tin	3.1	8.4	3.2	5.3	8.7	5.6	6.0	3.5	10.4	4.2	5.4	2.6	32.3	1.3	67.7
lead	2.9	8.9	2.5	4.0	6.1	8.3	2.5	4.3	7.3	2.4	2.4	4.8	1.7	41.9	58.1
TO	58.4	81.1	24.5	55.6	76.3	77.0	59.7	60.9	79.8	39.6	49.7	51.3	69.3	57.1	TCI
NET	2.3	17.2	-44.8	36.6	5.5	11.3	2.2	-3.3	20.2	-27.4	-8.1	-12.1	1.6	-1.0	60.0

Table 1 to Table 3 present the static spillover results for the fossil energy, metal, and clean energy systems at the return, volatility, and extreme risk levels, respectively. The analysis indicates that the system exhibits significant interconnectedness across different dimensions, with notable differences in the roles of each market and their transmission pathways.

First, there exists significant interconnectedness between energy and metal markets across all dimensions. The TCI exceeds 50% across all three levels, indicating that, against the backdrop of the energy transition, fossil energy, metals, and clean energy have formed a tightly interconnected composite system. Specifically, wind demonstrates significant spillover effects on markets such as copper, aluminum, and zinc, which may be related to the fact that clean energy development drives demand for key metals. The spillover index declines at the volatility level, suggesting that the transmission of uncertainty is more localized, and the diffusion of panic sentiment between markets is weaker than the propagation of price information. Notably, the spillover from wind to oil reaches 28.6% at this level. At the extreme risk level, the TCI increases again, indicating that certain contagion channels between markets are reinforced under extreme risk conditions.

Second, the roles of key markets in the risk transmission network exhibit clear "dimensional dependence." Within the fossil energy sector, oil acts as a mild net transmitter at the return level (NET=5%), transforms into a key net receiver at the volatility level (NET=-17%), and reverts to a weak net transmitter at the extreme risk level (NET=2.3%). Coal shifts from a net transmitter at the return and volatility levels to the largest net risk receiver at the extreme risk level (NET=-44.8%). This significant finding suggests that under extreme market conditions, coal, as a "dirty" energy source, can generate substantial spillover impacts on the entire system due to its sharp price fluctuations or sentiment shocks (Giglio et al., 2021; Sharma et al., 2023). In the metal markets, the "safe-haven" attribute of gold is most evident at the return level, with a NET value of -26.9%. Copper transitions from a net transmitter at the return level to a net receiver at the volatility level and then to a significant net transmitter at the extreme risk level (NET=20.2%). This shift reflects the extreme vulnerability of copper, as a cyclical asset, during market panics. Within the clean energy markets, most clean energy assets serve as significant net risk transmitters, particularly wind, which exhibits spillover effects of 114.5%, 94.5%, and 55.6% to other markets across the three dimensions, establishing it as the primary risk source in the system. This may be attributed to the high growth potential, policy dependency, and investor sentiment associated with clean energy markets.

The above analysis demonstrates that the risk linkages between energy and metal markets are multi-layered and asymmetric. In the context of the energy transition, risks do not propagate along fixed pathways but instead adapt to specific market conditions, leading to fundamental shifts in the roles of key markets.

4.2.2 Dynamic spillover effects

The static spillover effect can be used to measure the overall connectivity among three markets, but it also has limitations, such as its inability to capture the time-varying characteristics of spillover effects between markets (Kang and Yoon, 2019; Cui et al., 2021). Therefore, following Bouri et al. (2021) and Saeed et al. (2021), we employ a rolling window approach to examine the temporal fluctuations and spillover characteristics between markets. In our dynamic spillover analysis, we utilize a rolling window duration of 200 days with a forecast step size of 10 steps.

