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From Paris to Pandemic: How Climate Risk and Policy Uncertainty Shapes Fossil and Clean Energy Commodities

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Abstract: How do climate-policy uncertainty and climate shocks affect systemic risk within clean and fossil-fuel energy markets? Could more advanced connectedness models help reduce this risk? This study investigates these concerns through the dynamic interconnections between climate risk and the leading energy commodities: natural gas, crude oil, and clean energy. Employing innovative text-based climate uncertainty indices capturing natural disasters, global warming, international summits, and U.S. climate policy, we apply the frequency-Quantile VAR model to unveil the asymmetric spillovers across time horizons and return quantiles. Our results show that events like the U.S. withdrawal from the Paris Agreement and the 2024 U.S. presidential election, significantly enhance interconnections among both renewable and conventional fossil-fuel energy markets. We also find that climate-policy uncertainty stemming from U.S. climate policy and international summits, consistently transmits risk in the high quantiles, driving both short-term volatility and long-term structural repricing in the energy commodity market. Our findings are useful guidelines for traders, portfolio managers, and policymakers aiming to hedge against tail risks and adapt to a decarbonizing global economy.

Keywords: climate risks, text-based indicators, sustainable finance, frequency-QVAR connectedness

JEL Classification: C22, C58, C50, C51

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1. Introduction

Understanding the linkages between climate risks, geopolitical tensions and energy-sector transitions has become crucial, as policy instability and global political uncertainty continue to reshape energy markets. Recent global shocks, including climate-policy shifts such as the U.S. withdrawal from the Paris Agreement, geopolitical upheavals like the Russia–Ukraine conflict, the COVID-19 pandemic, ongoing tensions between the United States and China, and the Israeli–Palestinian crisis, stress the urgent need to better understand the complex interconnections between global commodity markets and climate-risk events. While there is extensive research showing the significant effect of geopolitical risks on specific industries (Zhang et al., 2023; Umar et al., 2022; Meng and Yu, 2023), their respective effect on global energy commodity markets remains relatively less explored. This paper aims to fill this gap in the literature by examining the dynamic interactions between climate risk and global energy commodity markets.

The recent climate finance literature has identified climate risk as an important source of systemic financial risk (Battiston *et al.*, 2017; Curcio *et al.*, 2023; Stolbova et al., 2018; Wu *et al.*, 2024; among others). For example, Curcio et al. (2023) show that changes in climate policy can significantly affect financial firms with exposures to either green or brown companies, and influence overall investment flows into low-carbon assets such as green bonds and CO₂ emissions-related assets. Furthermore, Stolbova et al. (2017) provide evidence of the systemic risk component of climate risk, by showing that climate-policy risk shocks can generate synchronous effects on financial and non-financial firms. Such shocks propagate through those interconnected sectors, creating feedback loops that pose risks to both financial and macroeconomic stability. Motivated by the systemic-risk nature of climate-related uncertainty shocks, we examine how climate shocks and uncertainty stemming from news surrounding climate policy affect major traditional energy commodity markets, including crude oil and natural gas. Climate risks, when combined with unstable or ambiguous policy regimes, generate significant repercussions for investment decisions across the entire energy commodity system. These effects resonate with the full supply chain, that is from resource extraction and raw-material processing to the delivery of fossil-fuel and clean-energy products to end users. Moreover, uncertainty about future climate policy can harm both supply-side expectations and consumption patterns, especially as cleaner energy technologies become increasingly integrated into global energy infrastructure. Given that a central objective of climate policy is the reduction of greenhouse gas emissions, uncertainty regarding the direction, timing, and

stringency of future policy decisions directly affects the aggregate demand and supply conditions for fossil fuels such as crude oil and natural gas.

This paper investigates the time-varying interconnectedness between climate risk, crude oil, natural gas, and a clean energy transition index. To proxy climate risk, we employ the text-based indicators developed by Faccini et al. (2023), which capture climate-related risks associated with natural disasters, global warming, and international climate-policy summits. We make use of the frequency-Quantile VAR (QVAR) connectedness framework, which enables us to identify the spillover effects across the entire quantile distribution of returns, including tail quantiles. This approach allows us to disentangle the respective contributions of U.S. and international summits (transition-related) climate risks to movements in traditional fossil-fuel markets and clean-energy assets. By jointly capturing both nonlinearities and asymmetries across quantiles and frequencies, our approach reveals important insights into how climate-policy shocks and geopolitical events propagate systemic-risk throughout global energy markets. Importantly, these insights carry important implications for designing effective risk-management strategies and policy interventions.

This study makes three key contributions to the existing body of literature focusing on climate-related risk and commodity markets. First, we examine media-based climate-policy uncertainty and systemic-risk, by employing the frequency-QVAR connectedness framework¹. In particular, we are the first to examine the time-varying relationship between climate risk and global commodity markets during major geopolitical events, including the U.S. withdrawal from the Paris Agreement, the COVID-19 pandemic, the Sino-American trade war, the Russian invasion of Ukraine, and the 2024 U.S. presidential election. More specifically, our econometric analysis is the first to show that the previously mentioned geopolitical events lead to sharp peaks in total connectedness across both fossil-fuel and renewable energy markets. Whereas existing studies have examined how geopolitical risks affect specific industries (Zhang et al., 2023a; Umar et al., 2022b; Meng & Yu, 2023), this study differently captures the dynamic financial market effects by using quantile- and frequency-sensitive spillover methodologies. In addition, unlike standard mean-based VAR models, our QVAR formulation offers a richer and more resilient characterization, by capturing the tail-risk behavior. This approach highlights the way in which policy-driven shocks persist over time and influence the jump tail risk in energy commodity markets.

¹ Our proxies for climate risk uncertainty are based on the perceptions of climate risk by the media and the financial press using textual analysis. For more details on the construction of the index, please see Faccini et al. (2023).

Second, by examining climate-policy indices, particularly the U.S. climate policy index and the international summits index, we provide the novel empirical evidence that climate-policy sentiment consistently acts as a net transmitter of risk to energy commodity markets, particularly in the upper quantiles. This finding aligns with Diaz-Rainey et al. (2021), who show that the signing of the Paris Agreement had a significant negative impact on the oil and gas sectors, though their analysis was limited to these two fossil-fuel commodities. Furthermore, these indices consistently induce market repricing during periods of heightened volatility (upper-tail quantiles) and on longer time horizons (low-frequency bands), thereby influencing valuations across the entire energy supply chain (i.e. from raw-material extraction to the supply of energy for everyday consumption). This dual role of climate policy, as both a short-term cause of volatility and a long-term driving factor, serves an essential gap in the analysis of commodity markets.

Third, this study contributes to the broader academic and theoretical foundations of climate-finance research. Specifically, our results indicate that perceived climate-policy shocks (by the media and the financial press) and their spillover effects are not immediately incorporated into asset prices but instead they are captured only after major policy announcements. This delayed adjustment provides further insights regarding the climate-related degree of market efficiency of the commodity and energy markets. More specifically, our findings indicate some information frictions in commodity futures markets on their incorporation and effective pricing of climate risk events. Moreover, the fact that spillovers are dependent on the quantile and the frequency bands, reveals that diversification benefits depend on the state of transition-policy uncertainty.

Overall, our results have several important implications. First, according to our findings, risk and portfolio managers should incorporate climate-policy incidents as fundamental inputs into their hedging and volatility forecasting models. Real-time monitoring of international summit outcomes and country-level climate agendas should therefore become an integral part of the decision-making process. Another policy implication of our findings is that a transparent, consistent and coordinated climate-policy communication mechanism can help reduce commodity price volatility, whereas unexpected or ambiguous announcements may trigger severe market turbulence. By treating these indicators as signals for the onset of climate-policy-driven financial contagion within the energy system, investors can more effectively align their portfolios with the global transition toward a low-carbon economy.

This paper is organized as follows. Section 2 reviews the essential background literature; Section 3 sets out the employed methodology; Section 4 outlines the data; Section 5

presents the empirical results; and finally, Section 6 concludes, discusses the policy implications, and provides ideas for future research.

2. Background Literature

2.1 The impact of climate uncertainty on global financial markets

Global energy consumption continues to rise, leading to higher greenhouse gas (GHG) emissions from the energy sector. Climate scientists warn that this upward trajectory is likely to persist, due to the ongoing economic growth and expanding global populations (IPCC, 2023). Moreover, the production and distribution of energy are expected to become increasingly challenging as climate change intensifies, causing higher temperatures, more frequent and severe weather events, and shifts in precipitation patterns. According to the Statistical Review of World Energy (ETI 2023), the primary energy consumption increased by 1% in 2022, and energy use in 2022 exceeded its pre-COVID 2019 levels by approximately 3%. Combined carbon dioxide emissions from energy consumption, industrial activities, flaring, and methane (expressed in CO₂-equivalent terms) increased by 0.8% in 2022, reaching their highest recorded levels. Emissions specifically attributable to energy use rose by 0.9% over the same period. Notably, the share of fossil fuels in global primary energy consumption remained unchanged at 82%. According to Campos-Martins and Hendry (2024), who examine the impact of climate-related news on oil and gas market volatility, the oil and gas sector requires proactive policy intervention to mitigate the risks associated with climate-driven information shocks.

The financial industry has increasingly recognized climate-related risks as significant sources of financial instability that are not fully reflected in stock market valuations. Campos-Martins and Hendry (2024) argue that investors may be systematically mispricing fossil-fuel equities, potentially giving rise to a risk-filled ‘carbon bubble’. There are two major categories of risks identified in the climate change literature, which are namely the physical risk arising from climate-related events and the transition risk mainly arising out of changes in climate policy. For example, Faccini et al. (2023) further show that U.S. climate-policy risks have been increasingly incorporated into stock prices since 2012, with investors displaying stronger incentives to hedge against transition risks, those rooted in government climate policy, than against direct physical risks linked to global warming, while Engle et al. (2020) employ textual analysis to construct climate-hedging portfolios, demonstrating the growing relevance of climate information in financial decision-making.

Ardia et al. (2023), using data on S&P 500 companies from January 2010 through June 2018, empirically show that green firms outperform brown firms during periods of unexpectedly heightened concern about climate change. Tsai and Wachter (2015) develop a theoretical model which demonstrates that stock markets exhibit time-dependent high volatility in the presence of rare disaster risks. Thus, understanding the role of uncertainty on volatility and cross-asset correlations is essential for risk management decisions and economic strategy development (Asgharian et al., 2023).

In addition to the existing literature, connectedness analysis has emerged as an increasingly important tool which can be used to examine climate policy uncertainty and commodity markets. For instance, Hoque et al. (2023) analyze the impact of U.S. climate policy uncertainty on carbon emissions futures, energy, alternative energy stocks, by using the VAR connectedness and MGARCH models, based on monthly data. They show that global energy stocks and carbon emissions futures are strongly linked to U.S. climate policy uncertainty. In terms of return spillovers, policy uncertainty and energy stocks are found to be shock transmitters, while the alternative energy and carbon markets are found to be shock receivers. Regarding the induced volatility, policy uncertainty, energy stocks, and carbon futures are found to be also transmitters, while the alternative energy stocks serve as receivers. Lastly, the paper also finds increased connectedness after the Paris Agreement, implying greater global climate commitments.

