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When Climate Risks Meet Equity Markets: Evidence from Return and Volatility Spillovers

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Abstract

Climate change presents significant risks to the global economy and financial markets through both physical and transition channels. This study examines the transmission of climate-related risks, measured by two news-based indicators—the Physical Risk Index (PRI) and the Transition Risk Index (TRI)—to equity markets. Using the Diebold–Yilmaz and Barun ̇k–Křehlík connectedness frameworks, we analyze three representative equity benchmarks: the S&P 500 (SP500), the iShares ESG MSCI KLD 400 Index (DSI), and the iShares Global Clean Energy Index (ICLN). The empirical results show three main findings. First, both the PRI and TRI have relatively weak spillover effects on equity markets but display strong mutual interactions, indicating interdependence between physical and transition risk dimensions. Second, return spillovers are more prominent in the short term, while volatility spillovers dominate over longer horizons, reflecting structural asymmetry in risk transmission. Third, major global shocks—including the 2011 Libyan conflict, the COVID-19 pandemic, and U.S. tariff shocks in 2018 and 2025—increase both return and volatility spillovers. Overall, the findings indicate that volatility is the primary channel for long-term transmission of climate-related uncertainty. Climate-related news, although not yet fully integrated into equity market dynamics, is increasingly relevant for financial stability and the broader energy transition. Therefore, incorporating climate risk considerations into financial market analysis and policy design is necessary.

Keywords: Climate risk, News-based indices (PRI, TRI), Spillover effects, Connectedness (Diebold–Yilmaz, Barun ̇k–Křehlík), Volatility transmission

1. Introduction

Climate change is one of the most pressing challenges to the global economy and financial stability. Its effects are typically categorized as physical risks, such as extreme weather events and rising sea levels, and transition risks, which result from policy shifts, regulatory changes, and technological advancements. Both types of risk have become increasingly relevant in shaping financial market dynamics. Recent global shocks—including the COVID-19 pandemic, oil price fluctuations, and trade tensions during the Trump administration—have heightened market uncertainty and intensified cross-market spillovers. Meanwhile, investors are placing greater emphasis on environmental, social, and governance (ESG) factors, with the clean energy sector playing a central role in the transition to sustainable growth.

This study presents a new method for capturing climate-related risks by using two news-based indices: Physical Risk Index (PRI) and the Transition Risk Index (TRI). These indices, constructed from newspaper coverage, measure the level of public and investor attention to climate-related issues. Unlike previous research that mainly examined ESG indices or green bonds (e.g., Mensi et al., 2022), this study analyses how climate-related discourse in the media can be systematically quantified and connected to financial market dynamics. By measuring language patterns related to climate risk, this research provides new insights into how public perceptions of climate risks are transmitted to market behavior.

The motivation for this work is both academic and practical. Hartzmark and Sussman (2019) show that mutual funds with low sustainability ratings experienced outflows exceeding USD 12 billion, while those with high ratings attracted inflows of more than USD 24 billion after Morningstar introduced its sustainability rating. Firms that neglect environmental risks tend to lose investor confidence, which undermines their long-term growth prospects.

Understanding how environmental and climate-related risks affect financial markets can help create a virtuous cycle in which investors reward responsible firms, thus advancing sustainable economic development. However, sustainability includes more than environmental performance. Companies that do not uphold labor standards or human rights cannot be considered genuinely sustainable, regardless of their environmental initiatives. Strong labor practices improve product quality and consumer trust, while effective governance—through transparency, internal controls, and accountability—reinforces the credibility of environmental and social commitments. Long-term responsible investment therefore requires balanced performance across all three ESG dimensions.

Our empirical analysis uses advanced connectedness methodologies, specifically the Diebold–Yilmaz (2012, 2014) spillover index framework and the Barun ík–Křehlík (2018) frequency-domain decomposition. These methods enable us to disentangle the transmission of climate-related risks to financial markets across various time horizons and through distinct channels of returns and volatilities. The main results show three key insights. First, the spillover effects of the PRI and TRI on equity markets are relatively weak, in contrast to previous findings that highlight the roles of ESG indices and green bonds. Second, return spillovers dominate in the short term, while volatility spillovers prevail in the long term, indicating a structural asymmetry in transmission. Third, return spillovers display two major spikes—during the 2011 Libyan conflict and the COVID-19 pandemic—whereas volatility spillovers show four peaks, associated with the Libyan conflict, the 2018 tariff shocks, the COVID-19 pandemic, and the renewed tariff shocks in 2025.

This study contributes to the growing literature by demonstrating that news-based climate risk indices interact with equity markets through both return and volatility channels, and by identifying volatility as the dominant mechanism for transmitting long-term uncertainty.

The remainder of this paper is structured as follows. Section 2 reviews related literature. Section 3 outlines the methodology, emphasizing the Diebold–Yilmaz and Barun ík–Křehlík frameworks. Section 4 describes the data. Section 5 presents the empirical results, including static and dynamic analyses. Section 6 concludes with key findings and policy implications.

