# Dynamic volatility dependence among fossil energy, clean energy, and metal markets: The role of climate risk or geopolitical risk

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**Abstract.** With the growing demand for energy transition, energy and metal markets exhibit complex interdependencies, while climate risk and geopolitical risk are recognized as key factors influencing their supply, demand, and price volatility. This study explores how these substantial risks impact the linkages among fossil energy, clean energy, and metal markets. Using time-varying parameter models and the generalized variance decomposition spillover index approach, we measure the volatility dependence across the markets. Our findings indicate that the clean energy market serves as a net exporter of price shocks, while fossil energy and metal markets act as recipients. Furthermore, we demonstrate that geopolitical risks exert significantly positive impacts on market linkages, where heightened geopolitical risks notably strengthen the volatility interdependence between energy and metal prices. In contrast, climate risks only exhibit observable effects on market dependence under high-quantile scenarios. Our in-depth analysis highlights the crucial role of moderate transition-related climate risks and extreme physical risks in risk propagation among the market systems.

**Keywords:** fossil energy-clean energy-metal, volatility dependence, climate risk, geopolitical risk.

## 1. Introduction

The increasing risks of climate change and geopolitical conflict have profoundly reshaped the economic and social environment, particularly impacting global energy supply, demand, and price fluctuations. Climate risks include natural disasters like hurricanes, floods, and extremely high temperatures that can cause major disruptions and losses in the energy markets. For example, early in 2021, a historic cold wave in the southern United States caused natural gas production to plummet and energy costs to rise significantly. And, climate transition risks have more significant long-term effects on the structure of the energy market, reducing demand for fossil fuels and driving the energy industry toward more sustainable and clean alternatives. [1-3]. Additionally, given the scarcity of energy resources and the uneven geographical distribution, the inherent geopolitical nature of energy commodities underscores their susceptibility to geopolitical risks, undoubtedly influencing energy price fluctuations [4-6]. Along this line, our study explores the significance of both climate risk and geopolitical risk on the fossil energy, clean energy, and metal markets, underpinned by two central motivations.

First, the global energy market is widely recognized as an intricate system involving the interplay of fossil and clean energy markets [7-10]. With the rise and rapid development of clean energy, metals, as crucial materials in the industry of new energy, significantly impact the energy system [11-13]. To be specific, a significant positive correlation between the demand for fossil energy and the prices of fossil fuels has been demonstrated [14-16]. The adoption of clean energy is frequently influenced by rising fossil fuel prices [3,17], and vice versa. Metal price fluctuations also significantly affect the energy transition [8,12]. As the worldwide shift to clean energy accelerates, certain metals are in significantly rising demand due to the need for clean energy, which results in higher prices of these metals [18,19]. Metals like copper and nickel, which serve as key materials in manufacturing and storing renewable energy technologies, can see their prices soar, potentially hindering the progress of low-carbon energy transition [20-22]. Additionally, the metal market is a high-energy-consuming sector, with the manufacture and smelting operations of metals requiring substantial fossil energy use [23,24]. Therefore, the interplay and impact among fossil energy, clean energy, and the metal market have become one of the key areas that require in-depth exploration.

Second, climate risks and geopolitical risks extend beyond affecting individual markets, and more substantially disrupt the volatility interconnectedness among fossil energy, clean energy, and metal prices. Existing literature mainly examines the impact of these two principal risk variables on select key energy markets [1,25]. For instance, Li et al. (2024) investigate how climate risk impacts the energy market, establishing that climate risk substantially alters the association among energy markets [26]. Dutta and Dutta (2022) demonstrate that heightened geopolitical risk diminishes the risk associated with green assets and enhances the probability of clean energy assets experiencing low volatility [5]. Accordingly, another question is how these two risk factors influence the interaction among fossil energy, clean energy, and metal markets, and whether there are differences in their impacts.

To address these questions, we begin by employing time-varying parameter models and the volatility spillover index technique to quantify the interconnections among the three markets. Specifically, we begin by comprehensively investigating the volatility dependence among three fossil energy markets, three clean energy markets, and eight metal markets. Our study transitions from static spillover analysis to dynamic spillover analysis, emphasizing the dominant role of clean energy in market shocks. Moreover, we demonstrate that under special conditions and during abnormal events, fossil energy markets such as crude oil and coal, along with metal markets, become the main net exporters and should therefore be the focus of regulatory attention. This is due to the substantial influence these markets exert on global energy and economic stability when encountering supply-demand mismatches or severe price volatility. Regulatory authorities need to closely monitor their dynamics to guard against potential risks and maintain market order.

Furthermore, we investigate how climate and geopolitical risks impact the volatility dependency of fossil energy, clean energy, and metal markets on volatility. To deeply analyze the impact mechanisms on energy-metal systems from a dual-risk perspective, the climate risk indices constructed by Bua et al. (2021) based on textual analysis and authoritative data [27], as well as the geopolitical risk index compiled by Caldara and Iacoviello (2022) from news reports on geopolitical tensions are employed [28]. We utilize the extracted dynamic total volatility spillover index to depict the interconnections among markets and employ the ordinary least squares regression to perform the standard examination. The results demonstrate that geopolitical risk can significantly enhance inter-market linkages, while the linear impact of climate risk is insignificant.

Along this line, does climate risk have no impact on the dependence of fossil energy, clean energy, and metal markets on volatility? To unveil this mystery, we further conduct a detailed analysis. The complex structure of climate risk results in its variable impact on energy markets under different situations [29-31], with simple linear regression sometimes unable to account for extreme conditions. Although quantile regression considers the tail conditions, the model still cannot capture the possibility of the explained variable being in different states, thus it also overlooks the intricate relationship between the independent and dependent variables [22,32]. We thus choose the quantile-on-quantile model to quantify the dynamics, nonlinearity, and asymmetry of the impacts between market interlinkages and climate risk. Our analysis reveals that climate risk, especially physical climate risk, increases the risk contagion between systems under high quantile conditions. This finding underscores the necessity of integrating climate risk factors into frameworks for risk management, as it emphasizes the possibility of increased systemic risk when encountering extreme climate events.

Our study makes the following contributions to the existing literature. First, we explore the time-varying volatility interrelationships among fourteen markets regarding fossil energy, clean energy, and metal from the systemic perspective. Prior literature has primarily concentrated on the correlations between some individual markets or mainstream energy markets and metal markets, including markets for crude oil and precious metals [33-35], and markets for metal and clean energy

[19,36]. Our study reveals that within the mentioned system, fossil energy, clean energy, and metal assume distinct roles in risk transmission across diverse market situations. Second, we identify and compare the overall interconnectedness of the relevant markets impacted by climate and geopolitical risk, rather than individual markets as in some related studies [37,38]. The substantial influence of geopolitical risk on this system has been verified based on ordinary least squares regression, while climate risk is found to be insignificant. Furthermore, by employing quantile-on-quantile regressions, we demonstrate that climate physical climate risk can intensify the risk contagion effects among fossil energy, clean energy, and metal markets, particularly under high quantile conditions.

The remainder of the paper is organized as follows. Section 2 presents the measurement of volatility dependence among markets. Section 3 covers data and previous analysis. Section 4 discusses spillovers between energy and metal markets. Section 5 examines the role of climate risks and geopolitical risks. Section 6 provides robustness analyses. Finally, Section 7 concludes.