Ren et al. (2025) examine the time–frequency–quantile nexus between climate risks, oil shocks, and China's energy futures market. They use the Quantile-on-Quantile regression to examine the effect of climate and oil shocks on energy futures, under different market conditions and investment horizons. In the same context, Yang et al. (2025) develop transition and physical risk perception indices to examine the time–frequency spillovers from climate risk perception to energy markets. Their findings point to increased transition risk perception in China following the Paris Agreement, while the physical risk perception has been relatively stable. Lastly, Wang et al. (2023) employ a quantile connectedness approach to examine the relationships between climate policy uncertainty, energy prices, green bond indices, and carbon trading prices. Their results exhibited high connectedness in the tails of the distribution during global events, such as the U.S. withdrawal from the Paris Agreement, the COVID-19 pandemic, and the Russia–Ukraine conflict.

In summary, earlier studies have explored the impact of climate policy uncertainty (CPU) on individual asset classes, like green bonds, carbon markets, or energy stocks (Siddique et al., 2023; Sarker et al., 2023; Ozkan et al., 2024), most of them typically using traditional

VAR or Quantile-based models, with the CPU index as a single policy-risk measure. However, these studies do not distinguish between the perceptions about physical climate risk (e.g. natural disasters) and transition policy risks (e.g. U.S. climate legislations and international summit announcements), nor do they jointly examine fossil-fuel and sustainable energy sectors. By incorporating the text-based climate indices of Faccini et al. (2023), our study addresses these gaps and is able to disentangle the effects of climate-policy perception on the global energy markets. In addition, compared to prior literature, we use a more recent dataset that captures major climate-policy events, including the latest developments under the Trump administration developments. This enables us to incorporate the policy shift toward supporting fossil-fuel agendas directly into the analysis. Moreover, much of the existing literature overlooks quantile-dependent spillovers and frequency-specific dynamics, both of which are crucial in determining how extreme climate events propagate systemic risk in global financial markets.

Our use of the frequency-QVAR connectedness framework addresses this research gap by allowing for nonlinear and asymmetric spillovers across both return distributions and time horizons. This approach yields insights that are highly valuable for policymakers seeking to stabilize markets under climate-risk conditions, as well as for investors aiming to optimize asset allocation in response to the global transition toward a low-carbon economy.

2.2 Hypothesis Development and Theoretical Framework

Building on the aforementioned literature, we propose that climate risk affects energy markets through two key transmission channels through the transition-policy channel, where climate-policy announcements and climate-related news change the investor's expectations and thus reallocate the capital between fossil fuel and clean energy assets (Campos-Martins and Hendry, 2024; Guo et al., 2022; Nam, 2021). For instance, Guo et al. (2022) identify a significant time-varying effect of climate-policy uncertainty on energy prices, while Nam (2021) shows that climate uncertainty shocks act as negative supply shocks for global energy markets. Furthermore, since the media-based climate indices can capture these changes in climate-risk perception, we expect them to transmit shocks to energy markets. Thus, based on this theoretical grounding, we hypothesize that:

(H1) Transition-policy transmission: Climate-policy sentiment acts as a net transmitter of spillovers to fossil fuel and clean energy markets.

(H2) Physical-risk spillovers: Perceptions about physical climate shocks have a weaker impact on volatility transmission toward fossil fuel and clean energy markets.

(H3) Asymmetric tail effects: Climate-risk spillover effects intensify under extreme market conditions (upper-tail quantiles), reflecting nonlinear climate-risk repricing.

All three hypotheses are tested using the frequency-QVAR connectedness framework, which allows us to examine spillover transmission across both quantiles (normal vs. stressed markets) and frequencies (short- vs. long-term horizons). More specifically, this model enables us to uncover how different categories of investors (short-term traders vs. long-term institutional allocators) respond to climate-risk information.

3. Methodology

In this section, we set out the methodological foundations of the frequency-QVAR connectedness (Chatziantoniou et al., 2022). The novel quantitative method incorporates the quantile vector autoregression (QVAR) of Chatziantoniou et al. (2021) and Ando et al. (2022), with the frequency-domain decomposition method, which was initially proposed by Baruník and Křehlík (2018). The methodology can be summarized in the following three subsequent steps: (i) quantile-specific VAR estimation, (ii) time-domain generalized forecast error variance decomposition (FEVD), and (iii) spectral decomposition into frequency bands. The method seeks to estimate financial market connectedness, capturing the interaction at various quantiles and at various time horizons, from short-run to long-run dynamics.

Particularly, at the first step, QVAR connectedness model serves as the initial step, capturing quantile-dependent relationships and distributional heterogeneity among multiple endogenous variables. Mathematically, the QVAR(p) model with lag p , is expressed as:

$$\mathbf{y}_t = \mathbf{c}_t(\tau) + \sum_{j=1}^p \mathbf{G}_j(\tau) \mathbf{y}_{t-j} + \mathbf{e}_t(\tau) \quad (1)$$

where \mathbf{y}_t denotes an $N \times 1$ vector of endogenous variables at time t , the $\tau \in [0,1]$ represents the quantile level of interest, $\mathbf{c}_t(\tau)$ is the $N \times 1$ quantile-specific conditional mean vector at time t , $\mathbf{G}_j(\tau)$ are the quantile-dependent coefficient matrices with dimensions $N \times N$, for $j = 1, \dots, p$ and $\mathbf{e}_t(\tau)$ is an $N \times 1$ quantile-specific residual vector with a quantile-dependent variance-covariance matrix denoted as $\boldsymbol{\Sigma}(\tau)$.

Thus, by using Wold's theorem, the QVAR model is then transformed into its quantile vector moving average (QVMA) equivalent representation:

$$\mathbf{y}_t = \mathbf{c}_t(\tau) + \sum_{h=0}^{\infty} \boldsymbol{\Psi}_h(\tau) \mathbf{e}_{t-h}(\tau) \quad (2)$$

where $\boldsymbol{\Psi}_h(\tau)$ is an $N \times N$ matrix, which denotes the impulse response functions at quantile τ .

Moving to the second part, we quantify the spillovers in the time domain by the generalized forecast-error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran & Shin (1998). For a forecast horizon T , the fraction of the T -step-ahead forecast-error variance received by variable i from shocks in variable j is given by:

$$C_{ij}(T; \tau) = \frac{(\boldsymbol{\Sigma}(\tau))_{jj}^{-1} \sum_{h=0}^T [(\boldsymbol{\Psi}_h(\tau) \boldsymbol{\Sigma}(\tau))_{ij}]^2}{\sum_{h=0}^T (\boldsymbol{\Psi}_h(\tau) \boldsymbol{\Sigma}(\tau) \boldsymbol{\Psi}_h'(\tau))_{ii}} \quad (3)$$

where the $\boldsymbol{\Sigma}(\tau)$ is the quantile-dependent variance-covariance matrix, and $\boldsymbol{\Psi}_h(\tau)$ is the impulse response functions at quantile τ , as denoted above.

Furthermore, due to the fact that the rows of C_{ij} do not sum to unity², we row-normalize to obtain:

$$\tilde{C}_{ij}(T; \tau) = \frac{C_{ij}(T; \tau)}{\sum_{m=1}^N C_{im}(T; \tau)} \quad (4)$$

From these normalized contributions, we define the directional connectedness for each market i and j as follows:

$$NPDC_{ij}(T; \tau) = (\tilde{C}_{ij}(T; \tau) - \tilde{C}_{ji}(T; \tau)) \quad (5)$$

$$TO_j(T; \tau) = \sum_{i=1, i \neq j}^N \tilde{C}_{ij}(T; \tau) \quad (6)$$

$$FROM_i(T; \tau) = \sum_{j=1, j \neq i}^N \tilde{C}_{ij}(T; \tau) \quad (7)$$

$$NET_j(T; \tau) = TO_j(T; \tau) - FROM_i(T; \tau) \quad (8)$$

where the NPDC (Net Pairwise Directional Connectedness) formula shows to what extent the variable j affects variable i through spillover effects, the TO formula provides the total spillovers that each asset transmits to the system, while the FROM formula indicates the total spillovers each asset receives from the system and lastly the NET formula, shows if a variable is a net transmitter (positive) or a net receiver (negative) of spillovers of the system.

² Specifically, the following equation holds: $\sum_{m=1}^N C_{im}(T; \tau) \neq 1$.

Finally, the TCI (Total Connectedness Index), measures the average spillover in the system:

$$TCI(T; \tau) = \frac{1}{N} \sum_{j=1}^N TO_j(T; \tau) = \frac{1}{N} \sum_{i=1}^N FROM_i(T; \tau) \quad (9)$$

In the last step three, we carry the time-domain spillover measures into the frequency domain by projecting the QVMA representation onto cycles of different lengths. Particularly, we define the frequency-response function, as follows:

$$\Psi(e^{-i\omega}; \tau) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h(\tau), \quad i = \sqrt{-1}, \omega \in (-\pi, \pi) \quad (10)$$

where the $\Psi_h(\tau)$ is the impulse response functions at quantile τ , as presented in eq. (2).

Therefore, we continue by defining the spectral density of \mathbf{y}_t at frequency ω as:

$$\mathbf{S}_y(\omega; \tau) = \sum_{h=-\infty}^{\infty} E(\mathbf{y}_t \mathbf{y}'_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega}; \tau) \Sigma(\tau) \Psi'(e^{i\omega}; \tau) \quad (11)$$

We then form the frequency-domain GFEVD, which combines the spectral density with the usual variance decomposition, as:

$$C_{ij}(\omega; \tau) = \frac{(\Sigma(\tau))_{jj}^{-1} \left| \sum_{h=0}^{\infty} (\Psi_h(\tau) e^{-i\omega h} \Sigma(\tau))_{ij} \right|^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h}; \tau) \Sigma(\tau) \Psi'(e^{i\omega h}; \tau))_{ii}} \quad (12)$$

As in the time domain, these contributions must be row-normalized so that:

$$\tilde{C}_{ij}(\omega; \tau) = \frac{C_{ij}(\omega; \tau)}{\sum_{m=1}^N C_{im}(\omega; \tau)} \quad (13)$$

These frequency-specific contributions can then be aggregated over any desired band $g \subset (-\pi, \pi)$ to yield the connectedness on short, medium, or long horizons, linking the quantile- and frequency-domain analyses.