2. Literature Review

The COVID-19 pandemic, oil price fluctuations, and political developments, such as tariff policies under the Trump administration, have significantly affected global financial markets. Research confirms that crises and geopolitical shocks shape financial uncertainty and spillover transmission across asset classes (Ali et al., 2020; Baig et al., 2020; Zhang, 2020a). These events increase volatility and systemic risk, as contagion spreads through increasingly interconnected financial systems.

To capture market uncertainty, scholars have often used benchmark indicators such as the Chicago Board Options Exchange Volatility Index (VIX) and the Economic Policy Uncertainty (EPU) index (Baker et al., 2016). During the COVID-19 pandemic, new measures—most notably the Infectious Disease Equity Market Volatility (ID-EMV) tracker—were introduced to quantify uncertainty caused by health crises (Bai et al., 2020). Using a time–frequency-domain framework, Liu, Nakajima, and Hamori (2022) examined the spillover effects of news-based economic uncertainty driven by COVID-19 on renewable energy stocks in the United States, Europe, and global markets. They found that return spillovers were concentrated at higher frequencies, while volatility spillovers persisted at lower frequencies, indicating that renewable energy markets were more sensitive to pandemic-related uncertainty than during the Global Financial Crisis.

Recently, research has focused on sustainable finance indicators—including ESG stock indices, clean energy benchmarks such as the iShares ESG MSCI KLD 400 Index (DSI), the iShares Global Clean Energy Index (ICLN), and green bond indices—as key elements of financial connectedness and systemic risk (Kılıç et al., 2022; Mensi et al., 2022). Evidence generally indicates a strong interdependence between clean energy and conventional financial markets. For example, Banerjee et al. (2024) found that green assets primarily transmit shocks, while brown assets mainly receive them. Similarly, Ziadat et al. (2024) examined spillover dynamics between clean energy markets and global stock indices, concluding that clean energy instruments can serve as effective diversification tools alongside traditional benchmarks such as WTI and CSI300.

The broader role of ESG investment and green finance has been extensively examined. Zeng et al. (2025) reported that large ESG indices (e.g., the S&P 500 ESG Index and the Dow Jones Sustainability World Index) and major technology firms such as Microsoft acted as net risk transmitters, while the Green Bond Index and firms such as Apple primarily served as net receivers. Mensi et al. (2022) found that green bonds and the S&P 500 (SP500) showed increased connectedness during crises, although green bonds remained relatively less volatile under extreme conditions. Similarly, Dogan et al. (2025) demonstrated an asymmetric relationship between green investments and international stock markets, with environmental and sustainability indices functioning mainly as net transmitters and green bonds as net receivers. Their analysis also showed that equity markets in the United States, the United Kingdom, Italy, Germany, and

France acted as major transmitters of shocks, whereas China and Japan were the main recipients.

Other strands of literature have examined carbon risk and renewable energy dynamics. Ha et al. (2024) found that carbon futures and renewable energy volatility alternated between transmitter and receiver roles before and after the pandemic. Karkowska and Urjasz (2025) showed that geopolitical risk changes the transmission patterns of ESG indices, with North American and developed European markets acting as dominant transmitters, while emerging European and Asia–Pacific markets primarily absorb shocks. Together, these findings show that ESG and clean energy markets are deeply integrated into global financial systems, with their transmission roles varying by crisis type, policy changes, and regional characteristics.

Building on this research, the present study examines spillover dynamics among five key variables—DSI, ICLN, SP500, PRI, and TRI—using the Diebold–Yilmaz (2012, 2014) and Barun ̊k–Křehlík (2018) frameworks. The objective is to assess how sources of economic and geopolitical uncertainty, including the COVID-19 pandemic, oil price volatility, and tariff shocks, affect clean energy and ESG-related equity markets. Following Dogan et al. (2025), who combined these approaches to analyze green investment connectedness, this study highlights the importance of time–frequency decomposition in identifying the asymmetric spillover patterns that characterize sustainable finance during periods of global disruption.

3. Empirical Methods

To examine the interconnectedness between climate-related risks and equity markets, we analyze five time series: two news-based climate risk indices—PRI and TRI—and three equity benchmarks, SP500, DSI, and ICLN. We employ the spillover index framework developed by Diebold and Yilmaz (2014) to quantify the extent and direction of return and volatility transmission among these variables.

Specifically, we estimate a vector autoregressive (VAR) model using daily log returns and compute the generalized forecast error variance decomposition (GFEVD). This approach attributes the H-step–ahead forecast error variance of each variable to shocks originating both from itself and from all other variables in the system, while remaining invariant to variable ordering. The resulting variance decompositions allow us to compute total, directional, and net spillover measures, thereby capturing how shocks propagate across climate and financial indicators.