## 2. Measurement of volatility dependence among markets

We follow related studies on exploring the connectedness among financial markets [39-41], and measure the volatility dependence among the markets of interest relying on the TVP-VAR model. Compared to standard VAR models, the TVP-VAR model boasts a notable edge in precisely depicting the evolving interconnections among variables across different periods. Specifically, the standard TVP-VAR(1) is expressed as:

$$Y_t = \varphi_t Y_{t-1} + \varepsilon_t, \tag{1}$$

$$vec(\varphi_t) = vec(\varphi_{t-1}) + v_t, \tag{2}$$

where $Y_t$ is an N×1 dimensional observed variable, $\varepsilon_t$is an error vector, $\varepsilon_t \sim N(0, \Sigma_t)$, $\Sigma_t$ is a time-varying variance-covariance matrix. $vec(\varphi_t)$ and $v_t$ are time-varying vectors, and $\Omega_t$ is a variance-covariance matrix. If the TVP-VAR process is stationary, it can be expressed using Wold's theorem as TVP-VMA(∞), given by:

$$Y_t = \sum_{i=0}^{\infty} \psi_{it}\, \varepsilon_{t-1}, \tag{3}$$

where $\psi_{it}$ is an N×N dimensional matrix.

Inspired by the influential literature of Diebold and Yilmaz [42-44], we employ the generalized forecast error variance decomposition (GFEVD) method to calculate volatility spillover indicators, which is widely applied to analyze the interconnections within financial institutions [8,10,34,45,46]. The total connectedness index and directional spillover indices for the markets of interest are constructed in this study to give a more thorough investigation of the dynamic spillover effects between the metal and energy markets, providing deeper insights into their interrelations.

The element of the dynamic H-step-ahead GFEVD can be written as:

$$\theta_{ijt}(H) = \frac{\sigma_{jjt}^{-1} \sum_{h=0}^{H-1} \left(e_i' \psi_{ht} \Sigma_t e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' \psi_{ht} \Sigma_t \psi_{ht}' e_i)}, \tag{4}$$

where $\Sigma_t$ is the time-varying covariance matrix of the error vector $\varepsilon_t$, $\sigma_{jjt}$ is the $j$th diagonal element of the time-varying covariance matrix $\Sigma_t$, and $e_i$ is a selection vector with $i$th element set to ones and others being zeros. Then, an $N \times N$ order spillover index matrix can be obtained, where each element represents the forecast error variance contribution of one variable to another (or to itself). Therefore, the diagonal members of the matrix reflect self-contribution while the off-diagonal elements represent spillovers to other factors.

To address the issue of non-orthogonal shocks and ensure the sum of contribution shares equals 1, we normalize the generalized forecast error variance as $\tilde{\theta}_{ijt}(H)$. This normalization achieves $\sum_{j=1}^{N}\tilde{\theta}_{ijt}(H) = 1$ and $\sum_{ij=1}^{N}\tilde{\theta}_{ijt}(H) = N$. The corresponding results can be written as follows:

$$\tilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\sum_{j=1}^{N}\theta_{ijt}(H)} \tag{5}$$

Based on this, $\sum_{j=1}^{N}\tilde{\theta}_{ijt}(H)$ and $\sum_{i,j=1}^{N}\tilde{\theta}_{ijt}(H) = N$ can be obtained. The total connectedness index (TCI) measures the extent to which internal shocks within the system's variables influence the aggregate forecast error variance over an H-step horizon. It can be mathematically represented in the following manner:

$$TCI_t = C_{total}^{(H)} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ijt}(H) \times 100. \tag{6}$$

Then, we introduce three directional spillover indices. The directional connectedness from market $i$ to other markets and from other markets to market $i$, are defined as:

$$T_{\cdot\leftarrow i}^{(H)} = \sum_{j=1,j\neq i}^{N}\tilde{\theta}_{jit}(H) \times 100. \tag{7}$$

$$F_{\cdot\leftarrow i}^{(H)} = \sum_{j=1,j\neq i}^{N}\tilde{\theta}_{ijt}(H) \times 100. \tag{8}$$

The net connectedness is defined as:

$$N_i^{(H)} = T_{\cdot\leftarrow i}^{(H)} - F_{\cdot\leftarrow i}^{(H)}. \tag{9}$$

In summary, we have provided the measurement details regarding volatility connectedness between the markets for metals, fossil, and clean energy. By integrating the TCI and directional spillover indices, we can analyze the interconnections between these markets from multiple perspectives, thereby laying a solid foundation for further discussions on how the market system is affected by geopolitical and climate change risks.

# 3. Data and previous analysis

## 3.1. Data set

This study aims to examine the volatility dependency among fossil energy, clean energy, and metals. We chose three fossil energy futures markets that are widely used in previous literature, including the West Texas Intermediate Crude Oil Futures, NYMEX Natural Gas Futures, and Rotterdam Coal Futures. For clean energy markets, we focus on three prevailing stock indices, namely, the First Trust Global Wind Energy ETF, Invesco Solar ETF; and iShares Global Clean Energy ETF. And, we select eight indices for the metal market, including COMEX gold, COMEX silver, LME copper, LME aluminum, LME tin, LME lead, LME zinc, and LME nickel. The daily data for WTI Crude Oil and Natural Gas Futures are collected from the U.S. Energy Information Administration (EIA) official website, while the data for COMEX gold and LME metals are derived from the iFind database, and other data are obtained through the website of Investing. Given the data availability across different sources, our study sample spans from January 1, 2015, to March 31, 2024. After excluding outliers such as April 20, 2020, we calculate the daily return $r_t = ln(p_t/p_{t-1})$ and apply the generalized autoregressive conditional heteroskedasticity (GARCH) model to estimate daily volatility series.

Another goal of this study is to explore how climate and geopolitical risks affect the volatility connectedness in metal and energy markets. In this regard, the climate risk indices crafted by Bua et al. (2021) are utilized for a thorough investigation into the climate risk impacts [27]. Relying on a text-based methodology, these indices are obtained from authoritative data sources and cover four dimensions of climate risks, including physical concern, physical risk, transition concern, and transition risk. Additionally, to measure the geopolitical risk effects, we adopt the geopolitical risk (GPR) index, accompanied by two derived sub-indices: geopolitical threat (GPRT) and geopolitical action (GPRA), compiled by Caldara and Iacoviello (2022) [28]. Derived from automated searches across ten major newspapers' electronic archives, these indices measure adverse geopolitical events and associated risks, offering a reliable framework to assess geopolitical risks.

### 3.2. Previous analysis

Table 1 displays the descriptive statistics for return data across fossil energy, clean energy, and metal markets. All of the return series' mean and median values are found to be around zero, but the standard deviation values are higher, especially notably in the three fossil energy return series exhibiting greater volatility. The kurtosis values for all return series exceed 3, indicating heavy-tailed characteristics across all return series. Our results demonstrate that the normal distribution assumption is rejected by the Jarque-Bera (JB) statistic at the 1% significance threshold in all cases, aligning with the skewness and kurtosis statistic results. Furthermore, by demonstrating stationarity across all market return series, we reject the null hypothesis that there is a unit root, as suggested by the ADF unit root test.