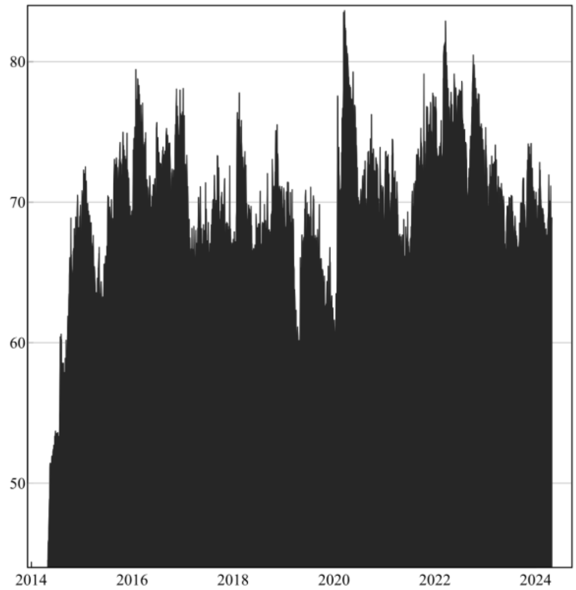

Figure 1. Dynamic spillover effects of return

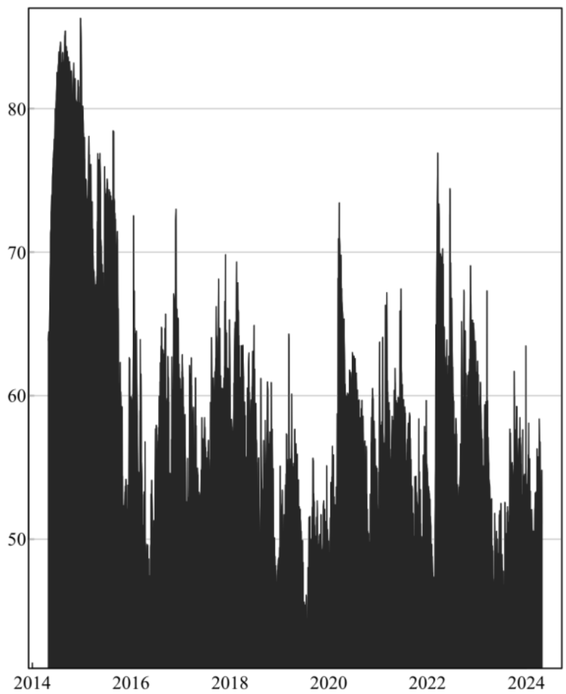

Figure 2. Dynamic spillover effects of volatility

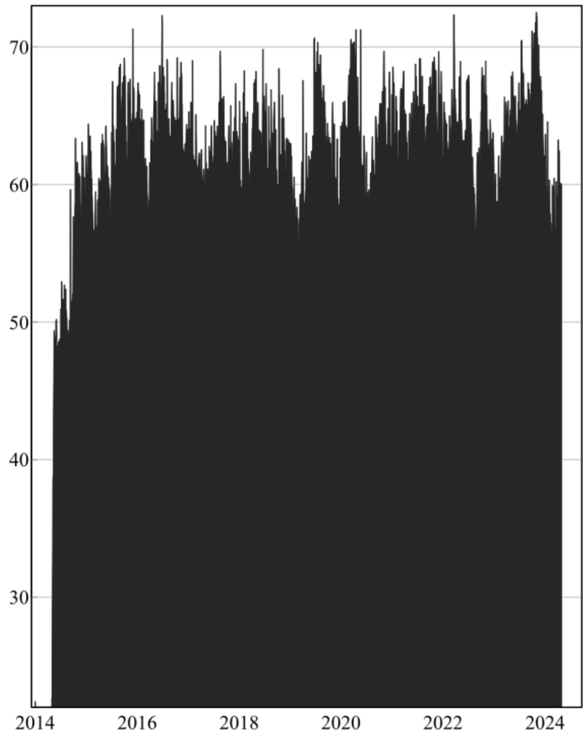

Figure 3. Dynamic spillover effects of extreme risk

Figures 1 to 3 illustrate the dynamics of total connectedness across three dimensions: return, volatility, and extreme risk. The results indicate that the Total Connectedness Index (TCI) across these three layers is not constant but exhibits considerable volatility. More importantly, the peaks of TCI are not randomly distributed; instead, they are closely concentrated around periods of major economic and geopolitical crises. Specifically, in early 2020, during the outbreak of the COVID-19 pandemic, the TCI across all three layers reached its highest or second-highest level within the sample period. This phenomenon suggests that the global public health crisis not only impacted various asset classes through real economic channels but also triggered widespread cross-market, cross-dimensional risk contagion through financial channels such as investor sentiment, liquidity stress, and policy resonance. Consequently, the interconnectedness between fossil energy, metals, and clean energy markets was significantly amplified in the short term. In early 2022, during the outbreak of the Russia-Ukraine conflict, the TCI across the three layers once again increased notably, forming a second distinct peak. During this period, risk contagion stemmed not only from the direct impact of the conflict on energy and metal supply chains but was also closely associated with heightened global inflation expectations, increased anticipation of monetary policy tightening, and the spread of market risk-aversion sentiment. Under the combined effect of multiple channels, the risk contagion effect was sharply magnified in response to external shocks.