To further understand the dynamics of interconnectedness across different time horizons, we adopt the Barun ̊k–Křehlík (2018) frequency-domain methodology. This technique decomposes the overall spillover effects into frequency-specific components, distinguishing short-, medium-, and long-term spillover behavior. Finally, to capture the time-varying nature of market interactions, we apply a rolling-window estimation of the spillover measures throughout the sample period, enabling us to track how the strength and direction of transmission evolve in response to major events and shifts in market sentiment.

3.1 Diebold–Yilmaz Approach

We use the Diebold-Yilmaz approach to measure connectedness based on the forecast error variance decomposition (FEVD) of a vector autoregression (VAR) model. For FEVD, see Pesaran and Shin (1998).

Let y_t represents an $N \times 1$ vector of daily log returns of equities and climate risk series at time t. We estimate an n-variable VAR with p lags,

$$y_t = \sum_{i=1}^{p} \Phi_i y_{i-1} + \varepsilon_t$$

and use the moving-average representation

$$y_t = \psi(\mathrm{L})\varepsilon_t$$

$$\varepsilon_t \; i.i.d. \sim (0, \Sigma)$$

where Φ denotes the $N \times N$ coefficient matrices, ε_t is a white noise error vector with covariance matrix Σ, ψ_h represents an $N \times N$ impulse-response coefficient matrix corresponding to lag h.

For an H-step horizon, the generalized FEVD share of shocks in variable k that contribute to the H-step forecast-error variance of variable j is

$$\theta_{jk}^{H} = \frac{\sigma_{kk}^{-1} \Sigma_{h=0}^{H} ((\psi_h \Sigma)_{jk})^2}{\Sigma_{h=0}^{H} (\psi_h \Sigma \psi_h')_{jj}}$$

where H is the forecast horizon, σ_{kk} is the kth diagonal element of the Σ, θ_{jk}^{H} is the contribution of the variable k to the variable j selected forecast horizon H.

Since generalized FEVD column sums need not equal one, we row-normalize

$$\theta_{jk}^{\sim H} = \frac{\theta_{jk}^{H}}{\Sigma_{k=1}^{N}\theta_{jk}^{H}}$$

$$\Sigma_{k=1}^{N}\theta_{jk}^{\sim H} = 1, \Sigma_{j,k=1}^{N}\theta_{jk}^{\sim H} = N$$

Total Connectedness Index (TCI) measures the overall level of spillovers in the system. It shows how much, on average, shocks in one market contribute to the movements of other markets. A higher TCI means stronger overall connectedness.

We then report connectedness by total spillovers, as an average off-diagonal share, and directional spillovers; FROM others, TO others, NET spillovers (TO - FROM). All measures are reported in percent and indicate how strongly the N series are connected in the time domain and directions in which shocks tend to affect.

$$S^{H} = 100 \times \frac{\Sigma_{k=1,k\neq j}^{N}\theta_{jk}^{\sim H}}{N}$$

3.2 Barun ̊k–Křehlík Approach

Following the Barun ̊k–Křehlík methodology, we decompose time-domain spillovers into frequency-specific components. We take the Fourier transform of the VAR impulse response to obtain the frequency response $\psi(e^{-i\omega})$ defined as

$$\psi(e^{-i\omega}) = \sum_{h} e^{i\omega h}\,\psi_{h}$$

This tells us how the system reacts at each speed and wave frequency ω.

$$(f(\omega))_{jk} = \frac{\sigma_{kk}^{-1}\psi(e^{-i\omega})\Sigma)_{jk}{}^{2}}{(\psi(e^{-i\omega})\Sigma\psi'(e^{+i\omega}))_{jj}}$$

The generalized causation spectrum $(f(\omega))_{jk}$ is the share of variable j's movement at frequency

$\omega \in (-\pi,\pi)$ that is due to shocks from variable k. It is order-invariant as the generalized FEVD idea shows.

$$\Gamma_{j}(\omega) = \frac{(\psi(e^{-i\omega})\Sigma\psi'(e^{+i\omega}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\psi(e^{-i\omega})\Sigma\psi'(e^{+i\omega}))_{jj}d\lambda}$$

$\Gamma_{j}(\omega)$ measures how important each frequency is for variable j. We use it as a weight.

$$\theta_{jk}(d) = \frac{1}{2\pi}\int_{a}^{b}\Gamma_{j}(\omega)(f(\omega))_{jk}d\omega$$

We choose a band $d = (a,b)$ and integrate the spectrum with the weight to get $\theta_{jk}(d)$, the share of j explained by k within that band.

$$\theta_{jk}^{\sim}(d) = \frac{\theta_{jk}(d)}{\Sigma_{k}\theta_{jk}(\infty)}$$

$\theta_{jk}(d)$ can be converted into a share $\theta_{jk}^{\sim}(d)$ by dividing by the total across all frequencies, and $\theta_{jk}^{\sim}(d)$ measures the pairwise spillover from the kth variable to the jth variable at an arbitrary frequency band d which is now comparable.

$$S_{\cdot\leftarrow k}^{F} = 100 \times \frac{\Sigma_{k=1,k\neq j}^{N}\theta_{jk}^{\sim}(d)}{N}$$

This equation builds To, From, and Net within each band as it compute directional TO spillovers on band d by averaging $\theta_{jk}^{\sim}(d)$ across receivers at $j \neq k$. You can also get FROM and NET by band in the same way.