**Table 1.** Descriptive statistics

| | Mean | Median | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | JB_stat | ADF_stat |
|---|---|---|---|---|---|---|---|---|---|
| Oil | 0.0002 | 0.0020 | 0.3196 | -0.6017 | 0.0330 | -2.7504 | 67.3266 | 390591.8483*** | -12.9126*** |
| Gas | -0.0002 | 0.0000 | 0.3817 | -0.3005 | 0.0388 | 0.1259 | 10.7562 | 5643.3263*** | -12.5204*** |
| Coal | 0.0002 | 0.0000 | 0.3262 | -0.5369 | 0.0288 | -3.1671 | 87.6583 | 675369.3663*** | -13.8119*** |
| Wind | 0.0002 | 0.0000 | 0.0986 | -0.1234 | 0.0136 | -0.6083 | 12.3967 | 8412.9736*** | -12.6503*** |
| Solar | 0.0001 | 0.0003 | 0.1266 | -0.1754 | 0.0243 | -0.1994 | 7.2021 | 1669.5563*** | -11.9211*** |
| Clean | 0.0002 | 0.0000 | 0.1080 | -0.1371 | 0.0177 | -0.3617 | 9.4988 | 4006.7763*** | -11.4449*** |
| Copper | 0.0002 | 0.0003 | 0.0724 | -0.0833 | 0.0130 | -0.1784 | 5.1772 | 456.1230*** | -12.7510*** |
| Aluminum | 0.0001 | -0.0002 | 0.0620 | -0.1357 | 0.0130 | -0.4621 | 11.2591 | 6472.1298*** | -13.5792*** |
| Zinc | 0.0000 | 0.0005 | 0.0978 | -0.0770 | 0.0160 | 0.0469 | 4.7859 | 299.7080*** | -13.0084*** |
| Nickel | 0.0000 | 0.0005 | 0.5462 | -0.1624 | 0.0245 | 4.7127 | 115.3619 | 1191411.7178*** | -13.7135*** |
| Lead | 0.0000 | 0.0002 | 0.0823 | -0.0852 | 0.0141 | 0.0442 | 5.2585 | 478.7305*** | -13.6522*** |
| Tin | 0.0001 | 0.0008 | 0.0933 | -0.1200 | 0.0158 | -0.6866 | 9.1403 | 3709.8014*** | -12.6745*** |
| Gold | 0.0003 | 0.0004 | 0.0629 | -0.0585 | 0.0094 | -0.1047 | 6.6330 | 1240.9467*** | -12.8042*** |
| Sliver | 0.0002 | 0.0002 | 0.0888 | -0.1239 | 0.0180 | -0.4893 | 9.1231 | 3603.0551*** | -13.2817*** |

*Note*: The table presents descriptive statistics for fossil energy, clean energy and metal markets. The "JB_stat" and " ADF_stat " represent the Jarque-Bera statistics and Augmented Dickey-Fuller unit root test statistics, respectively. *** , ** , and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

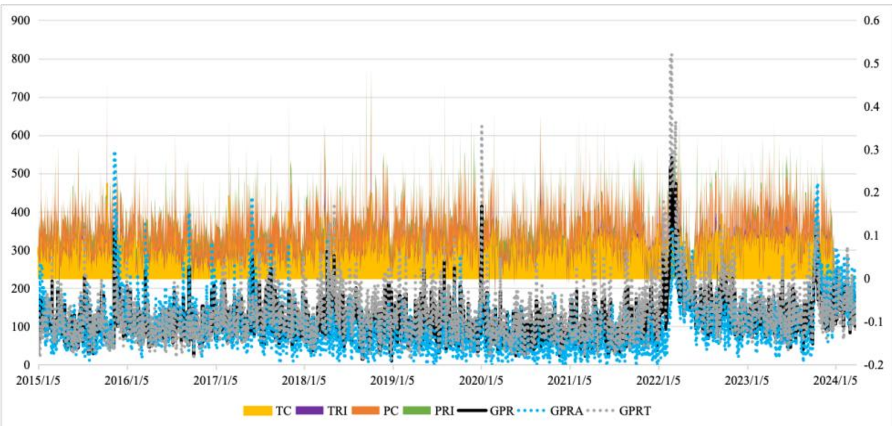


**Figure 1.** Time series trends of climate risk and geopolitical risk indices

Figure 1 illustrates the dynamic trends of the climate risk and geopolitical risk indices. On one hand, we observe differences in the numerical values and fluctuation between climate physical risk and transition risk indices. Specifically, climate physical risk exhibits relatively stronger volatility. Concerns regarding climate physical risk outweigh those of transition risk, particularly given the recent occurrences of severe weather, including intense heatwaves and heavy downpours. On the other hand, we find that geopolitical risk demonstrates higher volatility than climate risk, with more cases of peak. For instance, three indices related to geopolitical risk experienced significant fluctuations during the 2020 economic downturn triggered by the COVID-19 pandemic, reaching peak levels throughout the latter half of 2022. This sharp increase is probably influenced by the Russia-Ukraine conflict and the unrest in the Middle East, with the geopolitical threat index surpassing 800.

Figure 2 presents the volatility correlation results for all fourteen future markets. First, we observe a high correlation of volatility within these three market categories, which is particularly pronounced in the clean energy market. Second, a strong link emerges between the crude oil market and both the clean energy and metal markets, with the correlation between gold and crude oil hitting a notable 0.65. This implies that rising crude oil market volatility might improve gold's standing as a safe-haven investment. Third, compared to other metal markets, gold and silver show a stronger association with the energy sectors. The evidence on the correlations among markets has prompted us to further investigate the volatility dependence characteristics among these markets.

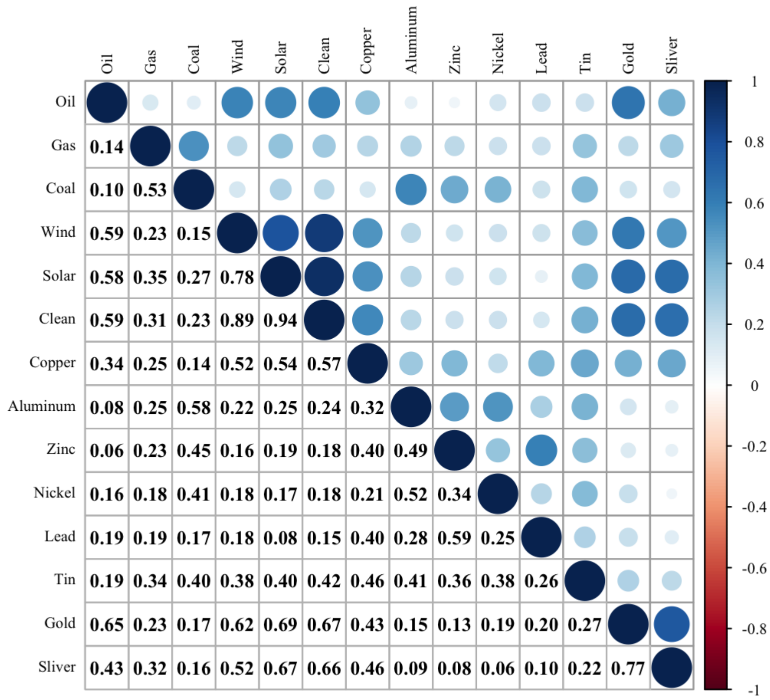


**Figure 2.** Heatmap of market inter-correlation

# 4. Spillovers among fossil energy, clean energy, and metal markets

## 4.1. Static volatility spillover effects

Table 2 presents the static volatility spillover effects among the fourteen markets including fossil energy, clean energy, and metals. At first glance, we find that these markets have some degree of mutual effect. The "NET" row data indicates that in the fossil energy-clean energy-metal system, the clean energy market is a net exporter of volatility spillovers, whereas the metal and fossil energy markets are both net receivers. The intuitive findings highlight the influential role of the clean energy market in the whole market system.