Thus, by aggregating eq. (13) over a frequency domain $g = (\omega_L, \omega_H) \subset (-\pi, \pi)$ we further define, the contribution of shocks in j to the spectrum of i over band g which can be short/long-term and it is given by:

$$\tilde{C}_{ij}(g; \tau) = \int_{\omega_L}^{\omega_H} \tilde{C}_{ij}(\omega; \tau) d\omega \quad (14)$$

from which we compute band-specific NPDC, TO, FROM, NET, and TCI exactly as in eq. (5–9), by replacing eq. (4) with the eq. (14).

Lastly, it is worth mentioning that, in practice, the usual partitions of spectrum are those divided into high-frequency (short-term) and low-frequency (long-term) bands, thus for example, $(\pi/5, \pi)$ to capture cycles shorter than five days and $(0, \pi/5)$ for cycles longer than five days, and thereby revealing how quantile-dependent spillovers showcase differently in transient versus persistent components of the system.

4. Dataset & Summary Statistics

4.1. Dataset

In this section, we analytically describe the commodity price and climate uncertainty data used in our QVAR analysis. Our dataset, covers the period from January 5, 2015, to January 31, 2025³, thereby capturing several major geopolitical events, including the U.S. withdrawal from the Paris Agreement, the COVID-19 pandemic, the Russia–Ukraine war, the Middle East turmoil, and the most recent re-election of Donald Trump. We use indices provided by S&P Global⁴ as proxies for renewable and non-renewable commodities. Specifically, we use the S&P GSCI Crude Oil Index (CrdOil) and the S&P GSCI Natural Gas Index (NatGas). In addition, to complement our analysis, we incorporate the S&P Global Clean Energy Transition Index (ClnEn) as a clean-energy proxy serving as an equity index. This allows us to identify and quantify the underlying interconnections between clean-energy assets and the aforementioned commodities, and to examine how these linkages are shaped by climate risks. Furthermore, for the measurement of climate risk, we employ the indices developed by Faccini et al. (2023) as a proxy for climate risk, reflecting how investors and institutional market participants interpret climate-related developments. These indices are comprised of four various risk factors based on textual and narrative analysis of news articles on climate change. In particular, these indices capture risks related to natural disasters, global warming, international summits, and U.S. climate policies. The U.S. climate policy index reflects domestic, policy-driven transition risk, whereas the international summits index captures global climate-policy risk, thereby incorporating policy announcements originating outside the United States. The method employed to quantify these climate indices is the Latent Dirichlet Allocation (LDA), which is a sophisticated text analytical technique that categorizes vast textual data into coherent and interpretable risk-based themes. This method allows for precise

³ Our dataset is expressed in business-day frequency, and to handle any NAs, we utilized the cubic splines as an interpolation method, which effectively captures the trend and the non-linearity of the dataset.

⁴ To retrieve these specific indices, one can visit the S&P Global website at <https://www.spglobal.com/>.

measurement of how salient each topic is in news sources over time, thus giving a dynamic and reliable proxy for establishing market-wide perceptions and implications of both US and international summits climate risks. Thus, media attention captures shifts in climate-policy and physical-risk uncertainty, and therefore serves as an observable, real-time measure of climate-risk sentiment rather than a study of media attention itself. A summarized representation of these indices is presented in the Appendix section A.

4.2. *Summary Statistics*

Prior to the empirical analysis, we conduct a detailed preliminary examination of the dataset to identify its key statistical properties, including the mean, variance, excess kurtosis, and stationarity. Table 1 reports the descriptive statistics for the log-returns (in percentages) of the variables described above. The climate-risk indices are presented in percentage terms as well, but, unlike the asset-price series, they are not transformed into log-returns.

Although the sample mean-log returns are positive for both assets (renewable and non-renewable), they are not statistically different from zero, at the 10% level, implying no clear evidence of significantly positive average returns over the period examined. The natural disasters index and U.S. climate policy index, however, exhibit noticeably high mean values. This implies that the indices capture events or sentiments being reported with high frequency in the media. For natural disasters, the strong values likely reflect the persistent frequency of severe weather events and their economic and social disruptions. For the climate-policy index, large values indicate periods of intensified reporting on policy debates and regime shifts, which often signal changes in investor attitudes and market sentiment. Persistent news coverage of this kind suggests that these policy-related risk factors play an important role in explaining asset-pricing dynamics and investors' behaviour in energy commodity markets.

Regarding the variance, we can see that the clean energy market indicates the lowest level of variance of 2.334, whereas the natural gas and crude oil markets indicate high variance values of 11.357 and 9.415, respectively. This suggests the crude oil and natural gas market are much more volatile throughout this period of interest, which shows more instability as compared to the clean energy market. Furthermore, regarding the climate-related indices, the natural disasters index is the one with the highest variance among the energy indices. From the plots in Appendix section **Error! Reference source not found.**, we observe cyclical behavior marked by recurring peaks and troughs that follow an overall positive trend, with variance becoming more pronounced in times of increasing geopolitical turmoil like the 2022 Russian invasion to Ukraine. This cyclical pattern, combined with a steady upward trend, can be

attributed to event-driven or seasonally driven spikes in media coverage, which in turn signal that market perceptions towards physical climate risks are intensifying over time.

In the same context, crude oil, natural gas, and clean energy all exhibit high negative skewness as well as large positive excess kurtosis, with the strongest impact displayed by the crude oil. This means that the return distribution of crude oil is heavy-tailed and skewed. In particular, negative skewness indicates that the left tail of the distribution is fatter than its right tail, indicating a higher frequency of extreme negative returns. At the same time, a high positive excess kurtosis implies that the distribution has fatter tails than the normal distribution and, as such, extreme values, both positive and negative, have greater probability. For instance, while most crude oil trading days might have moderate changes, there are higher probabilities of being able to have days with extreme losses, that is, steep falls due to geopolitical incidents or unexpected shocks, compared to a day in a market with returns that are normally distributed. In addition, the table indicates that none of the data series is normally distributed, as validated by the Jarque-Bera test, while all series are stationary according to the ERS test statistics. Moreover, all the variables exhibit ARCH/GARCH effects. This idiosyncratic pattern implies volatility clustering, where periods of high volatility tend to be followed by further high volatility, and tranquil periods are followed by low volatility.

| | USClim | IntSum | GlbWarm | NatDis | Crdoil | NatGas | ClEn |
|-------------|------------------------|--------------------------|-------------------------|------------------------|--------------------------|-----------------------|------------------------|
| Mean | 82.218*** (0.000) | 50.247*** (0.000) | 42.393*** (0.000) | 82.468*** (0.000) | 0.015 (0.811) | 0.002 (0.974) | 0.007 (0.827) |
| Variance | 7833.587 | 7691.161 | 2480.97 | 12798.616 | 9.415 | 11.357 | 2.334 |
| Skewness | 2.081*** (0.000) | 4.673*** (0.000) | 2.966*** (0.000) | 2.393*** (0.000) | -2.260*** (0.000) | -0.185*** (0.000) | -0.329*** (0.000) |
| Ex.Kurtosis | 5.842*** (0.000) | 33.719*** (0.000) | 15.908*** (0.000) | 7.147*** (0.000) | 66.369*** (0.000) | 2.705*** (0.000) | 7.583*** (0.000) |
| JB | 5465.893*** (0.000) | 130087.918*** (0.000) | 30626.390*** (0.000) | 7861.497*** (0.000) | 470186.995*** (0.000) | 792.108*** (0.000) | 6156.034*** (0.000) |
| ERS | -6.767 (0.000) | -8.898 (0.000) | -6.998 (0.000) | -6.972 (0.000) | -5.932 (0.000) | -13.028 (0.000) | -21.518 (0.000) |
| Q2(20) | 1829.411*** (0.000) | 1623.442*** (0.000) | 2542.976*** (0.000) | 4212.167*** (0.000) | 632.165*** (0.000) | 440.904*** (0.000) | 1397.708*** (0.000) |

Table 1: Summary statistics overview. 1%, 5%, and 10% significance levels are marked by ***, **, and *, respectively. Kurtosis is estimated by using the procedure developed by Anscombe and Glynn (1983), whereas skewness has been calculated by using D'Agostino's method (1970). Normal hypothesis is tested here by using Jarque-Bera (1980) (JB) test. In addition, Elliott et al. (1996) (ERS) developed the unit-root test, while Fisher and Gallagher (2012) (Q2(20)) constructed the weighted Portmanteau test statistic for residuals, testing for ARCH effects.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, Crdoil - Crude Oil, NatGas - Natural Gas and ClEn - Clean Energy

Lastly, Figure 1 displays a correlation heatmap of the relationships between the climate indices and the energy commodity futures (oil and gas) and clean-energy equity markets. From the heatmap, it is evident that there is no significant correlation between the climate indices and the crude oil, natural gas, or clean energy markets during the sample period. However, the energy market variables themselves have some weakly positive correlations with clean energy and natural gas markets. This shows that even though climate indices and energy markets are uncorrelated in terms of returns, there is evidence of interdependence between the energy commodities. These weak, positive relationships may reflect common market drivers or common external drivers, but climate risk would not appear to be driving price movement in these sectors.



Figure 1: Correlation heatmap of the variables.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

5. Empirical Results

The Quantile VAR (QVAR) model, introduced by White et al. (2015), was developed to capture and study tail dependence in multivariate distributions. Acknowledging that uncertainties affect investment decisions, market behavior, and the overall energy infrastructure, we adopt the frequency-QVAR connectedness methodology proposed by Chatziantoniou et al. (2022). The primary advantage of the adopted methodology lies in its ability to move beyond average effects and reveal how the relationships among variables evolve across the entire outcome distribution, specifically in the left, middle, and right tails. This feature of the QVAR framework is particularly important in the present economic setting, as both risk and policy responses tend to manifest most strongly in the extremes, i.e. in the tails. Moreover, the frequency-QVAR approach is inherently suited to such questions: it is robust to outliers and heavy-tailed behavior, uncovers heterogeneous effects, and is well aligned with tail-sensitive dynamics (Koenker, 2006). Consequently, this analysis enables us to identify the influence of both perceptions about physical and transition climate risks on traditional and clean energy markets.

Our approach begins by examining the median quantile to establish a benchmark that reflects typical market behavior, before extending the analysis to a range of quantiles to assess how linkages evolve under varying conditions. This investigation is supported by visual representations of system-wide interconnections and is further reinforced through robustness checks under alternative parameter specifications. In addition, we benchmark our findings against the established frequency-VAR model of Baruník and Křehlík (2018), which serves as a reliable standard benchmark. Through this strategy, we deepen our understanding of market dynamics by illustrating how interconnectedness shifts across distinct quantile environments and time horizons.