Summing short, medium and long run up equals the time-domain total. As they use the generalized decomposition results are order invariant.

4. Data

This study investigates the spillover effects between market returns and climate-related risk indices. The analysis focuses on three representative equity return series and two indices that quantify the physical and transition dimensions of climate risk. The equity variables include the SP500, representing the broad U.S. market; DSI, capturing ESG-oriented equities; and ICLN, reflecting climate-focused equities. The climate risk variables consist of the PRI and TRI, both developed from news-based textual analysis. All analyses and visualizations were conducted in R (https://www.r-project.org/).

The PRI measures unexpected shifts in media attention to physical risks such as extreme weather events, floods, droughts, and rising sea levels, whereas the TRI captures surprises in media coverage of transition risks, including new climate policies, carbon taxes, and clean energy technologies. These indices were constructed by researchers at PolicyUncertainty.com (https://policyuncertainty.com/Climate_Risk_Indexes.html) based on climate-related vocabularies derived from scientific texts.[1] The vocabularies were converted into numerical vectors using the term frequency–inverse document frequency (tf–idf) approach, and cosine similarity was then employed to assess the closeness of each news article to these climate-related vocabularies.[2] This process generates a "concern" series for both physical and transition risks. The PRI and TRI represent the unexpected components of these concern series, indicating days when climate risks received unusually high media attention. Accordingly, the two indices serve as timely measures of daily shocks in public and investor attention to climate-related risks.[3]

The dataset covers the period from June 26, 2008, to June 30, 2025, beginning when ICLN data first become available. The sample period spans major global events—including the Global Financial Crisis, U.S. trade tensions, and the COVID-19 pandemic—thus capturing multiple episodes of heightened uncertainty. Missing observations in the original series were addressed using forward-fill imputation, replacing missing values with the most recent available observation. The final dataset comprises 4,456 daily observations, which were used to estimate the VAR models.[4]

To obtain volatility measures, we applied an Autoregressive Moving Average–Generalized Autoregressive Conditional Heteroskedasticity (ARMA–GARCH) model to the return series of DSI, ICLN, and SP500, as well as to the two risk indices. The lag orders were selected using the Akaike Information Criterion (AIC), and model adequacy was verified through residual diagnostics based on the Ljung–Box test. The corresponding estimation results are summarized in Appendix A.

Table 1. Variable description

Variable	Data	Data Source
DSI	iShares ESG MSCI KLD 400 Index (U.S. ESG equity index)	Yahoo Finance
ICLN	iShares Global Clean Energy Index (Global clean-energy equity index)	Yahoo Finance
SP500	U.S. large-cap market Index	Yahoo Finance
PRI	News-based Physical Climate Risk Index (hazards like extreme weather, sea-level rise)	PolicyUncertainty.com (Climate Risk Indexes)
TRI	News-based Transition Climate Risk Index (policies and technology shifts for decarbonization)	PolicyUncertainty.com (Climate Risk Indexes)

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1 See Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2024).

2 The term frequency-inverse document frequency (tf-idf) method is a common text-mining technique. It assigns higher weights to words that occur frequency in a given document but less often across all documents, capturing their relative importance.

3 For recent papers on modern language models with news in finance, see Zhu, L., Wu, H., & Wells, M. T. (2023) and Zhang, Z., Xu, K., Qiao, Y., & Wilson, A. (2025).

4 We also applied listwise deletion, removing any date with missing variables in either risk or return series, resulting in 4456 observations. The analysis results remained robust to alternative treatments of missing observations.

Note: Stock market variables (DSI, ICLN, SP500) are obtained from Yahoo Finance via R and transformed into daily log returns, computed as ln (Pt/Pt-1). Climate risk indices (PRI, TRI) are downloaded from PolicyUncertainty.com (Climate Risk Indexes).

Table 1 summarizes all variables and their corresponding data sources. In our empirical framework, the three equity variables represent distinct segments of financial markets—broad market (SP500), ESG-focused (DSI), and clean energy (ICLN)—whereas the two climate risk indices, PRI and TRI, capture different dimensions of climate-related risks. This joint dataset enables an integrated analysis of cross-market and cross-risk spillovers. Unlike conventional uncertainty measures such as the VIX or the Economic Policy Uncertainty (EPU) index, the PRI and TRI directly reflect media-based attention to climate risks, making it possible to disentangle physical hazards from transition-related concerns.