**Table 2.** Static spillovers

| | Oil | Gas | Coal | Wind | Solar | Clean | Copper | Aluminum | Zinc | Nickel | Lead | Tin | Gold | Sliver | FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Oil** | 66.21 | 0.01 | 0.41 | 10.95 | 5.67 | 8.10 | 2.54 | 0.32 | 0.17 | 2.73 | 0.16 | 0.27 | 2.20 | 0.26 | 33.79 |
| **Gas** | 0.02 | 95.83 | 1.05 | 0.04 | 0.05 | 0.04 | 0.14 | 0.02 | 0.01 | 1.02 | 0.20 | 1.15 | 0.09 | 0.35 | 4.17 |
| **Coal** | 0.86 | 1.43 | 92.64 | 0.58 | 0.12 | 0.23 | 0.01 | 2.04 | 0.61 | 0.37 | 0.02 | 1.00 | 0.09 | 0.00 | 7.36 |
| **Wind** | 0.76 | 0.09 | 0.00 | 48.33 | 18.02 | 29.60 | 0.33 | 0.11 | 0.09 | 0.06 | 0.03 | 0.34 | 1.54 | 0.69 | 51.67 |
| **Solar** | 0.39 | 0.21 | 0.00 | 20.32 | 42.58 | 34.50 | 0.24 | 0.04 | 0.03 | 0.02 | 0.06 | 0.21 | 0.62 | 0.78 | 57.42 |
| **Clean** | 0.73 | 0.15 | 0.01 | 26.45 | 29.66 | 41.20 | 0.15 | 0.03 | 0.02 | 0.03 | 0.03 | 0.47 | 0.54 | 0.53 | 58.80 |
| **Copper** | 0.93 | 0.16 | 0.07 | 7.59 | 3.90 | 5.95 | 57.53 | 2.88 | 6.47 | 2.37 | 3.65 | 5.93 | 0.43 | 2.15 | 42.47 |
| **Aluminum** | 0.36 | 0.04 | 1.10 | 2.30 | 1.27 | 1.63 | 5.64 | 57.21 | 5.15 | 20.28 | 2.11 | 2.37 | 0.26 | 0.27 | 42.79 |
| **Zinc** | 0.11 | 0.00 | 0.29 | 1.33 | 0.67 | 0.94 | 7.60 | 3.80 | 60.78 | 7.70 | 12.17 | 2.70 | 0.64 | 1.26 | 39.22 |
| **Nickel** | 0.03 | 0.05 | 0.94 | 1.20 | 0.49 | 1.23 | 2.60 | 1.20 | 1.06 | 89.85 | 0.26 | 0.69 | 0.29 | 0.12 | 10.15 |
| **Lead** | 0.08 | 0.00 | 0.01 | 3.03 | 0.83 | 1.89 | 4.75 | 2.07 | 13.15 | 13.72 | 56.99 | 2.25 | 0.54 | 0.69 | 43.01 |
| **Tin** | 0.46 | 0.24 | 0.55 | 3.92 | 2.53 | 3.68 | 2.18 | 2.35 | 2.21 | 7.22 | 3.65 | 69.77 | 0.85 | 0.38 | 30.23 |
| **Gold** | 0.40 | 0.05 | 0.00 | 11.36 | 4.91 | 7.13 | 0.94 | 0.15 | 0.42 | 4.57 | 0.25 | 0.20 | 53.65 | 15.96 | 46.35 |
| **Sliver** | 0.03 | 0.26 | 0.01 | 9.55 | 4.71 | 7.13 | 0.56 | 0.08 | 0.81 | 0.32 | 0.19 | 0.12 | 16.70 | 59.54 | 40.46 |
| **TO** | 5.18 | 2.71 | 4.44 | 98.64 | 72.82 | 102.04 | 27.67 | 15.08 | 30.19 | 60.41 | 22.77 | 17.70 | 24.79 | 23.44 | |
| **NET** | -28.61 | -1.47 | -2.92 | 46.97 | 15.41 | 43.24 | -14.80 | -27.70 | -9.03 | 50.26 | -20.24 | -12.53 | -21.55 | -17.02 | TCI=36.28 |

*Note*: The table presents the static spillover of return based on the DY method. We provide the total spillover index (denoted by the term "TCI"), the directional spillover received (denoted by"FROM"), and transmitted (denoted by "TO") by each market. The *ij*th value is the directional connectedness from *j* to *i*.

Specifically, the key findings are detailed as follows. First, in the market for fossil fuels, particularly coal and natural gas, the self-spillover effect is extremely significant. Their self-spillover rates are as high as 95.83% and 92.64%, respectively, indicating that their influence within the fossil energy-clean energy-metal system is relatively small. Second, there are more noticeable spillovers inside the clean energy industry, particularly when it comes to the markets for crude oil and precious metals, which is consistent with the findings of our previous analysis of correlation. Third, regarding the price shocks transmitting from the fossil energy market to the metal market, coal has the most significant spillover on the aluminum and nickel markets, reaching 1.10% and 0.94%, respectively. This is the most prominent among all the spillovers from fossil energy to the metal market. Finally, within the metal market, there exists a pronounced spillover effect between gold and silver, showing strong volatility connectivity. And, the spillover impact of the nickel market on aluminum is particularly noteworthy, reaching a substantial 20.28%. This not only indicates a very high correlation between the aluminum and nickel markets but also suggests that the nickel market may experience abnormal fluctuations at certain times.

### 4.2. Dynamic volatility spillover effects

#### 4.2.1. Time-varying total spillovers

Given the limitations of the static spillover model, this section introduces the dynamic spillover results to provide a more nuanced exploration. Figure 3 illustrates the dynamic total volatility connectivity, revealing a pronounced temporal variation with fluctuations between 40% and 85%. This finding supports the idea that the dynamic interactions between the metal and energy markets are captured in their changing spillover dynamics [40]. A closer inspection of Figure 3 reveals three pronounced peaks in the spillover index, corresponding to the periods of 2015-2016, 2020, and 2022. During 2015-2016, significant climate-related events like El Niño, coupled with the ongoing surge in oil prices across the Middle East, drove the total spillover value to its peak. The year 2020 saw the global economic downturn, precipitated by the COVID-19 pandemic, emerge as the primary catalyst for the pronounced volatility in total spillover [47,48]. Fast forward to 2022, the Russia-Ukraine conflict ignited a series of geopolitical risks and an energy crisis, leading to a conspicuous upsurge in the total spillover index. These pronounced peaks profoundly reveal the considerable influence of geopolitical and climate risks, while also highlighting the importance of market regulation under extreme conditions.

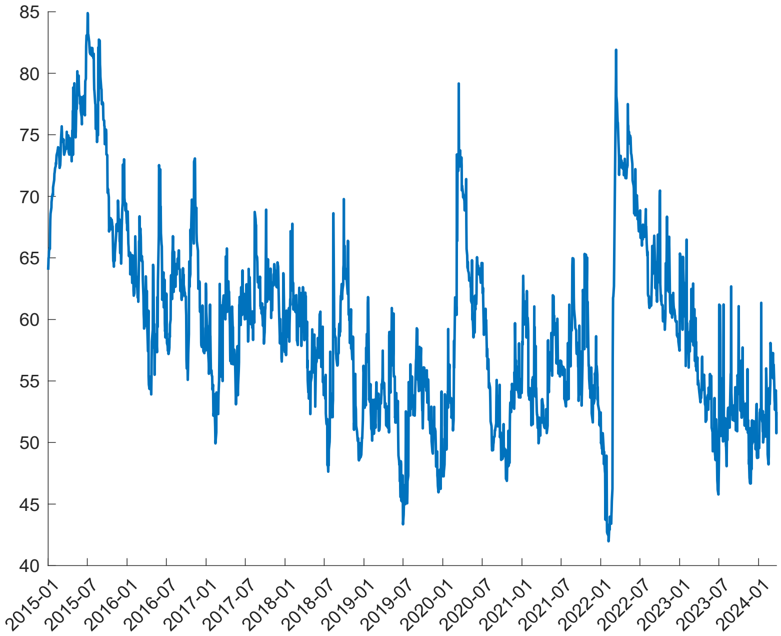


**Figure 3.** Time-varying total connectedness

### 4.2.2. Directional spillovers

We further focus on the directional spillover effects to deeply comprehend the time-varying character of the volatility connectivity. Figure 4 report the directional spillovers for all markets, where blue line indicates the “TO” direction and red line indicates the “FROM” direction. Overall, it is evident that the "TO" direction exhibits a broader range of volatility spillovers, while the "FROM" direction is relatively more stable.