In terms of response differences, the TCI of the return layer remained above the other two curves for most of the period, particularly during the two major crises, indicating that the spillover of returns is the most sensitive and intense in response to external shocks, and market uncertainty tends to propagate more rapidly in the return dimension.

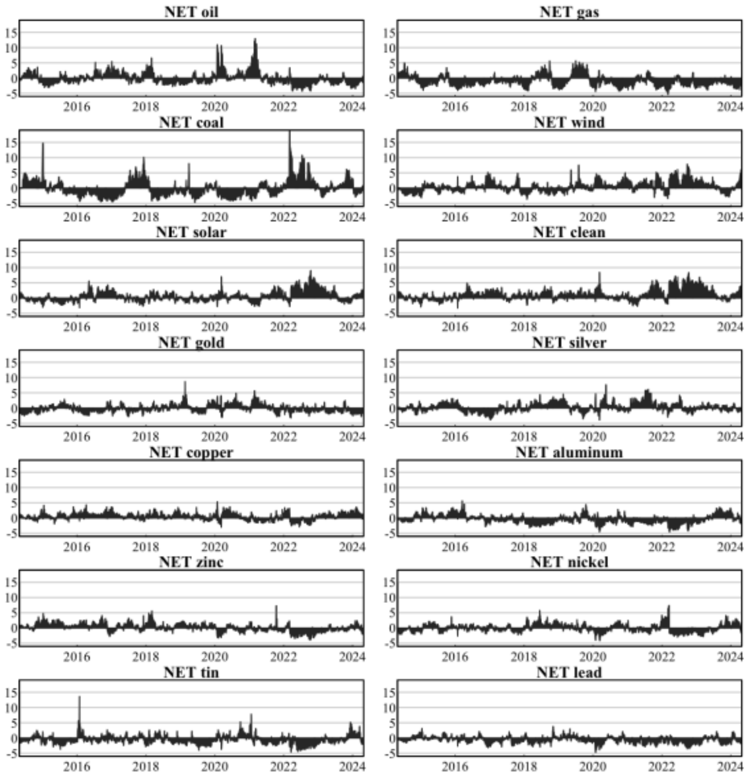

Figure 4. Time-varying net spillovers of return

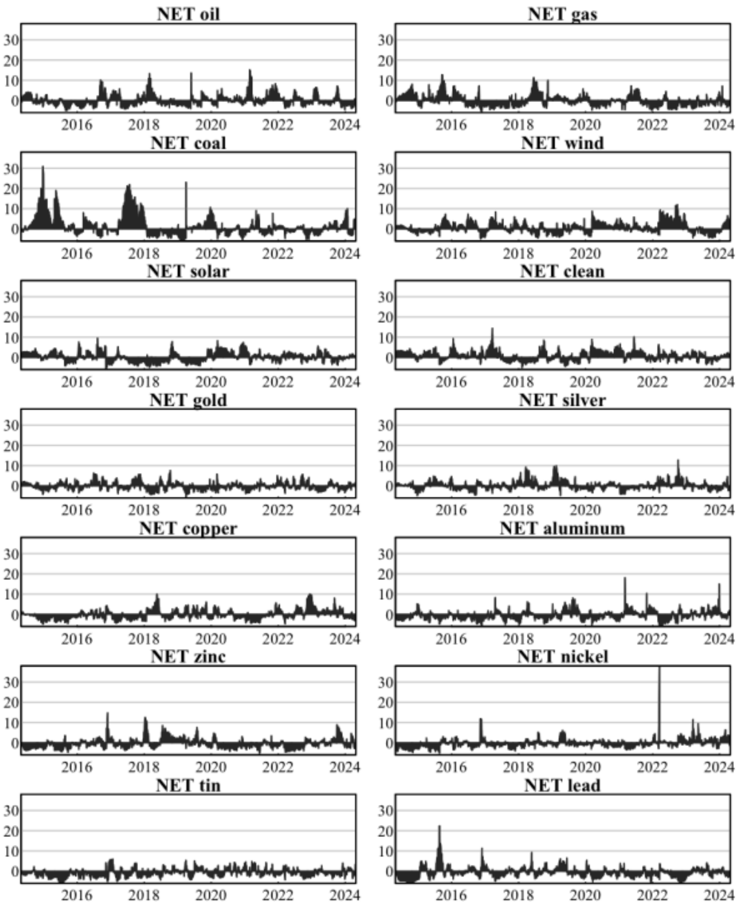

Figure 5. Time-varying net spillovers of volatility

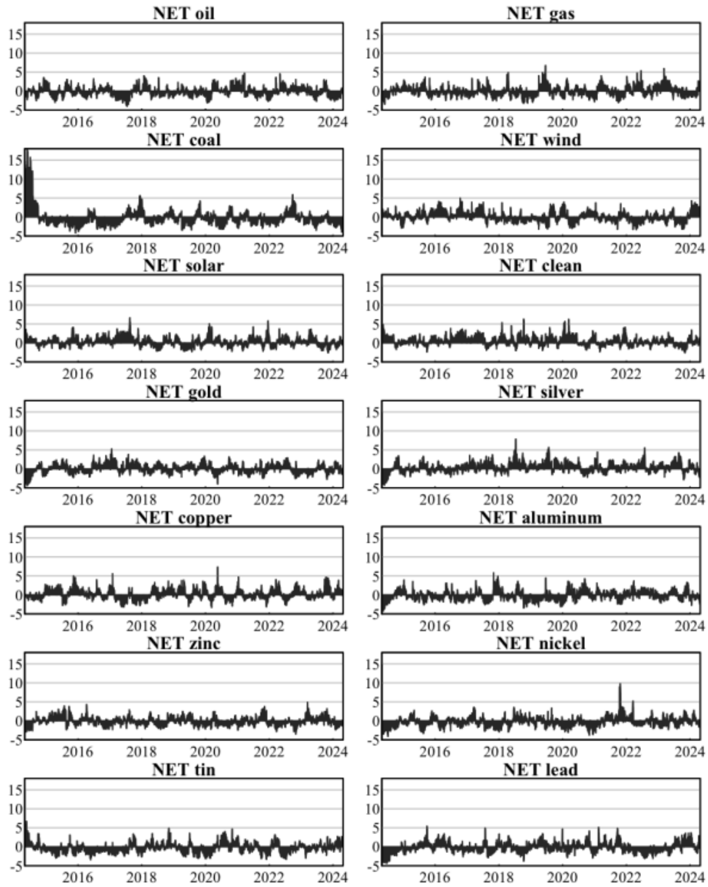

Figure 6. Time-varying net spillovers of extreme risk

To gain deeper insights into the dynamic nature of spillover effects across fossil energy, metals, and clean energy markets, this section constructs dynamic net spillover indices across three dimensions: returns, volatility, and extreme risk. Figures 4, 5, and 6 present the time-series results for these three layers, respectively. A comprehensive analysis indicates that spillover effects among markets and their dominant roles exhibit significant time-varying characteristics, closely linked to specific major events.

Dynamic analysis reveals that, whether in terms of returns, volatility, or extreme risk, the net spillover indices are non-stationary over the entire sample period, instead displaying sharp fluctuations and distinct phase-specific features. As shown in Figure 4, net spillovers from oil exhibit significant positive spikes during the 2018-2019 trade friction period, the initial outbreak of the COVID-19 pandemic in early 2020, and following the Russia-Ukraine conflict in 2022, indicating its role in releasing substantial price shocks during global crises. In contrast, net spillovers from the clean energy market show a noticeable increase and greater volatility after 2021, reflecting its growing yet less stable influence on the system amid the global green transition. The fluctuation amplitude and frequency of net spillover indices in the volatility layer are significantly greater than those in the returns layer. Notably, nickel reached a net volatility spillover of 30% in March 2022, corresponding to the “LME nickel short squeeze” event. In the extreme risk layer, spillover effects also undergo marked changes during major shocks, albeit with smaller fluctuation amplitudes compared to the volatility layer.