Specifically, the PRI quantifies the salience of physical climate hazards—including natural disasters, extreme weather, sea-level rise, droughts, and heat waves—based on the frequency of related terms in newspaper articles. The TRI, by contrast, captures transition risks by tracking the prevalence of policy and technological terms linked to decarbonization processes, such as carbon taxes, regulatory shifts, and clean-energy innovation. Each day's Reuters news coverage is compared against climate-related vocabularies (physical and transition) using text-based similarity measures to generate a "concern" score. The PRI and TRI are then defined as the innovations from an AR(1) process applied to these concern series—that is, they represent the unexpected components of daily climate-related attention. Hence, a spike in the PRI or TRI denotes days when physical or transition climate risks received unusually strong media focus.

All climate risk indices (PRI and TRI) were obtained from PolicyUncertainty.com (Climate Risk Indexes), while daily equity prices for the SP500, DSI, and ICLN were collected from Yahoo Finance via R and converted into logarithmic returns.

To assess spillovers across the general equity market and climate-sensitive sectors, we analyze three return series: the SP500, DSI, and ICLN. The SP500 reflects the performance of large-cap U.S. firms, DSI represents a free-float market capitalization index of U.S. firms with strong ESG characteristics, and ICLN tracks approximately 100 companies engaged in clean energy production and technology.

Table 2 presents the descriptive statistics for equity and clean-energy returns (DSI_Return, ICLN_Return, SP500_Return), their volatility proxies (DSI_Vol, ICLN_Vol, SP500_Vol), and the climate risk indices (PRI, TRI). The mean returns are close to zero (ranging from −0.0002 to 0.0004), with ICLN_Return exhibiting the highest dispersion (Std. Dev. = 0.0205), while DSI_Return and SP500_Return show the lowest volatility (Std. Dev. = 0.0126). All three return series display negative skewness (−0.46 to −0.55) and high excess kurtosis (around 15). The Jarque–Bera (JB) statistics strongly reject normality ($p = 0.000$), confirming the presence of heavy left tails and extreme movements—typical features of financial return distributions. Finally, the augmented Dickey–Fuller (ADF) test rejects the null hypothesis of a unit root for all series, confirming stationarity.

The volatility series are strictly positive, exhibiting very small mean values on the order of 10^{-4}, but display pronounced right skewness (approximately 6.7–7.5) and exceptionally high kurtosis (around 56–78). The Jarque–Bera (JB) test rejects normality for all volatility proxies ($p = 0.000$), while the augmented Dickey–Fuller (ADF) test confirms stationarity by rejecting the null of a unit root ($p = 0.01$).

For the climate risk indices, both PRI and TRI have slightly negative means (−0.0018 and −0.0011, respectively) and standard deviations of 0.0208 and 0.0235—magnitudes comparable to those of equity return variability. Their positive skewness (ranging from 0.75 to 0.96) and excess kurtosis (between 4.56 and 6.96) indicate episodic upward spikes in public and policy attention to climate-related risks. As with the return and volatility series, both normality and unit-root hypotheses are decisively rejected (JB $p = 0.000$; ADF $p = 0.01$).

Overall, the descriptive statistics reveal pervasive non-normality, heavy tails, and asymmetry across all variables. These distributional properties underscore the necessity of employing econometric techniques that are robust to heteroskedasticity and outliers. In particular, the spiky, heavy-tailed nature of the volatility and risk indices provides a key motivation for our subsequent spillover analysis and frequency-domain decomposition. As will be shown, cross-market volatility transmission remains relatively muted over short horizons but becomes dominant in the long run.

Table 2. Summary Statistics

Variable	Mean	Std. Dev.	Skewness	Kurtosis	JB Stat	ADF Stat
Return						
DSI_Return	0.0004	0.0126	−0.4604	14.9572	26703.038 (0.000)	−15.912 (0.01)
ICLN_Return	−0.0002	0.0205	−0.5540	13.5038	20712.678 (0.000)	−12.269 (0.01)
SP500_Return	0.0004	0.0126	−0.4907	15.8557	30863.757 (0.000)	−15.996 (0.01)
Volatility						
DSI_Vol	0.0002	0.0003	7.4560	77.5764	1073897.055 (0.000)	−9.030 (0.01)
ICLN_Vol	0.0004	0.0008	6.6637	56.3042	560520.022 (0.000)	−6.612 (0.01)
SP500_Vol	0.0002	0.0004	7.0559	68.1549	825158.657 (0.000)	−8.181 (0.01)
Risk Index						
PRI	−0.0018	0.0208	0.7478	4.5594	866.825 (0.000)	−10.602 (0.01)
TRI	−0.0011	0.0235	0.9557	6.9637	3595.367 (0.000)	−9.696 (0.01)

Note: The table reports descriptive statistics for returns (DSI_Return, ICLN_Return, SP500_Return), volatility proxies (DSI_Vol, ICLN_Vol, SP500_Vol), and risk indices (PRI, TRI). Returns are expressed in decimals. “Std. Dev.” is the standard deviation; “Skewness” (<0/>0) indicates left/right-tail asymmetry; “Kurtosis” measures tail thickness (values far above 3 imply heavy tails). “JB Stat” is the Jarque–Bera normality test; p-values are shown in parentheses below each row. The JB test rejects normality for all series at conventional levels ($p = 0.000$). “ADF Stat” is the Augmented Dickey-Fuller test; p-values are shown in parentheses below each row. The ADF test rejects the unit root for all series at conventional levels. Volatility variables are strictly positive and extremely right-skewed with very high kurtosis, consistent with volatility clustering. Return means are close to zero with negative skewness and large kurtosis-typical of financial returns. PRI and TRI display positive skewness and elevated kurtosis, indicating episodic spikes in policy/transition risk. All statistics are computed on the full sample; minor discrepancies reflect rounding.