5.1. Connectedness Analysis

In this section, we apply the frequency-QVAR connectedness framework at the median (50%) quantile to evaluate the underlying relationships between the climate indices and both conventional and renewable energy markets. This approach extends the standard frequency-VAR methodology by incorporating interconnectedness across different quantiles, including those associated with extreme market conditions. By focusing on quantile-specific dynamics, we capture not only the central tendency behaviour of the market, but also the transmission of shocks and stress events under adverse or turbulent environments. This extended framework

enables us to observe how the network structure shifts across market regimes and strengthens our understanding of how climate policy uncertainties affect both normal and extreme interdependencies. Overall, the results provide valuable insights for decision-makers, offering practical guidance for policymakers, risk managers, investors, and firms operating within energy markets and exposed to climate-driven risks.

Despite its strengths, the methodology also has some well-known limitations. First, the model does not accommodate regime-switching dynamics, meaning that parameter estimates remain fixed within each quantile. Second, estimation in the distributional tails requires a sufficiently large sample to ensure statistical reliability. Third, this framework is computationally intensive to estimate and therefore requires tuning choices⁵ (e.g. window size, lag order, quantile grid). Fourth, due to both computational and interpretability constraints, only a limited number of variables (nodes) can be incorporated simultaneously in the system, a restriction shared by most connectedness and spillover models in the literature (Diebold & Yilmaz, 2009, 2012, 2014; Baruník & Křehlík, 2018; Chatziantoniou et al., 2021). Finally, while the model effectively captures climate-related spillovers conditional on the included set of variables, it cannot fully account for other determinants of energy prices, such as macroeconomic announcements or OPEC production decisions, which may also influence the observed relationships.

Table 2, below presents the computed connectedness measures for the system. More specifically, each cell in the intersection of row for variable i and column for variable j contains the pairwise connectedness, which measures the extent to which variable j affects variable i , through spillover effects. The row marked as TO provides the total spillovers that each asset transmits to the system, while the column marked as FROM indicates the total spillovers each asset receives from the system. The NET row, which is the difference between TO and FROM, shows if a variable is a net transmitter (positive) or a net receiver (negative) of spillovers of the system, while in the lower right corner, the Total Connectedness Index (TCI) presents the overall measurement of the system's interconnectedness. Note that the analysis separates between short-term (1–5 days) and long-term (5–100 (inf) days) connectedness, with window size of 200 and lag of 1. The values in parentheses are divided into two parts: the left-hand

⁵ We have validated these choices in Appendix **Error! Reference source not found.** by varying the window sizes (150, 200, 250, 300 days) and the number of lags (1, 2, 3), and we have concluded that our model is robust to the specific parameter selection.

value is the short-term connectedness measure, whereas the right-hand value is the long-term connectedness measure.

The table offers several insights into how shocks propagate across the system. First, the climate-risk indices appear to have only a marginal impact on the median returns of crude oil, natural gas, and clean energy markets over the full sample and across all frequencies. Their pairwise directional connectedness measures are very low, which implies that, at least within the studied period, market participants do not treat day-to-day information in climate indices as an immediate driver of energy-sector price movements. In practice, price discovery in both fossil-fuel and renewable-energy markets remains therefore dominated by classic energy-specific fundamentals, such as supply disruptions, inventory releases, OPEC announcements, and technology-cost dynamics, rather than short-run shifts in climate sentiment.

Regarding the energy sectors, the clean energy sector exerts the strongest pairwise directional spillover on crude oil, in total-term with value of 6.19 percent, driven largely by the short-term component of 4.69 percent. In other words, unexpected return fluctuations in clean-energy equities tend to ripple quickly into crude-oil returns, which might be attributed to the fact that investors revise expectations about the pace of the energy transition or future policy incentives. However, the influence is not one-sided. Crude oil also sends shocks back to the clean-energy sector, in the total-term with value of 5.67 percent, with 4.27 percent being concentrated in the short-term. This means that a sudden geopolitical supply disruption, that pushes oil prices up sharply, can make renewables more competitive on a levelized-cost basis and promptly lift clean-energy equity valuations.

These reciprocal spillovers carry several practical implications. Given the rapid transmission of policy shocks across energy domains, the implementation of a stringent carbon-pricing scheme that compresses crude-oil margins can directly catalyse capital reallocation toward renewable energy. This reflects a deliberate mechanism embedded in transition-policy frameworks rather than a by-product of their implementation. In this sense, our findings suggest that climate-policy news can speed up capital reallocation, and that financial spillovers materialize before underlying fundamentals adjust. For energy-intensive industries, such as airlines, petrochemicals, and shipping, this implies that effective hedging strategies should account not only for traditional oil market indicators but also for clean-energy price dynamics, which increasingly foreshadow near-term fuel-cost fluctuations. Likewise, portfolio managers may exploit the bidirectional short-run channel to refine asset-allocation decisions or adjust hedging positions over shorter horizons. These dynamics do not imply arbitrage opportunities;

rather, they enhance timing and risk-management decisions in anticipation of transition-policy news shocks.

Shifting our focus to total directional spillovers, crude oil and clean energy markets emerge as the system's main shock receivers. They receive 11.59% and 11.35% of the variance transmitted by the network, and with 8.65% and 8.25% (or a 75% and 73% spillover portion attributed to the short-term of the total-term), respectively, which arrives within the short-term band (up to about one business week). However, the relationship is not one-way. Clean energy and crude oil are also among the leading transmitters, transmitting 11.60% and 10.46% of the total-term, and with 8.50% and 7.95% (or roughly 73% and 76% spillover portion being attributed to the short-term of the total-term) concentrated in the short-term.

Further, a notable observation is that, the three climate indices, international summits, global warming and U.S. climate policy indices export significant spillover effects to the system, with values for the total-term of 29.9%, 24.8% and 18.8%, respectively. Their effects are more balanced between short and long horizons (about 51% short-term, 49% long-term out of the total-term for the international summits and about 56% short-term, 44% long-term out of the total-term for the other two climate indices), and these do not seem to directly influence the energy markets in the median connectedness. Thus, regulators tracking financial stability around climate policy should therefore look beyond traditional energy benchmarks and monitor these connectedness measures as early-warning indicators.

Regarding the net total directional connectedness, the crude oil and natural gas, appear to be modest net receivers, while the clean energy appears to be modest net transmitter across all frequency bands. In other words, the shocks that the non-renewable energy sectors absorb from the system slightly outweigh those they transmit, indicating that there is no persistent, one-sided contagion originating from these two energy markets. Finally, the total connectedness index of the entire system is found to be relatively low, at 16.05%, with a substantial portion (9.54%, or approximately 60% out of total-term) concentrated in the short-term. Such a network, characterized predominantly by these interactions, suggests for example, airlines or petrochemical firms, which are sensitive to sudden fluctuations in energy prices, might prefer short-term (one-week) hedging contracts rather than relying extensively on longer-term positions, effectively protecting themselves against the sharp but brief waves of spillovers identified in this analysis.

Lastly, Figures 2 and 3 visually summarise the findings discussed above. Specifically, except for the natural disaster index, the climate indices form a cluster with only thin outgoing connections, while crude oil and clean energy are linked by thick, bidirectional spillover

channels. For the net pairwise directional connectedness (NPDC), the graphical analysis shows that, in the total-term, international summits transmit the strongest NPDC to natural gas, followed by crude oil and clean energy. Notably, these effects are observed exclusively at short-term horizons. Importantly, only the international summits of the climate indices induce spillovers to crude oil markets, particularly in short-term horizons, but in such a case, spillover effects are restricted in the median quantile connectedness. Finally, according to net pairwise directional spillovers in the short-term horizon, clean energy market shows a high transmission of shocks to the crude oil market. This is in alignment with earlier empirical evidence by Ferrer et al. (2018) and Umar et al. (2022a), who also reported significant short-run spillovers from renewable assets to the crude oil market.

Overall, these findings highlight the critical role of the international, climate-related, summit events, which play a significant role in shaping the energy market dynamics. Policymakers and regulators should pay special attention to the timing and content of such global summits, since announcements or commitments made at such international forums can have the capability of rapidly changing investor expectations, investment decisions, and risk perceptions in energy markets⁶. Thus, energy-intensive sectors, investors, and risk managers, ought to keep close track of international climate policy developments to be able to anticipate and manage the short-term financial effects and to proactively adjust and develop suitable hedging or investment strategies.

⁶ For instance, a major international agreement or stringent emissions reduction target announced on the day of a worldwide climate summit, could immediately increase volatility and shift market prices in policy-sensitive demand-change-exposed sectors, such as fossil fuels and sustainable energy.

| | USClim | IntSum | GlbWarm | NatDis | CrdOil | NatGas | ClnEn | FROM |
|---------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| USClim | 79.03 (55.15, 23.88) | 8.12 (4.29, 3.83) | 7.28 (4.04, 3.24) | 3.28 (1.63, 1.65) | 0.75 (0.56, 0.19) | 0.58 (0.41, 0.17) | 0.97 (0.60, 0.37) | 20.97 (11.54, 9.43) |
| IntSum | 6.43 (3.24, 3.19) | 78.17 (43.26, 34.91) | 11.71 (6.20, 5.51) | 1.92 (0.90, 1.02) | 0.46 (0.25, 0.21) | 0.52 (0.33, 0.19) | 0.79 (0.51, 0.28) | 21.83 (11.43, 10.40) |
| GlbWarm | 7.00 (3.81, 3.19) | 15.44 (7.31, 8.13) | 72.48 (51.52, 20.96) | 2.69 (1.68, 1.01) | 0.58 (0.46, 0.12) | 0.71 (0.51, 0.20) | 1.09 (0.70, 0.39) | 27.52 (14.48, 13.04) |
| NatDis | 2.51 (1.40, 1.11) | 2.49 (1.16, 1.33) | 3.23 (1.74, 1.49) | 89.45 (59.05, 30.40) | 0.73 (0.44, 0.29) | 0.85 (0.56, 0.29) | 0.74 (0.54, 0.20) | 10.55 (5.84, 4.71) |
| CrdOil | 0.82 (0.65, 0.17) | 0.92 (0.59, 0.33) | 0.88 (0.66, 0.22) | 1.05 (0.71, 0.34) | 88.41 (72.58, 15.83) | 1.74 (1.35, 0.39) | 6.19 (4.69, 1.50) | 11.59 (8.65, 2.94) |
| NatGas | 0.91 (0.69, 0.22) | 1.53 (0.98, 0.55) | 1.06 (0.79, 0.27) | 0.97 (0.68, 0.29) | 2.26 (1.96, 0.30) | 91.45 (74.60, 16.85) | 1.82 (1.46, 0.36) | 8.55 (6.56, 1.99) |
| ClnEn | 1.15 (0.77, 0.38) | 1.36 (1.04, 0.32) | 0.69 (0.49, 0.20) | 1.03 (0.64, 0.39) | 5.67 (4.27, 1.40) | 1.45 (1.04, 0.41) | 88.65 (68.42, 20.23) | 11.35 (8.25, 3.10) |
| TO | 18.83 (10.56, 8.27) | 29.85 (15.37, 14.48) | 24.83 (13.91, 10.92) | 10.93 (6.24, 4.69) | 10.46 (7.95, 2.51) | 5.86 (4.22, 1.64) | 11.60 (8.50, 3.10) | 16.05 (9.54, 6.51) |
| Net | -2.14 (-0.97, -1.17) | 8.02 (3.94, 4.08) | -2.68 (-0.57, -2.11) | 0.38 (0.40, -0.02) | -1.13 (-0.69, -0.44) | -2.69 (-2.35, -0.34) | 0.25 (0.25, 0.00) | |