5. Conclusion

This study systematically investigates the risk transmission mechanisms among fossil energy, clean energy, and metal markets against the backdrop of the energy transition by constructing a multi-layer information spillover network across three dimensions: returns, volatility, and extreme risk.

Based on the TVP-VAR model and rolling-window estimation, the following key conclusions are drawn:

First, there exists a complex and tightly interconnected relationship between energy and metal markets. Static spillover analysis reveals that the total spillover index exceeds 50% across all three dimensions, confirming that the three markets are closely linked through industrial chains, investor sentiment, and policy expectations in the context of the energy transition.

Second, the spillover relationships between energy and metal markets exhibit time-varying characteristics. The study finds that during major external shocks, such as the COVID-19 pandemic and the Russia-Ukraine conflict, the total connectedness of the system undergoes significant changes, with the volatility dimension being the most sensitive to such shocks.

Third, the spillover roles of key markets are dimension-dependent. Clean energy assets predominantly act as net risk transmitters, while the roles of key fossil energy and metal markets vary across risk dimensions. For instance, copper transitions from a net transmitter at the return level to a net receiver at the volatility level and then to a significant net transmitter at the extreme risk level. Similarly, coal shifts from a net receiver at the return and volatility levels to the largest net risk receiver at the extreme risk level.

The findings of this study offer clear implications for both market participants and policymakers. For policymakers, it is essential to recognize the asymmetric characteristics of interconnectedness across different risk dimensions. By accurately identifying the specific directions and magnitudes of risk spillovers among fossil energy, metals, and clean energy, regulatory authorities can more effectively deploy policy tools, strengthen cross-market coordination mechanisms, and implement differentiated prudential supervision based on varying market conditions.

For investors, close attention should be paid to the dynamic evolution of cross-market risk spillover effects. In asset allocation and risk management, it is necessary to incorporate multi-dimensional information, including returns, volatility, and extreme risk, to dynamically adjust hedging strategies and diversify investment portfolios. This approach will help effectively mitigate downside risks and ensure the stable performance of investment portfolios.

References

[1] Tiwari S, Shahzad U, Alofaysan H, Walsh S T, Kumari P. How do renewable energy, energy innovation and climate change shape the energy transition in USA? Unraveling the role of green finance development[J]. Energy Economics, 2024, 140: 107947.

[2] Huang J Y, Liu Z H, Guo K. Climate risks and the connectedness between clean and dirty energy markets[J]. Finance Research Letters, 2025, 74: 106799.

[3] Chen J Y, Liang Z P, Ding Q, Liu Z H. Extreme spillovers among fossil energy, clean energy, and metals markets: Evidence from a quantile-based analysis[J]. Energy Economics, 2022, 107: 105880.

[4] Liang Q, Li Z, Hao X C. The internationalization of Chinese stock market: Based on information spillover[J]. Economic Research Journal, 2015, 50(4): 150-164.

[5] Yarovaya L, Brzeszczynski J, Goodell J W, Lucey B, Lau C K M. Rethinking financial contagion: Information transmission mechanism during the COVID-19 pandemic[J]. Journal of International Financial Markets, Institutions and Money, 2022, 79: 101589.

[6] Sohag K, Hassan M K, Bakhteyev S, Mariev O. Do green and dirty investments hedge each other?[J]. Energy Economics, 2023, 120: 106573.

[7] Zhu Y G, Gong Y, Yang L Y, Xu D Y. The rise of clean energy markets: Evidence from frequency-domain spillover effects between critical metals and energy markets[J]. Energy Economics, 2025, 141: 108126.

[8] Geng J B, Liu C, Ji Q, Zhang D. Do oil price changes really matter for clean energy returns?[J]. Renewable and Sustainable Energy Reviews, 2021, 150: 111429.

[9] Chen J, Chen Y, Zhou W. Relation exploration between clean and fossil energy markets when experiencing climate change uncertainties: substitutes or complements? [J]. Humanities and Social Sciences Communications, 2024, 11: 691.