5. Empirical Results

This section presents the empirical findings on the spillover effects between equity markets and climate risk indices. Two complementary approaches are employed: the Diebold–Yilmaz (DY) method in the time domain and the Baruník–Křehlík (BK) method in the frequency domain. The lag length of the VAR models for both returns and volatilities is determined using the Akaike Information Criterion (AIC). Using the generalized forecast error variance decomposition (FEVD), the DY approach captures how shocks are transmitted across markets over time. The BK method further decomposes these spillovers into three frequency bands: short term (1–5 days), medium term (6–20 days), and long term (≥21 days).

Dynamic spillovers are then estimated through a rolling-window framework. The baseline window length is set to 200 days, while alternative lengths (150 and 250 days) are used for robustness checks. Since the results remain consistent across specifications, only the 200-day case ($w = 200$) is reported. Section 5.1 discusses the full-sample spillover results in the time and frequency domains, while Section 5.2 summarizes the time-varying spillover dynamics.

5.1 Static Analysis

This subsection reports the spillover effects among index returns in both the time and frequency domains using the DY and BK approaches. Table 3 displays the spillover matrices for five variables. The upper panel presents the DY (Diebold–Yilmaz) results, while the lower panel provides frequency-specific results based on the BK (Baruník–Křehlík) decomposition. Each block lists the Total Connectedness Index (TCI) for its respective band (DY: 39.03; short term: 24.88; medium term: 9.71; long term: 4.44).

In each matrix, the rows represent the source markets and the columns represent the recipient markets. Each cell shows the directional spillover (%) from the row market to the column market. The rightmost “From” column reports the total contribution a market sends to others (off-diagonal row sum), while the bottom “To” row reports the total contribution a market receives from others (off-diagonal column sum). The last row provides the “Net (= To − From)” measure, where positive values indicate net transmitters and negative values indicate net receivers. Under the BK framework, analogous matrices and corresponding TCIs are presented for each frequency band—short, medium, and long term—as indicated in the table headings.

Over the full sample, the Total Connectedness Index (TCI) of 39.03 indicates a moderate level of interdependence across markets. Based on the net spillover definition (Net = To − From), the SP500 (+4.94) and DSI (+3.39) act as net transmitters, whereas ICLN (−8.64) is a clear net receiver. Including both the SP500 and DSI in the model helps distinguish general market dynamics from ESG-specific behavior. When DSI diverges from SP500, it reflects incremental influences unique to ESG-oriented equities. Both PRI (+0.07) and TRI (+0.24) appear largely neutral. Bilaterally, the DSI↔SP500 channel stands out (DSI→SP500 = 38.06; SP500→DSI = 37.54), indicating strong comovement between these two indices.

Turning to the frequency decomposition, the short-term (1–5 days) TCI of 24.88 accounts for the majority of total connectedness, confirming that spillovers are predominantly short-term in nature. In this frequency band, SP500 (+1.94) and DSI (+1.78) are net transmitters, while ICLN (−3.99) and TRI (−0.91) are net receivers, and PRI (+1.18) is slightly transmitter-leaning. In the medium term (6–20 days), the TCI declines to 9.71, with SP500 (+1.91) and DSI (+1.43) remaining transmitters, and ICLN (−3.33) continuing as a receiver. At this horizon, TRI (+0.46) switches to a transmitting role, while PRI (−0.47) becomes a receiver. In the long term (≥21 days), the TCI further decreases to 4.44. SP500 (+1.10) and DSI (+0.17) continue as net transmitters, ICLN (−1.33) and PRI (−0.61) act as receivers, and TRI (+0.68) remains a transmitter. The sum across the three bands (24.88 + 9.71 + 4.44 ≈ 39.03) aligns with the full-sample TCI, validating the decomposition.

Overall, SP500 and DSI consistently serve as net transmitters of shocks, primarily through short-term channels, while ICLN remains a persistent net receiver across all frequencies. Interestingly, the roles of TRI and PRI vary with the time horizon—TRI behaves as a receiver in the short and medium term but becomes a transmitter in the long term, whereas PRI exhibits the opposite pattern.

These results can be interpreted in two key ways. First, return spillovers are clearly dominated by short-term dynamics, highlighting the value of the BK decomposition alongside the DY framework. While the DY approach effectively captures the overall strength and direction of market spillovers, it does not distinguish between transitory and persistent effects. The BK method addresses this limitation by decomposing spillovers into short-, medium-, and long-term components using the Fourier transform of the VAR impulse response. The predominance of the short-term TCI implies that index returns respond quickly to climate-related shocks and news, though these effects tend to dissipate rapidly. In this sense, the BK framework provides more nuanced and temporally informative insights into financial connectedness than the aggregate DY measure alone.