Table 2: Static connectedness table of the median frequency – QVAR model for our variables, for total, short and long terms, with the short-term corresponding to 1–5 days and the long-term to 5–100 (inf) days, using a window size of 200 and lag 1. Note that the left value in the parentheses represents the short-term connectedness measure, whereas the right value represents the long-term connectedness measure.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

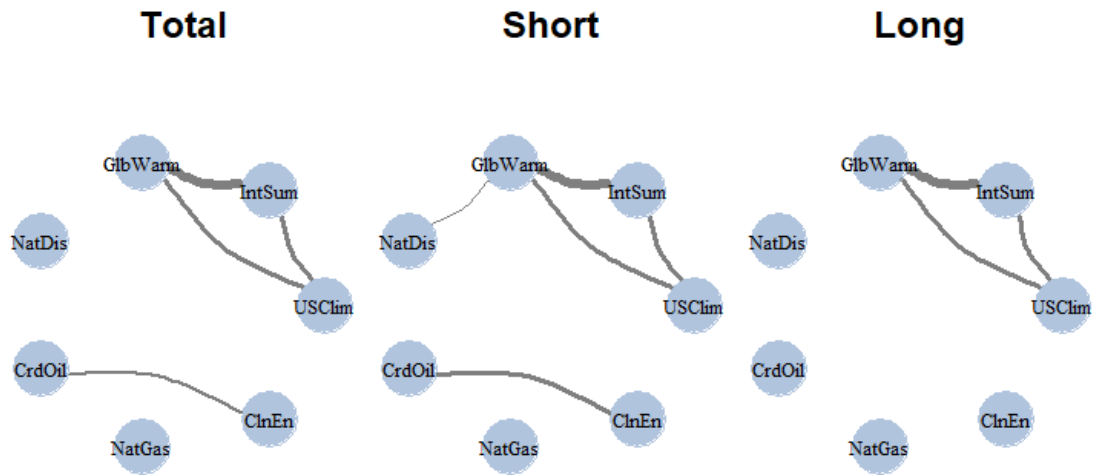


Figure 2: Pairwise connectedness plots of the median frequency QVAR model, for total, short and long terms, with the short-term corresponding to 1–5 days and the long-term to 5–100 (inf) days, using a window size of 200 and lag 1.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

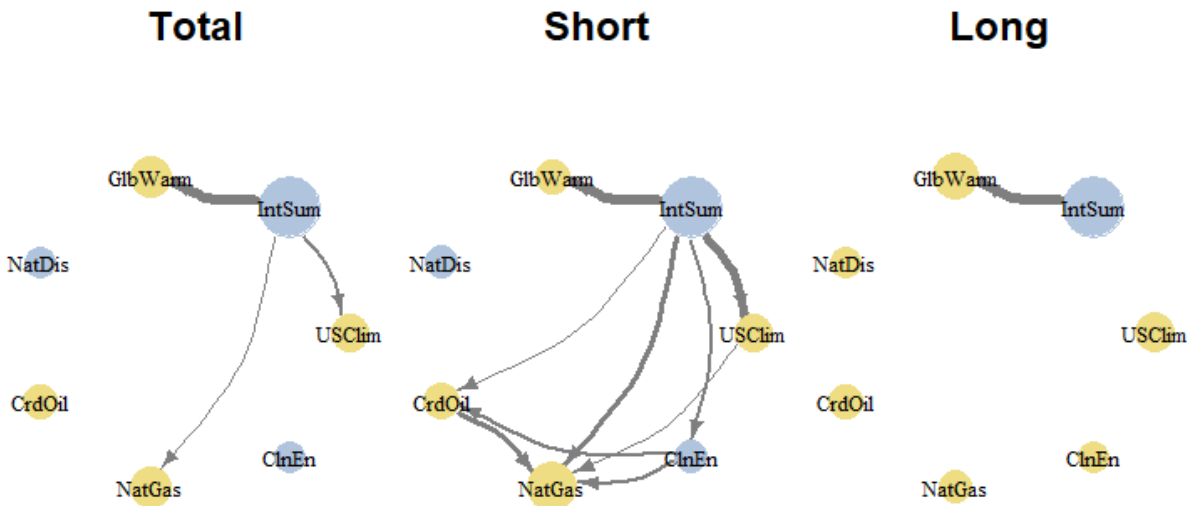


Figure 3: NPDC connectedness plots of the median frequency QVAR model, for total, short and long terms, with the short-term corresponding to 1–5 days and the long-term to 5–100 (inf) days, using a window size of 200 and lag 1. Note that the light-blue nodes indicate the net transmitters, while the light-yellow nodes denote the net receivers.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

5.2. Benchmarking

To benchmark and validate⁷ our frequency-QVAR connectedness findings, we replicate the analyses using the established Baruník & Křehlík (2018) frequency-VAR connectedness framework. Because this method is widely used in the literature, comparing its outputs at the median to our QVAR results, provides a sound reference point. This comparison verifies that the QVAR enhancements provide genuine analytical benefits beyond what the standard VAR approach can capture.

To maintain clarity, we present graphically the main results of the connectedness measures. Specifically, Figure 4 and Figure 5 display, the pairwise spillover network and the net pairwise directional connectedness network derived from the frequency-VAR model, respectively. Each node corresponds to one of our variables, four climate indices plus crude oil, natural gas, and clean energy, where the edges indicate the strength and direction of spillovers in both the short-term (high-frequency band) and the long-term (low-frequency band).

Visually, the frequency-VAR networks reproduce our main insights: the climate-risk indices, apart from the natural disaster index, are grouped in a tightly connected cluster with only thin outgoing links to the rest of the system, while crude oil and clean energy form a second, strongly interconnected pair for the total- and the short-term period. This confirms that, even under a standard VAR approach, the spillover effects flow primarily within the climate cluster and within the two energy markets, with only limited cross-group spillovers. In other words, physical and transition-risk sentiment continues to circulate mainly among the climate indices themselves, whereas the two energy sectors exchange shocks most intensely with one another, particularly in the total- and the short-term horizon. Moreover, when we examine net pairwise directional connectedness under frequency-VAR (Figure 5), we observe that, the overall pattern of transmitter and receivers of the spillovers remains almost the same in both short- and long-term bands. Thus, our utilized QVAR approach not only uncovers tail-sensitive dependencies beyond the median, but also consistently replicates the established VAR-based picture of the climate–energy network when restricted to median dynamics.

⁷ We also tested the sensitivity of our frequency-VAR connectedness results to alternative parameter choices, by varying the rolling window of 150, 200, 250 and 300 days and lag order of 1, 2 and 3. The network plots, indicate that different window sizes and lags produce nearly identical network structures and connection patterns. This confirms that our model is robust to the specific parameter selection we made. Specifically, for larger windows tended to smooth away meaningful link strengths, while shorter windows introduced excessive volatility and therefore unstable quantile estimates, and additional lags substantially increase computational time without improving or altering the results. Network plots for each specification appear in Appendix C.4.

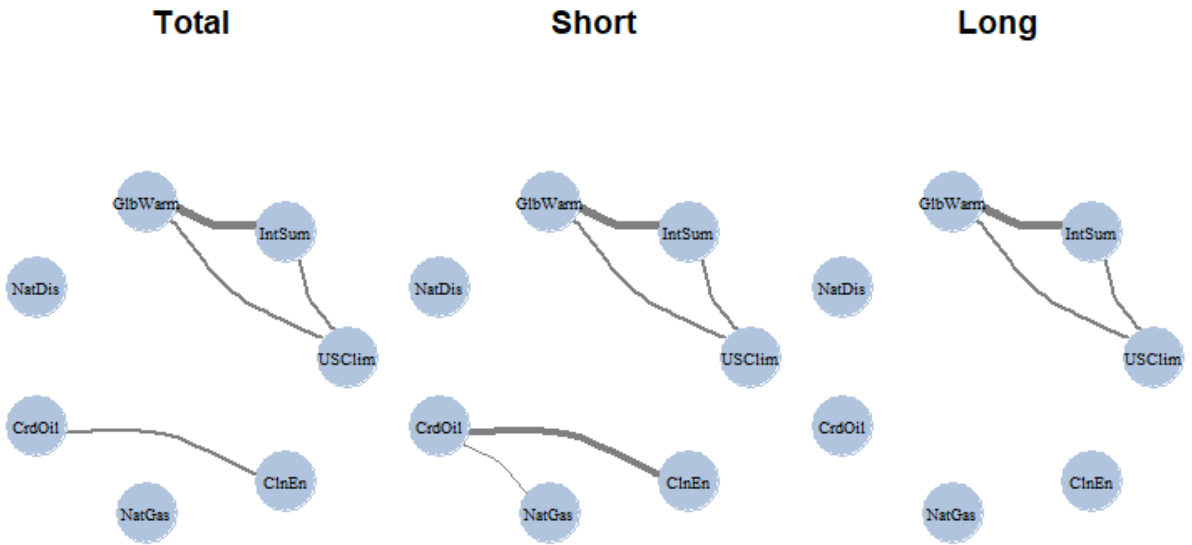


Figure 4: Pairwise connectedness plots of the frequency VAR model, for total, short and long terms with the short-term corresponding to 1–5 days and the long-term to 5–100 (inf) days, using a window size of 200 and lag 1.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

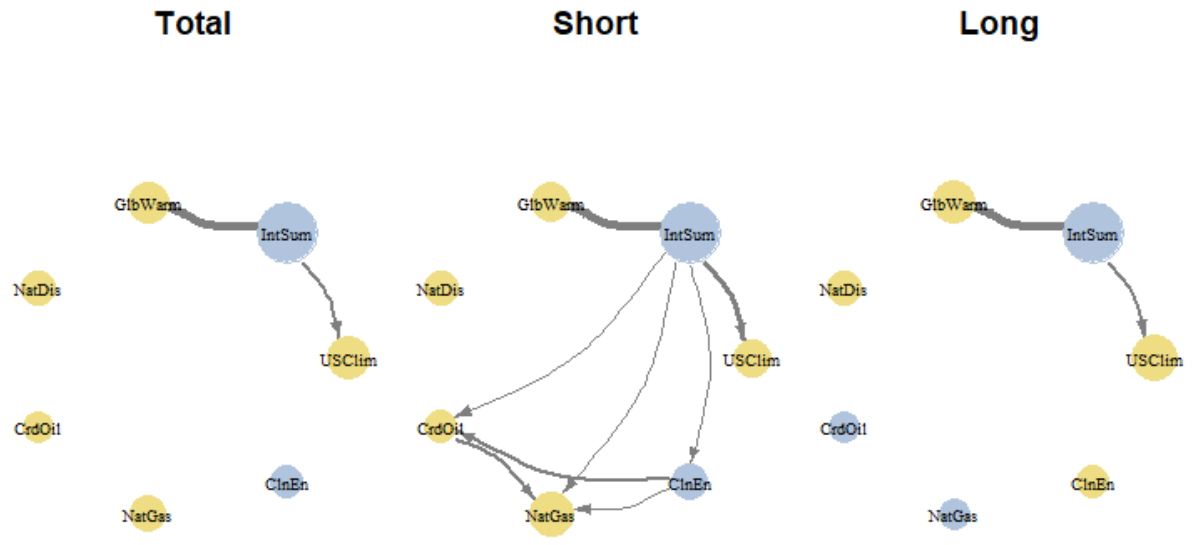


Figure 5: Connectedness plots of the frequency VAR model, for total, short and long terms, with the short-term corresponding to 1–5 days and the long-term to 5–100 (inf) days, using a window size of 200 and lag 1. Note that the light-blue nodes indicate the net transmitters, while the light-yellow nodes denote the net receivers.