[10] Cagli E C, Taskin D, Mandaci P E. The short-run and long-run efficiency of energy, precious metals, and base metals markets: evidence from the exponential smooth transition autoregressive models[J]. Energy Economics, 2019, 84: 1-9.

[11] Zhou Y, Wu S, Zhang Z. Multidimensional risk spillovers among carbon, energy and nonferrous metals markets: evidence from the quantile VAR network[J]. Energy Economics, 2022, 114: 106319.

[12] Zhang D Y, Ji Q, Kutan A M. Dynamic transmission mechanism in global crude oil prices: Estimation and implications[J]. Energy, 2019, 175: 1181-1193.

[13] Ren X H, He Y, Liu C W, Tao L Z. Extreme risk spillovers between SC, WTI and Brent crude oil futures-Evidence from time-varying Granger causality test[J]. Energy, 2025, 320: 135495.

[14] Xie Q C, Bi Y H, Xi Y Y, Xu X. The impact of geopolitical risk on higher-order moment risk spillovers in global energy markets[J]. Energy Economics, 2025, 144: 108292.

[15] Gustafsson R, Dutta A, Bouri E. Are energy metals hedges or safe havens for clean energy stock returns? [J]. Energy, 2022, 244: 122708.

[16] Bouri E, Lei X, Xu Y H, Zhang H W. Connectedness in implied higher-order moments of precious metals and energy markets[J]. Energy, 2023, 263: 125588.

[17] Wang P, Wang Q C, Han R R. Nexus between low-carbon energy and critical metals: literature review and implications[J]. Resources Science, 2021, 43(4): 669-681.

[18] Dai Z F, Tang R, Zhang X T. A new multilayer network for measuring interconnectedness among the energy firms[J]. Energy Economics, 2023, 124: 106880.

[19] Huang S P, Wang X Y, Ji Q. How unexpected geopolitical risk affect the nonlinear spillover among energy and metal markets? [J]. Energy Economics, 2025, 142: 108143.

[20] Lin B Q, Zhang Z Y. Extreme spillovers among green finance, energy, and energy metals markets in China: Evidence under the dilemma of energy transition[J]. Renewable Energy, 2025, 241: 122403.

[21] Vidal O, Rostom F, Francois C, Giraud G. Global trends in metal consumption and supply: the raw material-energy nexus[J]. Elements, 2017, 13(5): 319-324.

[22] Khalfaoui R, Mefteh-Wali S, Viviani J L, Jabeur S B, Abedin M Z, Lucey B M. How do climate risk and clean energy spillovers, and uncertainty affect US stock markets?[J]. Technological Forecasting and Social Change, 2022, 85: 122083.

[23] Dawar I, Dutta A, Bouri E, Saeed T. Crude oil prices and clean energy stock indices: lagged and asymmetric effects with quantile regression[J]. Renewable Energy, 2021, 163: 288-299.

[24] Umar M, Farid S, Naeem M A. Time-frequency connectedness among clean-energy stocks and fossil fuel markets: comparison between financial, oil and pandemic crisis[J]. Energy, 2022, 240: 122702.

[25] Yahya M, Ghosh S, Kanjilal K, Dutta A, Uddin G S. Evaluation of cross-quantile dependence and causality between non-ferrous metals and clean energy indexes[J]. Energy, 2020, 202: 117777.

[26] Liow K H, Song J, Zhou X. Volatility connectedness and market dependence across major financial markets in China economy[J]. Quantitative Finance and Economics, 2021, 5(3): 397-420.

[27] Liao J, Zhu X, Chen J. Dynamic spillovers across oil, gold and stock markets in the presence of major public health emergencies[J]. International Review of Financial Analysis, 2021, 77: 101822.

[28] Ji Q, Liu B Y, Nehler H, Uddin G S. Uncertainties and extreme risk spillover in the energy markets: a time-varying copula-based CoVaR approach[J]. Energy Economics, 2018, 76(10): 115-126.

[29] Xu Y Y. Risk spillover from energy market uncertainties to the Chinese carbon market[J]. Pacific-Basin Finance Journal, 2021, 67: 101561.

[30] Sadorsky P. Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies[J]. Energy Economics, 2012, 34(1): 248-255.