Table 3. Return Spillover Table

DY spillover results: TCI = 39.03

	DSI_Return	ICLN_Return	SP500_Return	PRI	TRI	From
DSI_Return	41.61	20.13	38.06	0.12	0.08	58.39
ICLN_Return	24.13	49.84	25.74	0.13	0.16	50.16
SP500_Return	37.54	21.22	41.01	0.15	0.08	58.99
PRI	0.06	0.05	0.08	86.15	13.67	13.86
TRI	0.05	0.12	0.05	13.53	86.24	13.75
To	61.78	41.52	63.93	13.93	13.99	195.15
Net(=To-From)	3.39	-8.64	4.94	0.07	0.24	

BK spillover results (Frequency 1-5 days): TCI = 24.88

	DSI_Return	ICLN_Return	SP500_Return	PRI	TRI	From
DSI_Return	27.71	12.91	25.02	0.09	0.07	38.09
ICLN_Return	14.68	30.05	16.23	0.06	0.08	31.06
SP500_Return	25.12	14.08	28.06	0.13	0.07	39.40
PRI	0.04	0.04	0.06	59.70	7.29	7.43
TRI	0.02	0.05	0.03	8.32	59.88	8.42
To	39.87	27.07	41.34	8.61	7.51	124.39
Net(=To-From)	1.78	−3.99	1.94	1.18	−0.91	

BK spillover results (Frequency 6-20 days): TCI = 9.71

	DSI_Return	ICLN_Return	SP500_Return	PRI	TRI	From
DSI_Return	10.67	5.45	9.76	0.02	0.00	15.23
ICLN_Return	7.17	14.75	6.97	0.03	0.02	14.19
SP500_Return	9.46	5.39	9.70	0.01	0.00	14.86
PRI	0.01	0.01	0.01	13.23	2.33	2.35
TRI	0.02	0.03	0.02	1.83	11.53	1.90
To	16.66	10.86	16.77	1.88	2.36	48.54
Net(=To-From)	1.43	−3.33	1.91	−0.47	0.46	

BK spillover results (Frequency 21-infinity): TCI = 4.44

	DSI_Return	ICLN_Return	SP500_Return	PRI	TRI	From
DSI_Return	3.24	1.78	3.28	0.01	0.00	5.07
ICLN_Return	2.28	5.05	2.54	0.04	0.06	4.91
SP500_Return	2.95	1.75	3.25	0.01	0.01	4.72
PRI	0.01	0.00	0.00	13.23	4.05	4.06
TRI	0.01	0.04	0.00	3.38	14.83	3.44
To	5.24	3.58	5.82	3.45	4.12	22.21
Net(=To-From)	0.17	−1.33	1.10	−0.61	0.68	

Note: The table reports the directional spillover matrix (percent) for five variables. The upper panel presents full-frequency results from the Diebold–Yilmaz (DY) framework, and the lower panel shows the Barun ǩ–Křehlík (BK) frequency decomposition into short (1-5 days), medium (6-20 days), and long (≥21 days) bands. Off-diagonal cells report spillovers from row i to column j; diagonal entries are own contributions. The rightmost From column gives the off-diagonal row sum (total sent by that market), and the bottom To row gives the off-diagonal column sum (total received). Net (= To − From) is the difference between the two (positive = net transmitter; negative = net receiver). Each block also reports the band-specific Total Connectedness Index (TCI): DY = 39.03; short = 24.88; medium = 9.71; long = 4.44. Row totals are approximately 100% (subject to rounding). The sum of TCIs across the three BK bands approximately equals the DY TCI, with small differences due to rounding.