Abbreviations: USClim - U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

Switching our focus to the dynamic connectedness, Figure 6 (frequency-VAR) and Figure 7 (frequency-QVAR) plot the Total Connectedness Index (TCI) across time and frequency bands. From both frameworks we observe similar patterns, where in major

geopolitical and systemic shocks, this connectedness increases. Specifically, from mid-2017 through early 2018, TCI heightens significantly in both plots, coinciding with President Trump's announcement on June 1, 2017 that the U.S. would withdraw from the Paris Agreement. Within the mean-based frequency-VAR framework, the TCI rises sharply on 1–2 June, with the effect most visible in the long-term horizon. The median-based frequency-QVAR, by contrast, does not exhibit this extreme surge due to its robustness to outlier events, although it still reflects a distinct upward movement. Trump's announcement drove the international summits and U.S. climate policy indices sharply up, triggering immediate spillovers to crude oil, natural gas, and clean-energy markets, where those heightened linkages persisted and peaked at June 2 as markets adjusted the expected Federal emissions policy and renewables incentives.

Apart from that, a second major peak appears in early 2020, which coincides with the World Health Organization (WHO) officially characterizing COVID-19 as a pandemic on 11 of March 2020 (WHO, 2020). That announcement, triggered unprecedented cross-asset volatility, sharply raising connectedness across climate and energy indices. Later, on February 24, 2022, Russia's full-scale invasion of Ukraine pushed TCI even higher, as energy-security fears and geopolitical risk surged. Similarly, on October 7, 2023 the Palestine-Israel conflict produced another TCI bump, especially in the short-term horizon, reflecting renewed uncertainty over oil and gas supply routes. Finally, the November 2024 U.S. presidential re-election of Trump, drove a fresh upward trend in connectedness, as markets braced for potential policy reversals on climate and energy. These episodes demonstrate that, beyond traditional supply-demand drivers, policy decisions and geopolitical crises can amplify system-wide spillovers and that frequency-QVAR, with its median foundation, offers a particularly resilient lens for tracing these shocks.

Figure 8 and 9 show the net total directional connectedness of the frequency VAR and the frequency QVAR connectedness methods, respectively. Both methods yield in general terms the same network structure and timing, where the spillover effects rise sharply around the key geopolitical and climate-policy events we have examined. Particularly, after President Trump's June 1, 2017 Paris Agreement withdrawal announcement, crude oil, natural gas, and clean energy markets all emerge as clear net receivers of shocks steaming from the U.S. climate policy and international summits indices. In other words, these three energy sectors absorbed most of the risk transferred by climate sentiment in the days around the announcement. In addition, another upward trend in the net total directional connectedness, occurred in early–mid of 2023, where the index measuring international summits delivers strong, long-term

spillovers to every other variable of the study. This outcome aligns well with major meetings such as the G7 summit in Hiroshima (May 2023) and the preparatory talks for COP28, where renewed commitments on decarbonization targets and climate finance reshaped investors' long-run transition expectations. As a result, energy-market valuations adjusted not only to immediate supply-demand fundamentals, but also to revised policy trajectories, a shift that is most clearly visible in the long-horizon connectedness measures.

Finally, Figure 10 and 11 show the net pairwise directional connectedness measures for these two connectedness frameworks. Although both connectedness frameworks share the same overall structure, the VAR-based measures spike more sharply around outlier events, especially following the U.S. withdrawal from the Paris Agreement, reflecting their greater sensitivity to extreme shocks. In both models, the international summits index consistently transmits long-term spillovers into the crude oil, natural gas, and clean energy markets, underscoring how major policy commitments reshape investors' long-run expectations.

Overall, the frequency-VAR connectedness method performs well as a benchmark, with comparable results to those of our frequency-QVAR model. However, because the frequency-VAR model is mean-based estimation, it is more sensitive to extreme outliers, whereas the frequency-QVAR method, as median-based estimator, is robust. Our analysis show that dynamic measures of the total connectedness rise sharply in response to major policy and geopolitical shocks, including President Trump's June 2017 withdrawal from the Paris Agreement, the WHO's March 2020 announcement of a pandemic, Russia's February 2022 invasion of Ukraine, the October 2023 conflict between Palestine and Israel, and the November 2024 U.S. presidential elections. This illustrates how individual shocks can amplify system-wide spillovers. Moreover, the net pairwise directional connectedness measures show that, in response to such shocks, energy markets consistently absorb risk transmitted from both the U.S. climate-policy and international summits indices. Notably, the international summits index emerges as an early long-run transmitter, indicating that global agreements and negotiations continually shape investors' expectations surrounding the energy transition.

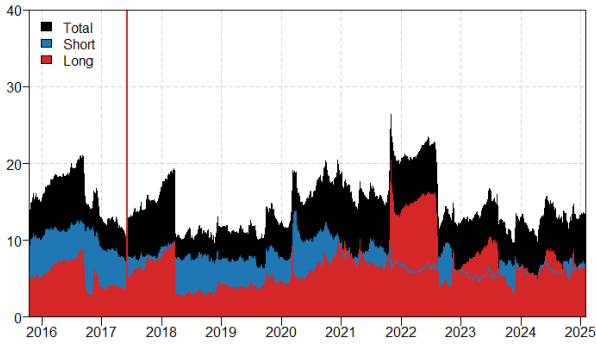


Figure 6: TCI of the frequency VAR connectedness method.

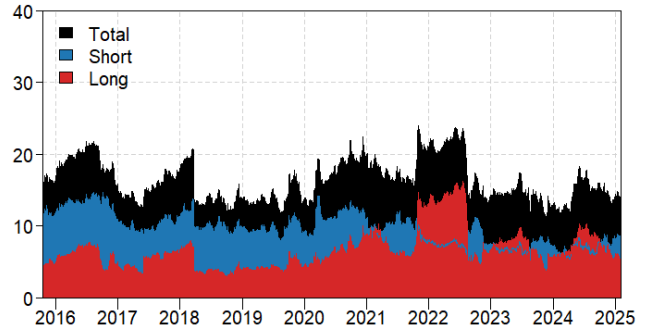


Figure 7: TCI of the median frequency QVAR connectedness method.

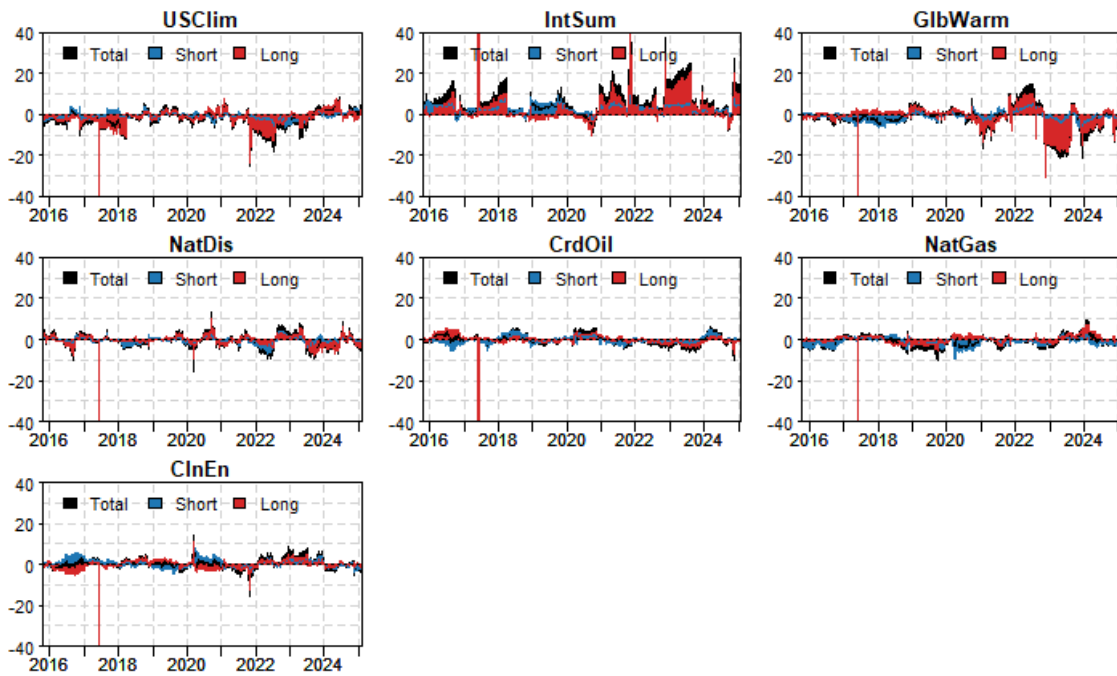


Figure 8: NTDC of the frequency VAR connectedness method.