Analyzing the "TO" direction spillover in Figure 4, we observe the following findings. First, the crude oil market notably impacts other markets, as evidenced by spillover peaks surpassing 20%. The significant drop in demand, supply imbalances, financial market responses, and geopolitical issues resulting from the COVID-19 epidemic are all responsible for this effect. Second, the coal market causes intense spillovers to other markets between 2017 and 2018, which might be linked to tensions in the global coal supply and carbon market changes like the EU carbon market reform agreement. Coal is not only an energy source but also a key raw material for metal smelting [12]. Consequently, any shifts in its market dynamics have a ripple effect, profoundly influencing both the energy market and metal industries [49]. Third, the nickel market saw a notable increase in spillover effects during specific periods, such as March 2022, with spillover values exceeding 50%. This is mainly due to the dramatic market fluctuations triggered by the "LME nickel squeeze event". Additionally, the gold and silver markets typically exhibit more significant spillover effects on other markets than other metals. Lastly, the clean energy market's spillover effect to other markets is relatively high and stable, fluctuating mainly around 10%.

Further observation of the "FROM" directional spillover reveals an interesting phenomenon: fossil energy markets, especially the coal market, exhibit heightened sensitivity to spillover effects emanating from other markets, which suggests that fossil fuel markets are more vulnerable to external influences regarding volatility connectedness. In contrast, the clean energy market varies mostly about 6%, making it reasonably stable in terms of sensitivity to spillovers from other markets. Therefore, the dependence among energy and metal markets on volatility exhibits distinct time-varying features, and the degree to which different markets are influenced by other markets varies significantly.

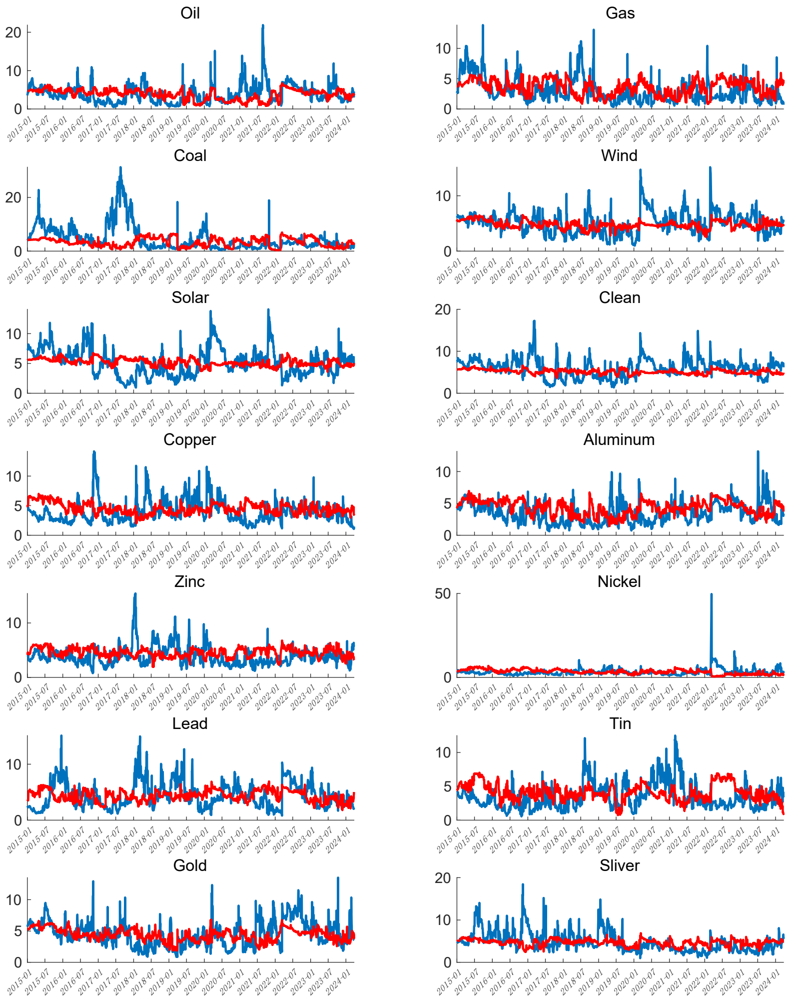


**Figure 4.** Time-varying directional spillovers

### 4.2.3. Net spillovers

Based on the analysis of directional spillover indices, as depicted in Figure 5, we obtain the net spillovers utilizing Eq.9. The difference between the market's contribution to the system's volatility and the volatility it absorbs from it is captured by the net spillover index, providing us with an intuitive tool to analyze the changes in market spillovers over time. The positive or negative value of net spillover respectively reflects the shocks that the specified market transmits to all other markets, as well as the shocks it receives from all other markets.

As evidenced in Figure 5, the net spillover indices of various markets exhibit varying patterns over time, with notable fluctuations in 2020 and early 2021 likely due to global market uncertainties from the COVID-19 pandemic. Fossil energy markets are generally more volatile in net spillover indices, while the clean energy market remains stable. Clean energy markets mostly act as shock exporters, but during extreme events, fossil energy markets become the main exporters with higher net spillover values. For example, the coal market peaked at a 30% net spillover index during 2017-2018, and the crude oil market exceeded 20% between 2021 and 2022. Metal markets' net spillover indices show fluctuations between positive and negative values with smaller amplitudes, indicating a moderate interaction with energy markets, albeit to a lesser extent. Notably, the nickel futures market exhibited a significant net volatility spillover effect of over 40% during the "LME nickel squeeze event".

In summary, we have confirmed the critical role that clean energy plays in the metal and energy systems. As we shift from a static perspective to a dynamic analysis, we point out that strengthening regulation is particularly crucial amid significant market price volatility, particularly in the coal and crude oil markets. Simultaneously, it's imperative to proactively implement safeguards against the significant disruptions in the metal market that can arise from unforeseen or extraordinary events.