[31] Lan Y Q, Chen J T, Huang Z H, Zhao Y Q. Volatility spillover between carbon market and related markets in time-frequency domain based on BEKK-GARCH and complex network analysis[J]. Energy, 2024, 311: 133343.

[32] Diebold F X, Yilmaz K. Measuring financial asset return and volatility spillovers, with application to global equity markets[J]. Journal of Economics, 2009, 119: 158-171.

[33] Ahmad W. On the dynamic dependence and investment performance of crude oil and clean energy stocks[J]. Research in International Business and Finance, 2017, 42: 376-389.

[34] Song Y, Ji Q, Du Y J, Geng J B. The dynamic dependence of fossil energy, investor sentiment, and renewable energy stock markets[J]. Energy Economics, 2019, 84: 104564.

[35] Zheng Y R, Hsiao C Y, Liao C H, Chen H H. Analysis of dynamic spillover effects between carbon emission rights price, renewable energy index, and electricity sector index in China[J]. Journal of Renewable and Sustainable Energy, 2024, 16: 055902.

[36] Zhang T, Tang J, Chen Y D, Ren Z Y, Bu H M. The dynamic linkage and network connectivity of renewable energy and electricity markets from a time-frequency perspective[J]. Journal of Renewable and Sustainable Energy, 2025, 17: 016304.

[37] Pham L, Nguyen C P. How do stock, oil, and economic policy uncertainty influence the green bond market?[J]. Finance Research Letters, 2022, 45: 102128.

[38] Feng H, Zhang J, Guo N. Time-varying linkages between energy and stock markets: Dynamic spillovers and driving factors[J]. International Review of Financial Analysis, 2023, 89: 102714.

[39] Dong Q L, Zhao Y Z, Ma X J, Zhou Y N. Risk spillover between carbon markets and stock markets from a progressive perspective: Measurements, spillover networks, and driving factors[J]. Energy Economics, 2024, 129: 107228.

[40] Engle R F, Manganelli S. CAViaR: conditional autoregressive value at risk by regression quantiles[J]. Journal of Business and Economic Statistics, 2004, 22(4): 367-381.

[41] Wang G J, Chen Y Y, Si H B, Xie C, Chevallier J. Multilayer information spillover networks analysis of China's financial institutions based on variance decompositions[J]. International Review of Economics and Finance, 2021, 73: 325-347.

[42] Musmeci N, Nicosia V, Aste T, Di Matteo T, Latora V. The multiplex dependency structure of financial markets[J]. Complexity, 2017, 2017: 9586064.

[43] Antonakakis N, Chatziantoniou L, Gabauer D. Refined Measures of Dynamic Connectedness Based on TVP-VAR[J]. Journal of Risk and Financial Management, 2017, 13(4): 84.

[44] Deng X, Xu F. Connectedness between international oil and China's new energy industry chain: A time-frequency analysis based on TVP-VAR model[J]. Energy Economics, 2024, 140: 107954.

[45] He Z, Liu Z K, Zhang C Z, Zhao Y J. How do carbon pricing spillover effects impact green asset price volatility? An empirical study based on the TVP-VAR-DY model[J]. Economic Analysis and Policy, 2025, 85: 2162-2179.

[46] Giglio S, Maggiori M, Rao K, Stroebel J, Weber A. Climate change and long-run discount rates: Evidence from real estate[J]. Review of Financial Studies, 2021, 34(8): 3527-3571.

[47] Sharma D. Financial markets, energy shocks, and extreme volatility spillovers[J]. Energy Economics, 2023, 126: 107031.

[48] Kang S H, Yoon S M. Financial crises and dynamic spillovers among the Chinese stock and commodity futures markets[J]. Physica A, 2019, 531: 1-18.

[49] Cui J X, Goh M, Zou H W. Coherence, extreme risk spillovers, and dynamic linkages between oil and China's commodity futures markets[J]. Energy, 2021, 225: 1-27.

[50] Bouri E, Saeed T, Vo X V, Roubaud D. Quantile connectedness in the cryptocurrency market[J]. Journal of International Financial Markets, Institutions and Money, 2021, 71: 101302.

[51] Saeed T, Bouri E, Alsulami H. Extreme return connectedness and its determinants between clean/green and dirty energy investments[J]. Energy Economics, 2021, 96: 1-14.