Abbreviations: USclim – U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

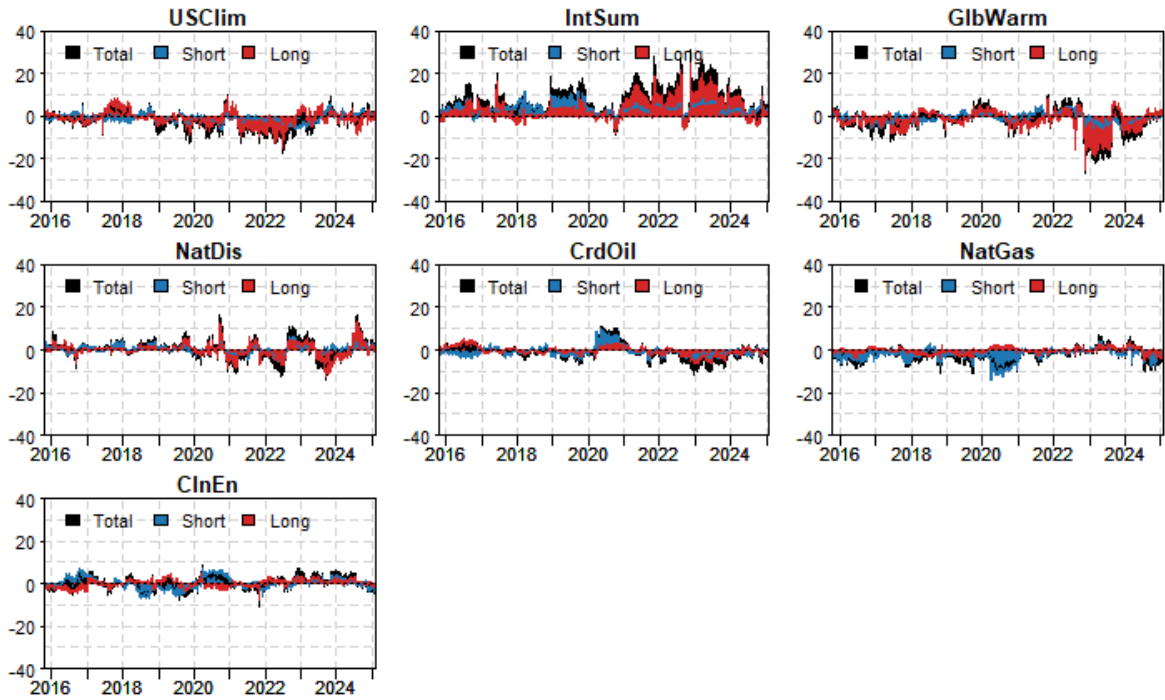


Figure 9: NTDC of the median frequency QVAR connectedness method.

Abbreviations: USclim – U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

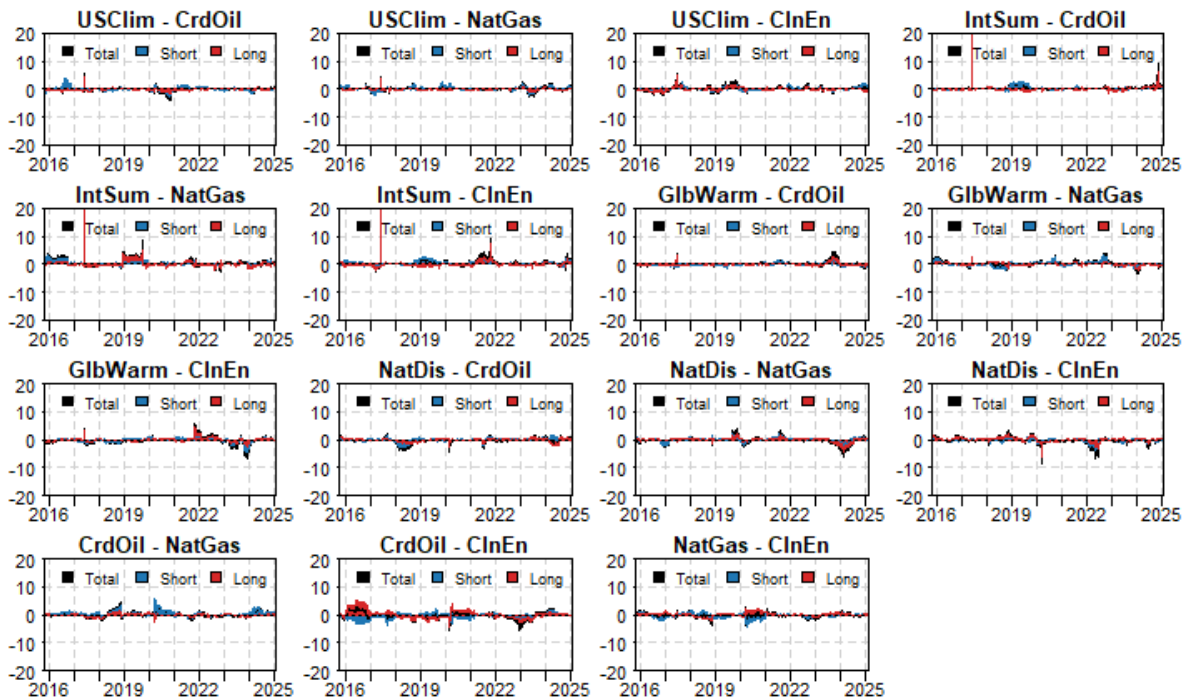


Figure 10: NPDC of the frequency VAR connectedness method.

Abbreviations: USclim – U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

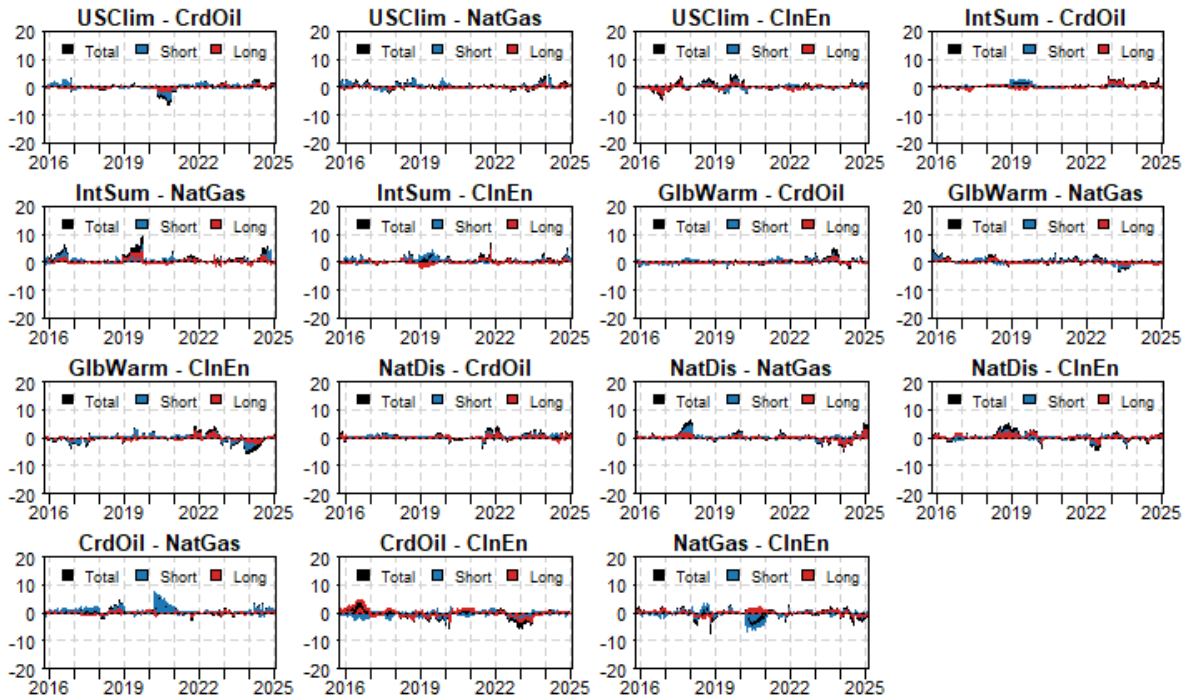


Figure 11: NPDC of the median frequency QVAR connectedness method.

Abbreviations: USclim – U.S. climate policy, IntSum - International summits, GlbWarm - Global warming, NatDis - Natural disasters, CrdOil - Crude Oil, NatGas - Natural Gas and ClnEn - Clean Energy.

5.3. Analysis Across Quantiles

In this final part of our empirical analysis, we investigate spillover effects across different quantiles of the return distribution. This step is crucial, as it allows us to detect heterogeneity in spillover transmission under varying market conditions, from severe downturns (e.g., 0.05 quantile) to strong upswings (e.g. 0.95 quantile). Mean-based approaches, such as the frequency-VAR, do not account for nonlinear behaviour in spillover transmission. The quantile-based frequency-QVAR framework, however, enables a clearer assessment of whether risk spillovers strengthen during crises or persist even under tranquil market conditions. Therefore, by studying these spillovers across a wide quantile interval, we gain improved and more informative knowledge of tail-dependent interlinkages between climate indices and energy markets, which is essential for policymaking, risk management, and wise investment decision-making, in the context of growing climate and geopolitics uncertainty.

Specifically, we created visualizations for the Total Connectedness Index (TCI), the Net Total Directional Connectedness (NTDC) of each variable, and the Net Pairwise Directional Connectedness (NPDC) between selected pairs, such as the climate indices versus crude oil, natural gas, and clean energy. From the TCI heatmaps, darker areas signal increased system-

wide connectedness, whereas lighter regions correspond to lower TCI values, indicating weaker overall linkages within the system. In the NTDC and NPDC heatmaps, warmer colours denote stronger spillover transmission (either positive or negative), while cooler tones represent lower values or a net-receiving position. These visual representations therefore enable us to identify, across time and quantiles, whether a given index acts predominantly as a transmitter or receiver of shocks. The vertical axis represents the quantile level of the connectedness measure, while the horizontal axis corresponds to the time dimension. To improve interpretability⁸, outliers exceeding a threshold of 0.01 were excluded, and all connectedness measures (TCI, NTDC, NPDC) were calculated within the [0.05, 0.95] quantile range to avoid distortion from extreme tails that may be noisy or uninformative. For brevity, the graphs are provided in Appendix Sections C.1 and C.2.

For TCI, the mid-quantile band ($\tau \in [0.40, 0.60]$) yields values of roughly 20 percent in the total-term decomposition, suggesting moderate average interconnectedness between climate indices and energy markets. However, as we are moving away from this mid-quantile band, total connectedness rises sharply. In the lower tail ($\tau \leq 0.20$) and, even more visibly, in the upper tail ($\tau \geq 0.80$) the system becomes distinctly more connected. At the extreme upper quantiles ($\tau \geq 0.80$), TCI values often exceed 40 percent and, during well-identified geopolitical or policy shocks, they surpass 60 percent. However, the effects in the long-term frequency band are more pronounced than in the short-term. The surge in high-quantile connectedness is mainly driven by the climate-risk cluster. When climate-related news coverage intensifies, reflected by a marked rise in the climate indices, whether driven by major policy developments (e.g., the U.S. withdrawal from the Paris Agreement) or severe physical-risk events (e.g., wildfires, extreme temperatures, or destructive storms), the four climate indices reinforce their internal interconnectedness and transmit stronger spillovers to the three energy markets. At the same time, the bidirectional linkages between crude oil and clean energy also strengthen, reflecting investors' simultaneous repricing of fossil-fuel demand expectations and renewable-energy prospects.