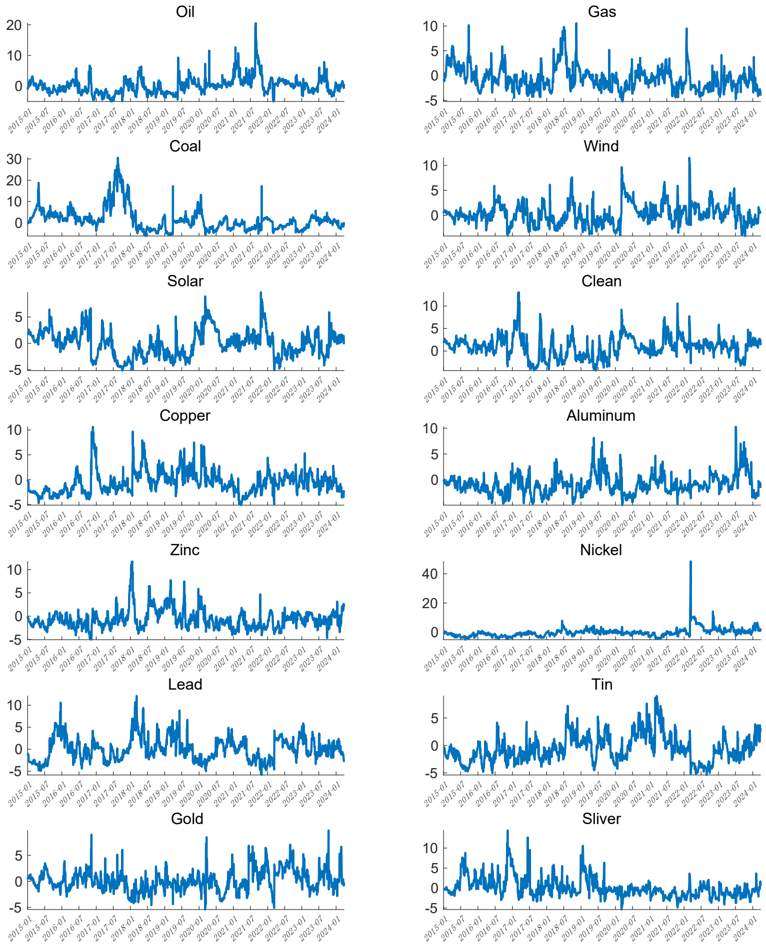


**Figure 5.** Time-varying netl spillovers

# 5. The impact of climate risk or geopolitical risk on volatility connectedness

In this section, we delve into the collective impact of climate and geopolitical risks on the energy and metal markets from a systematic perspective. Climate risks are classified as physical and transition risks, while geopolitical risks encompass not only potential threats but also the risks associated with actual actions. By employing Ordinary Least Squares (OLS) regression and Quantile-on-Quantile (QQ) regression, we meticulously analyze how these risk factors affect the markets' dependency under varying conditions. Through this detailed analysis, we aim to uncover the specific effects of climate and geopolitical risks on the connectivity of the three categories of markets, thereby providing a clearer perspective on understanding these complex relationships.

## 5.1. Estimation results based on OLS regression

### 5.1.1. OLS regression model

We start by investigating the effects of geopolitical and climatic risks on the volatility connectedness of market systems for metals and energy using a simple linear regression technique. In our model, we incorporate a one-period lag of the time-varying total connectedness index to account for dynamic variable adjustments over time and improve stability.

$$TCI_t = \alpha + \beta S_t + \gamma TCI_{t-1} + \mu_t, \qquad (10)$$

where $\mathrm{TCI_t}$ represents the dynamic total spillover index for energy and metal markets based on Eq.(6), $S_t$ is the influential factor, which includes four climate risk indicators and three geopolitical risk indicators. And, α is the intercept, β and γ are the coefficients for the explanatory variables, $\mu_t$ denotes the error term.

Following Eq.(10), we further investigate the combined effects of the two types of influential factors:

$$TCI_t = \alpha + \beta_1 C_t + \beta_2 G_t + \gamma TCI_{t-1} + \mu_t \tag{11}$$

where $C_t$ and $G_t$ are the factors of climate risk and geopolitical risk, respectively. α is the intercept, $\beta_1$, $\beta_2$ and c are the coefficients for the explanatory variables, $\mu_t$ is the error term.

### 5.1.2. Which risk has a direct impact on the market system?

As shown in Table 3, we not only analyze the separate influences of climate risk and geopolitical risk on market volatility connectivity but also examine their combined effects. The direct conclusion from the single-factor regression analysis is that a notable positive linear correlation exists between geopolitical risk and the total spillover index. Specifically, the impact coefficient of the GPR on market total connectivity is 0.0020 and is significant at the 10% confidence level, suggesting that rising geopolitical risk correlates with stronger market spillover effects. This positive relationship may reflect the potential threat of geopolitical tensions to the global supply chain, which could lead to increased prices of energy and metals, and consequently, higher volatility in the futures market [6, 46]. In contrast, climate risk's effect on the total connectedness index, while negatively trending, is consistently insignificant. This phenomenon can be ascribed to the tendency of climate risk to affect the market in a slower, more roundabout manner, largely driven by shifts in energy production and consumption over extended periods [22]. In contrast, geopolitical risk tends to have a more direct and immediate influence on market dynamics in the short term [50]. There is no straightforward linear synergistic effect between climate risk and geopolitical risk, according to additional analysis of the combined effect of the two variables. In the two-factor regression, geopolitical risk continues to exert a notably positive effect on the overall spillover index, while the negative impact of climate risk remains insignificant.

**Table 3.** The estimation results based on the OLS regression

| | | **variables** | **coefficients** |
|---|---|---|---|
| **Univariate factor** | Climate risks | TC | -1.6544<br>(-0.9292) |
| | | TRI | -0.9716<br>(-0.5276) |
| | | PC | -0.9623<br>(-0.5157) |
| | | PRI | -0.1285<br>(-0.0667) |
| | Geopolitical risks | GPR | 0.0020***<br>(2.7539) |
| | | GPRT | 0.0011**<br>(1.9648) |
| | | GPRA | 0.0018***<br>(2.8805) |
| **Bivariate factors** | *GPR with specific climate risk* | GPR | 0.0020***<br>(2.7125) |
| | | TC | -1.5901<br>(-0.8943) |
| | | GPR | 0.0021***<br>(2.7555) |
| | | TRI | -1.2341<br>(-0.6702) |
| | | GPR | 0.0020***<br>(2.7062) |
| | | PC | -0.7654<br>(-0.4105) |
| | | GPR | 0.0021***<br>(2.7315) |
| | | PRI | -0.4048<br>(-0.2100) |

*Note*: The table shows the results of OLS regressions. This table provides the results of single and double factor regression, with all regressions including a one-period lag of TCI, specifically referring to Eq.(10) and (11). In the table, the t-values for each regression are shown within parentheses in each column, with ***, **, and * indicating significance at the 1%, 5%, and 10% confidence levels, respectively.

### 5.2. Secti on Headings

Our earlier analysis has not shown any evidence of climate risks affecting the volatility dependency between energy and metal markets. This raises the question of whether climate risks indeed do not influence this volatility dependence. In this section, the Quantile-on-Quantile regression model is employed to delve deeper into how climate risk affects the systems of metals, fossil energy, and clean energy, and analyze whether this impact varies with different quantile conditions. Furthermore, we will compare the effects of climate risk on various subsystems to deepen comprehension of the risk contagion chains between markets.

#### 5.2.1. Quantile regression model

The Quantile-on-quantile (QQ) regression is a standard technique to elucidate how the conditional quantiles of the dependent variable are affected by the quantiles of the explanatory factors. In this study, we rely on the QQ regression based on the OLS linear regression to delve deeper into the mechanisms by which climate risks affect the connectedness among fossil energy, clean energy, and metal markets. Following Duan et al. (2021); Sim and Zhou (2015); Zhou et al. (2023), we employ cross-validation to precisely determine the optimal bandwidth, ensuring the best balance between bias and variance in the estimation process [22,51,52]. Based on these research findings, we have developed a regression model aimed at revealing the intricate relationship between climate risks and energy markets:

$$TCI_t = \alpha^q + \beta^q(climate_t) + \gamma^q TCI_{t-1} + u_t^q \tag{12}$$

where $u_t^q$ is an error term that has a zero q-quantile, and $\alpha^q$, $\beta^q$ and $\gamma^q$ are the coefficients to be estimated. $\beta^q(\mathrm{climate}_t)$ denotes the effect of climate risks on the interconnectedness index of energy and metal markets, approximated through a first-order Taylor expansion:

$$\beta^q(climate_t) \approx \beta^q(climate^\tau) + \beta^{q'}(climate^\tau)(climate_t - climate^\tau) \tag{13}$$

Rewriting $\beta^q(climate^\tau)$ and $\beta^{q'}(climate^\tau)$ yields the transformation of the aforementioned formula to:

$$\beta^q(climate_t) \approx \beta_0(q,\tau) + \beta_1(q,\tau)(climate_t - climate^\tau) \tag{14}$$

Replacing Eq.(14) to Eq.(12), we can get the following formula:

$$TCI_t = \beta_0(q,\tau) + \beta_1(q,\tau)(climate_t - climate^\tau) + \gamma(q)TCI_{t-1} + u_t^q \tag{15}$$

where $\beta_0(q,\tau)$ and $\beta_1(q,\tau)$ are the coefficients to be estimated.$\beta_0$ and $\beta_1$ can encapsulate the influence of $\tau$ quantiles of climate risk on q quantiles of the TCI.

#### 5.2.2. How do climate risks impact the systems under quantile conditions?

Climate risk has been confirmed as a key threat to the energy and financial system [22, 29, 53-55]. We also use the QQ regression model to investigate the nonlinear effects of climate risk on market interconnectedness to better comprehend this risk. In addition to examining how the markets for metals, clean energy, and fossil energy react to four different kinds of climate risk, we also examine how climate risk affects the pairwise market systems' overall connectedness index.

Figure 6 illustrates how different climate risk categories have varying effects on the overall volatility spillover index for the metal and energy markets at different quantile levels. Nonetheless, the upside risk of the total spillover tends to be more strongly influenced by all four forms of climate risk, with physical climate risk being the most dominant, outweighing the contribution of transition climate risk. Additionally, our findings reveal that high levels of physical climate risk positively affect the total connectedness index at a very high quantile, suggesting that severe climate risks could strengthen the interconnections among markets for fossil energy, clean energy, and metals. Public attention to physical risks, such as the minimum extent of Arctic sea ice and biodiversity protection, as well as reactions to actual physical risks like hurricanes and global warming, may amplify the risk contagion between these markets. This finding aligns with, which suggests that when facing climate risks, an increased awareness of environmental protection among investors leads them to lessen reliance on fossil fuels like crude oil and coal, cut carbon footprints, and boost the demand for metals, thus strengthening the linkages among systems of fossil energy, clean energy, and metals. In contrast, the very high quantile total connectedness index has a negative response to high quantile transition climate risk and a positive response to low quantile transition climate risk. This may be because, at low quantile levels, transition climate risk may be seen as an opportunity for market adjustment and adaptation, while at high quantile levels, it may be perceived as a serious threat.

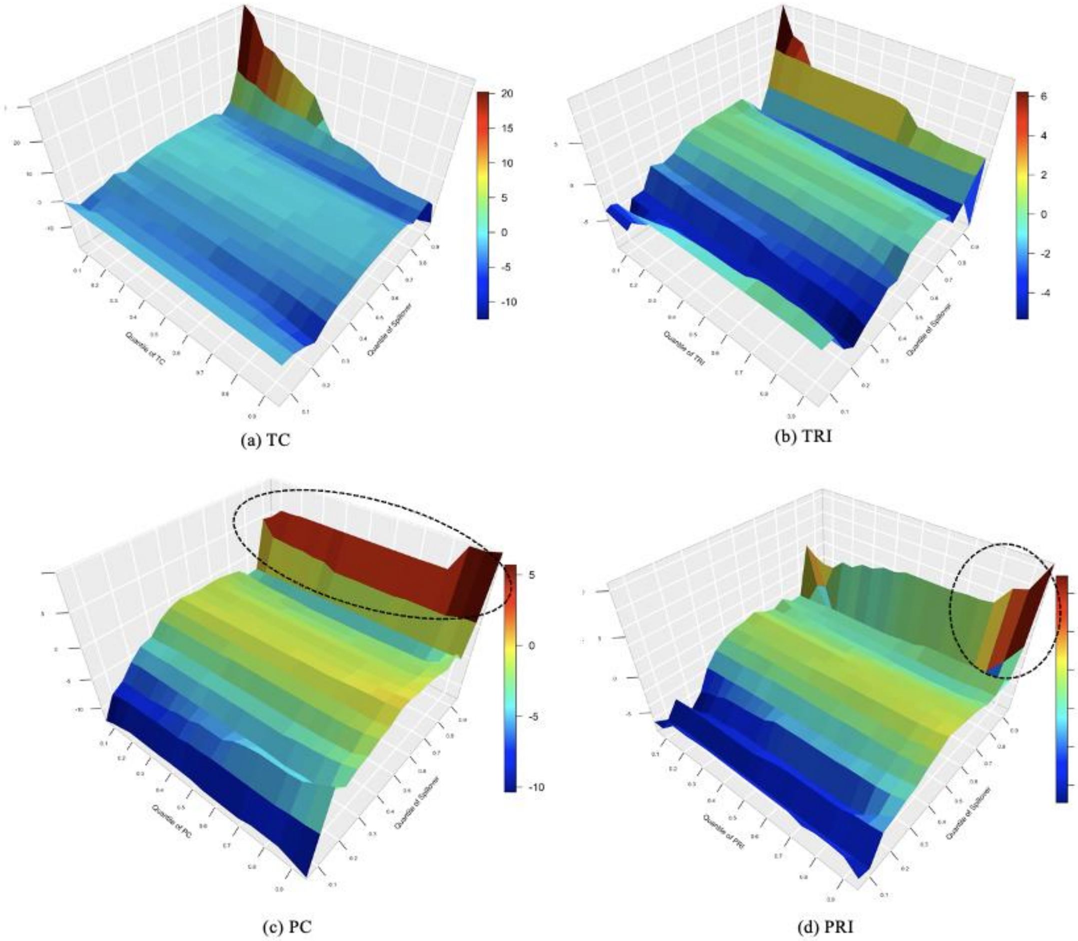


**Figure 6.** Quantile-on-quantile regression of climate risks to the fossil energy-clean energy-metal markets

Figure 7 further reveals the impact of climate risk on pairwise market systems. First, we can still draw similar conclusions: the upside risk of total spillover in the fossil-clean and clean-metal systems is more significantly influenced by the four forms of climate risk than the downside risk, with physical risk exerting a greater impact on upside spillover than transition risk. Second, moderate levels of transition climate risk appear to impact the high quantile system's total spillover index more significantly. Additionally, an important finding is that the high quantile clean energy-related system total connectedness index exhibits a significant positive influence relationship with high quantile physical climate risk. This not only demonstrates how strong the link between markets is strengthened by extreme climate risk, but it also emphasizes how important the clean energy market is as a vital link that supports the interdependencies between the energy and metal markets and as the foundation of the energy transition.

Finally, we conduct a comprehensive comparison of the climate risk responses of fossil energy-clean energy-metal system, along with three subsystems at high quantile levels. Under extremely high spillover conditions in each system, moderate transition risks and extreme physical risks have a deeper impact on the fossil energy-clean energy-metal system. This further emphasizes the crucial role that metals play in the contagion risk chain in energy and metal markets. The strong relationship between metal manufacturing and elevated carbon emissions, along with significant energy usage, underscores the importance of metal prices in both energy and carbon trading, which amplifies the influence of climate concerns on the interconnectivity of these markets.