⁸ It is important to note that the exclusion applies only to extreme outliers beyond the selected quantile range and not to the tail quantiles themselves. The frequency-QVAR model is still estimated across the full quantile distribution, thus it includes the lower and upper tails (0.05 and 0.95 quantiles). Furthermore, removing the extreme outliers improves numerical stability and prevents highly noisy, non-informative observations from distorting the spillover decomposition, while preserving the ability of the model to capture tail-dependent spillovers.

For NTDC, the U.S. climate policy and international summits indices emerge as the dominant net transmitters in the upper tail ($\tau \geq 0.80$) of the connectedness distribution, while transmitting spillovers across the entire system. This transmission spike coincides with President Trump's June 1, 2017 announcement to withdraw from the Paris Agreement and endures into early 2018, marking the most prolonged and intense period of net risk transition from climate sentiment. Other geopolitical and policy events, such as the WHO's March 2020 pandemic declaration and Russia's February 2022 invasion of Ukraine, also trigger high net spillovers from these indices, but each episode was shorter in terms of duration and lower in magnitude than the Paris-withdrawal shock. Simultaneously, crude oil, natural gas, and clean energy markets absorb significant portions of this risk at the extreme upper quantiles, underscoring how tail movements in climate policy and global-summit expectations reshape energy-sector risk profiles.

Finally, for the NPDC, we similarly observe that the spillover patterns are highly aligned with major geopolitical and climate-policy events. As in the NTDC results, the U.S. climate policy and international summits indices are the most significant net transmitters in the upper tail ($\tau \geq 0.80$) of the distribution, by transmitting strong positive spillovers to the crude oil, natural gas, and clean energy markets. The most notable episode of this transmission is associated with the June 2017 U.S. withdrawal from the Paris Agreement, where spillovers weren't only peaked very steeply but also persist into the early part of 2018. These effects are observed both over short- and long-run frequency horizons, illustrating the way in which a single high-impact policy decision can shape return dynamics at several horizons.

Alongside the climate indices, we further notice that, crude oil systematically transmits spillovers to natural gas, across quantiles and across the whole sample period. This broad-ranging impact reflects crude oil's central role in the global energy system and its sensitivity to both market fundamentals and more broadly defined macroeconomic shocks. During the COVID-19 period, natural gas was particularly affected, emerging as a major net shock receiver across all quantiles, especially in the short run. This dynamic reflects the sharp decline in gas demand resulting from global lockdown measures. Notably, the effect weakens substantially over longer horizons, suggesting that short-run market disruptions, rather than persistent structural forces, were the dominant drivers.

Lastly, it is worth mentioning that both crude oil and natural gas have similar transmitting behavior to the clean energy market, and this relationship is amplified during two significant periods, i.e. the withdrawal of the Paris Agreement, and the COVID-19 pandemic. These findings illustrate major economic dynamics. The U.S. exit from the Paris Agreement prompted

a swift reassessment of long-horizon expectations concerning carbon policy, emission regulations, and the relative competitiveness of fossil-fuel technologies. As a consequence, clean-energy equities were repriced upward, reflecting market anticipation of a policy-driven shift toward sustainable energy-oriented assets. Secondly, as we have observed in the case of Covid 19 pandemic, sharp collapses in fossil-fuel demand and the heightened global focus on sustainability contributed to stronger linkages between traditional and renewable energy assets. The increased spillovers from oil and gas to clean energy during such periods underscore the degree to which transition shocks are policy-driven or crisis-related.

6. Conclusions and Policy Implications

The present research sheds light on the relationships between climate risks, geopolitical tensions and the energy commodity markets. Recognizing that these uncertainties have a significant impact on investment behavior, market dynamics, and the broader energy infrastructure, this study applies the highly relevant frequency-QVAR connectedness methodology, which allows us to unveil hidden linkages across the full range of market outcomes, including the extremes events captured by the tail quantiles, as well as to identify short- and long-run impacts. This enables us to identify and distinguish the roles of physical and transition climate risks in influencing traditional fossil-fuel markets, as well as clean energy markets.

Our empirical analysis reveals a clear alignment between major climate-policy indices, such as the U.S. climate policy and international summits, and abrupt increases in systemic connectedness across the energy markets. This finding supports H1 hypothesis, as these transition-policy climate indices act as net transmitters of shocks. Specifically, peaks in the frequency-QVAR total connectedness index closely correspond with key international geopolitical and climate-related incidents, including President Trump's announcement of the U.S. withdrawal from the Paris Agreement in June 2017, the WHO's declaration of the COVID-19 pandemic in March 2020, Russia's invasion of Ukraine in February 2022, the October 2023 Palestine–Israel conflict, and the most recent U.S. presidential Trump's re-election in November 2024. These episodes demonstrated that summit-level declarations and high-publicity policy announcements act as powerful shock transmitters, that reshape investors' expectations and risk perceptions, across both fossil-fuel and renewable-energy sectors.

We show that rapid shifts in climate-policy sentiment may temporarily override fundamental market forces, compelling energy-market participants to reprice assets and recalibrate hedging strategies in response to evolving transition-risk expectations. The U.S. climate policy and international summit indices are found to be the most important net transmitters of spillover effects, particularly during periods exhibiting prominent climate-policy events in the upper quantiles. This highlights their valuable role as leading indicators of systemic risk transmission across the energy finance domain. Their consistent behavior across quantiles and frequency domains makes them useful tools for researchers and practitioners interested in predicting the direction and size of future market-wide contagion. This behavior supports H3 hypothesis, confirming that climate-policy spillovers intensify under extreme market conditions (tail quantiles). In contrast, the physical-risk indices (e.g., natural disasters, climate-change events) exhibit weak and non-persistent spillover transmission, thereby supporting H2. This suggests that energy-market repricing is driven not by physical shocks but by transition-policy expectations, meaning that media coverage of climate hazards or natural disasters has only a limited influence on fossil-fuel and clean-energy assets.

These results demonstrate how vital it is for policymakers to implement specific policies, which combat both energy and geopolitical market issues, stemming from the climate change risk indices of Faccini et al. (2023). The withdrawal of the Paris Agreement, Russia-Ukraine conflict, alongside the Israeli-Palestinian crisis reveal how global tensions and climate-related incidents affect energy markets intensely, weakening both renewable energy progress and intensifying fossil fuel dependence (Qin et al., 2020). Policy development must establish frameworks that can manage ongoing geopolitical disruptions while simultaneously fostering sustained support for the expansion of green energy, which forms the foundation for transitioning toward a low-carbon economy. This need is urgent, as geopolitical risks now directly influence energy-market price stability and volatility, posing a threat to global financial stability (Zhang et al., 2023b).

Government efforts should prioritise enhancing sustainable financial products so they can be more effectively integrated into traditional financial markets. Sustainable project financing requirements are increasing (OECD, 2016), while investment in fossil fuels continues to decline – evidence pointing that market structures are undergoing transformation. Public authorities should adopt tax incentives and supportive regulatory frameworks that encourage investment in sustainable development. The ongoing innovation in financial markets, through instruments such as green bonds and sustainable energy indices, enhances

investor access to climate-aligned assets and contributes to progress toward global decarbonisation goals (Campos-Martins & Hendry, 2024).

The highly uncertain energy market environments demand better risk management systems that allow investors to handle intricate market complexities. The study highlights the importance of the frequency-QVAR connectedness method, which measures the spillover effects across multiple quantiles and short- and long-term horizons, enabling policymakers to develop improved risk mitigating strategies. Financial institutions need policymakers to establish proper mechanisms for spillover transmission between different markets, including bond and commodity markets that show growing connections to global economic and geopolitical instability (Asgharian et al., 2023). Government-led financial risk solutions that pool resources together create a defense system, which protects both financial institutions and economic stability from major climate and geopolitical disturbances.

Thus, by monitoring these media-based climate risk indicators as signals of financial contagion across the energy system, investors can better align portfolios with the global transition toward a low-carbon economy and reduce systemic risk in commodity markets. Finally, from a regulatory perspective, our findings suggest that climate-policy uncertainty should be incorporated directly into the systemic risk frameworks. Thus, the regulators could perform the following: (i) require climate stress-testing of portfolios against transition-policy shocks, and (ii) consider capital buffers for institutions with exposures to fossil-fuel futures during periods of elevated climate-policy uncertainty. The above measures would shift market behavior from reactive repricing toward proactive systemic risk management.

The present situation demands global cooperation because climate policies require agreement with geopolitical strategies. Governments need to work together to develop a single method for climate risk management which includes geopolitical elements since climate change continues to intensify. Global markets will maintain their resilience when geopolitical risks have no negative impact on clean energy investment. Policymakers who advance international sustainability frameworks linked with geopolitical stability create a strong future-proofed financial system enabling economic growth and environmental preservation. Ultimately, as this study has established, policymakers and governments need to remain particularly vigilant because the U.S. climate policy and international summit indices have been found to be the most significant net transmitter of spillover effects, especially when climate-policy heightens in the upper quantiles. This emphasizes the uneven impact such policy changes can have on energy markets and the broader financial system. These identify some information frictions surrounding climate-risk news in commodity futures markets, since the

climate-policy information is not immediately priced into these markets, and it supports the modern portfolio theory by demonstrating that diversification efficiency becomes dependent on the state of climate transition-policy uncertainty. From an academic perspective, this study advances the climate-finance literature by demonstrating that transition-policy risk is the dominant driver of systemic spillover effects. The separation of climate risk into physical and transition dimensions, combined with a frequency-QVAR connectedness framework, reveals that climate-risk transmission is asymmetric, quantile-dependent and horizon-specific divided into short/long periods. Thus, this introduces a new understanding on how climate policy shocks propagate through heterogeneous commodity futures (oil and gas) and clean-energy equity markets.

Future research could extend this study by examining the influence of climate indices on other major commodity markets, such as agricultural commodities, industrial metals, and additional energy products, which are increasingly exposed to both physical and transition-related climate risks. This would also build on the existing literature examining spillovers between the climate-related indices of Faccini et al. (2023), with crude oil and agricultural commodity markets (Dahl et al., 2020; Nazlioglu et al., 2013; Yip et al., 2020; Zeng et al., 2025). By applying the frequency-QVAR framework to these markets, future research could uncover asymmetric spillover patterns across quantiles, particularly in the tails where climate shocks have the potential to disrupt supply chains and destabilise price dynamics.

In addition, future research could investigate the evolution of quantile- and frequency-specific hedging instruments, enabling commodity investors and producers to manage climate-related volatility more effectively. Expanding the scope of climate-policy measures, such as carbon-pricing frameworks, ESG regulation, and country-level climate-finance commitments, would further improve understanding of global policy transmission channels. Furthermore, incorporating high-frequency climate-sentiment indicators extracted from news or policy text using natural language processing techniques could provide real-time insights into market-wide contagion dynamics. These additions would yield valuable information for researchers, practitioners, and policymakers aiming to analyze and reduce the broader commodity market risks from evolving climate policy regimes.

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