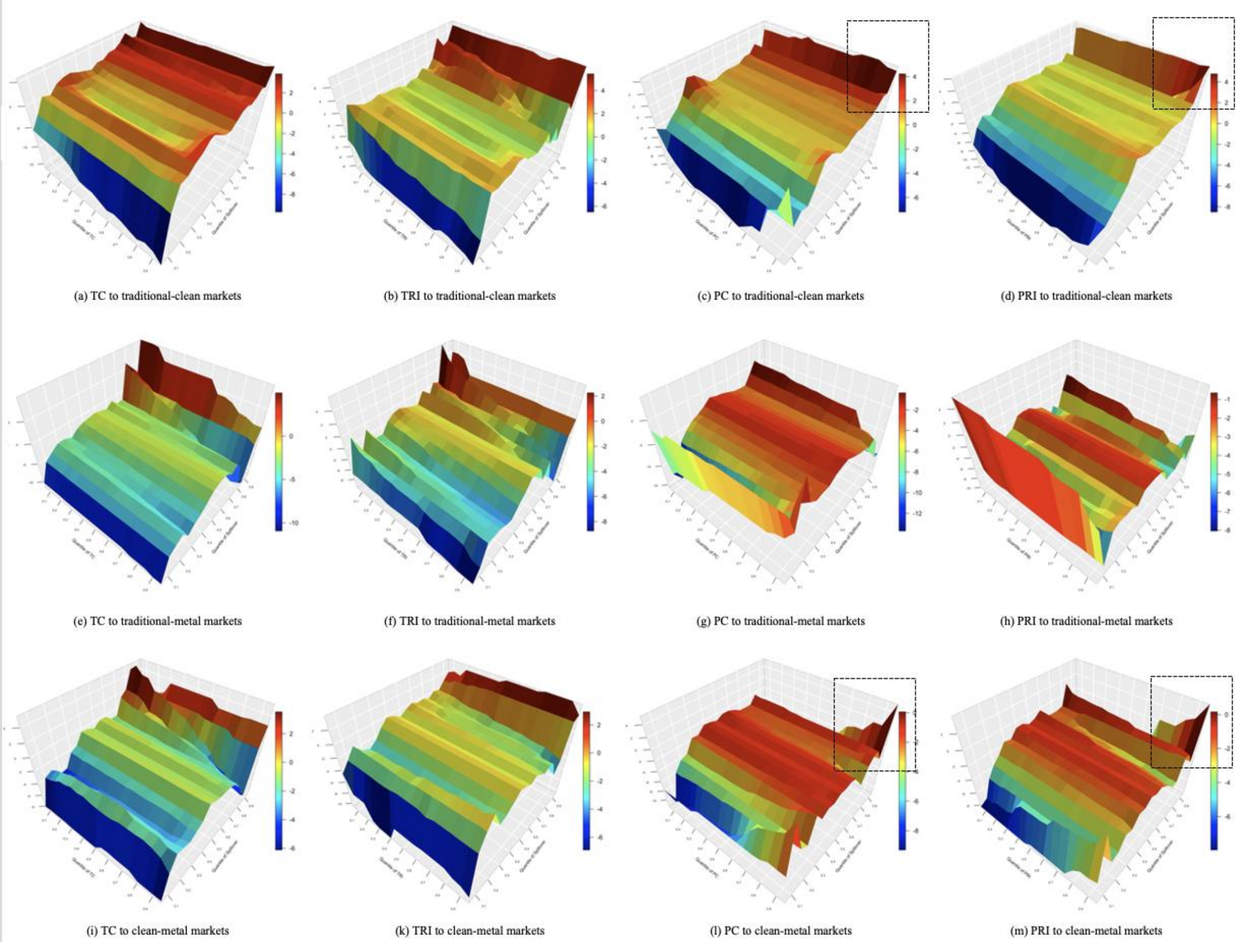


**Figure 7.** Quantile-on-quantile regression of climate risks to the fossil energy-clean energy-metal markets

## 6. Robustness test

In this section, to verify the stability of the TVP-VAR-DY model, we assess the dynamic total spillover index across different forecast horizons. We adjust the forecast horizon, extending it from 12 days to 24 days and 36 days.

As shown in Figure 8, although the specific values of the total volatility connectedness index fluctuate under different forecast horizons, the overall trend remains consistent with Figure 3. We can observe that under three different forecast conditions, the dynamic total spillover values all exhibit three significant peaks, occurring in 2015-2016, 2020, and 2022, respectively. This result indicates that the dynamic total volatility spillover index remains consistent in both qualitative and quantitative terms, irrespective of the forecast horizon selected. This consistency further validates the reliability and robustness of our research results.

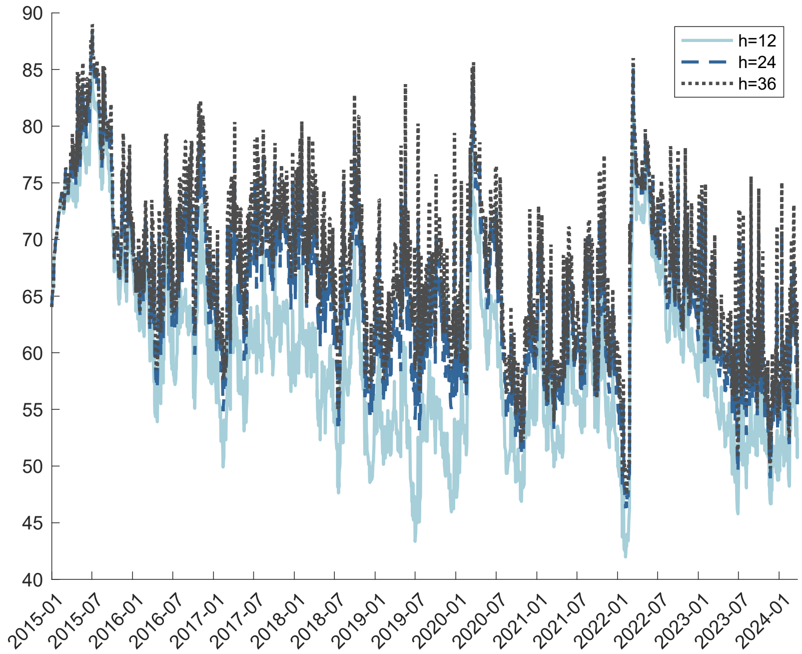


**Figure 8.** Robustness test

## 7. Conclusions

In this study, we leverage a time-varying parameter model alongside the generalized variance decomposition spillover index approach to explore the interconnectedness of volatility across markets for fossil energy, clean energy, and metals. Additionally, we incorporate ordinary least squares (OLS) and quantile-on-quantile (QQ) regression techniques to examine how climate risk and geopolitical risk influence the mechanisms of risk transmission between these markets from a macroeconomic standpoint. Principal results are detailed below.

First, we identify significant interdependencies among fossil energy, clean energy, and metal markets. The clean energy market contributes to the whole market as a net exporter, yet under extreme risk conditions, the regulation of fossil energy markets becomes particularly crucial. Second, we observe differences in the impact of geopolitical and climate risks on the market system. Geopolitical risks influence the metal and energy markets more directly, whereas climate risks are more complex in their influence. Mild transitional climate risks and extreme physical risks are particularly significant in the transmission of risks between markets. Third, our analysis further underscores how crucial the metal market is to the spread of climate concerns. Compared with fossil energy-clean energy-metal system with other subsystems, the presence of the metal market significantly amplifies the propagation effect of climate risks.

Our study offers critical guidance for investors and regulatory authorities when formulating investment strategies and regulatory policies. On one hand, while governments continue to promote the transition to clean energy, it is imperative to strengthen market supervision and risk assessment, especially under extreme market conditions, to prevent and mitigate potential market shocks. On the other hand, authorities should enhance the efficiency of risk management to guard against the propagation of risks between markets, particularly during significant geopolitical occurrences including the Russia-Ukraine conflict and extreme climate risks. Furthermore, when formulating investment strategies, investors should create diversified portfolios to mitigate the negative impacts of associated extreme occurrences throughout various timeframes. For instance, in most clean energy portfolios, the inclusion of metal assets can be considered to achieve diversified returns, although the hedging costs and effectiveness will depend on the specific types of clean energy stocks. Simultaneously, investors must diligently assess the effects of climatic and geopolitical risks to enhance their investment decision-making.

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