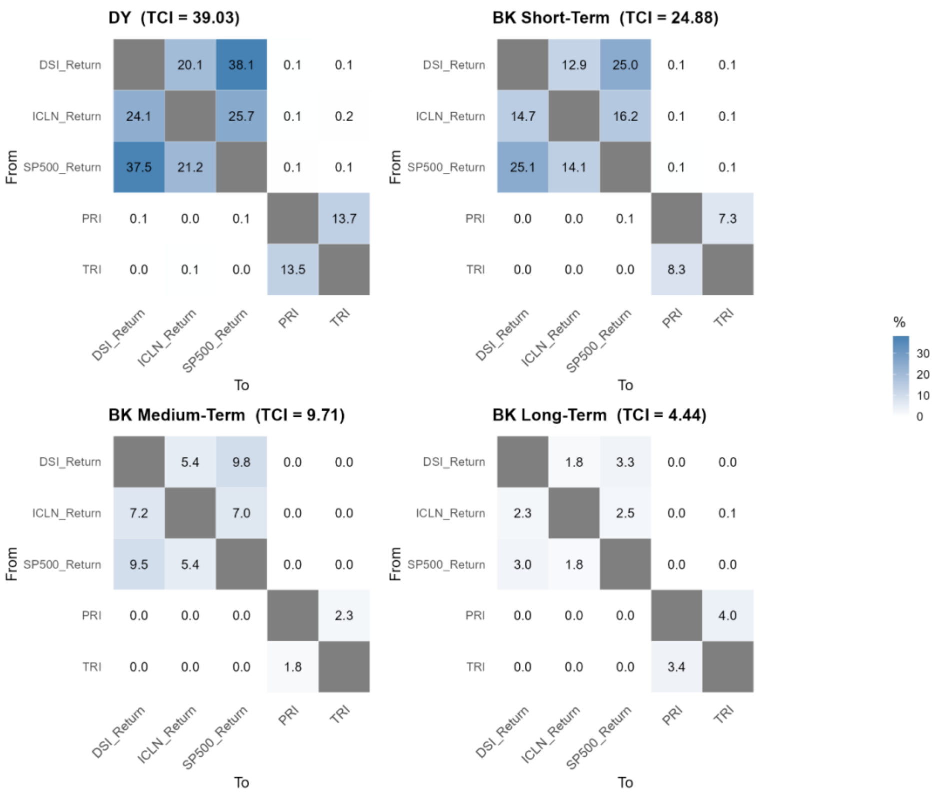

Figure 1. Return-spillover heatmaps at the full frequency (DY) and by frequency bands (BK)

Note: Each off-diagonal cell shows the share (%) of the forecast-error variance of the column market (To) explained by shocks to the row market (From). Diagonal (own) contributions are left blank for readability. Numbers inside cells are rounded to one decimal. A common color scale is used across panels to permit cross-band comparison. Total Connectedness Index (TCI): DY = 39.03; BK short = 24.88 (1-5 days), BK medium = 9.71 (6-20 days), BK long = 4.44 (≥21 days).

Second, the contrasting transmitter–receiver roles of DSI and ICLN are economically intuitive. DSI serves as a benchmark ESG index composed mainly of large-cap U.S. firms such as NVIDIA Corporation, Microsoft Corporation, and Alphabet Inc. These firms are highly liquid, broadly held, and exert substantial influence on global financial markets, making DSI a natural transmitter of shocks. In contrast, ICLN is concentrated in renewable energy companies—including First Solar, Inc., Vestas Wind Systems A/S, and Iberdrola S.A.—that are more specialized and sensitive to fluctuations in capital flows and sector-specific shocks. Rather than driving broader markets, ICLN tends to respond to them. The difference in index composition (approximately 400 firms for DSI versus about 100 for ICLN) and geographic scope (U.S.-focused versus global) further reinforces these contrasting roles. Hence, our empirical results align with the expectation that DSI operates as a transmitter, while ICLN functions as a receiver across different horizons.

Figure 1 visualizes the directional return spillovers using generalized FEVD at both the aggregate (DY) and frequency-specific (BK) levels. The figure confirms a moderate overall degree of connectedness (TCI = 39.03), with spillovers concentrated in high-frequency movements: the short-term band accounts for roughly 63.7% of total connectedness (24.88 / 39.03), the medium-term band for 24.9%, and the long-term band for 11.4%. Equity markets (DSI_Return and SP500_Return) exhibit strong bilateral spillovers, with large, reciprocal flows (e.g., DSI → SP500 = 37.5%; SP500 → DSI = 38.1%). ICLN_Return consistently acts as a net receiver across frequency bands (negative Net values), while DSI_Return and SP500_Return behave as net transmitters (positive Net values).

By contrast, PRI and TRI interact only weakly with equity markets but display a strong two-way linkage with each other (≈13–14% in the DY panel), with near-zero net effects. The BK decomposition shows that these directional patterns remain stable across horizons, although the magnitude of spillovers declines from short to long horizons.

Table 4 reports the generalized FEVD–based directional spillovers among DSI_Vol, ICLN_Vol, SP500_Vol, PRI, and TRI. The full-frequency Diebold–Yilmaz (DY) results indicate an overall connectedness of approximately 41% (TCI, computed as the off-diagonal sum divided by the number of variables). Volatility transmission is concentrated within the equity and clean-energy block: SP500_Vol receives the largest inflows (To = 77.26), followed by DSI_Vol (65.06), while ICLN_Vol emerges as the only significant net receiver (Net = −28.60). In contrast, the policy and transition indices remain peripheral to the equity complex and mainly interact with each other (PRI → TRI = 13.53; TRI → PRI = 13.41), resulting in near-zero net effects for PRI (−0.05) and a small net receiver role for TRI (+0.77). Overall, SP500_Vol (+19.60) and DSI_Vol (+8.28) act as the dominant net transmitters of volatility.

Turning to the frequency decomposition, the Barun ǩ–Křehlík (BK) panels reveal that connectedness is almost entirely a low-frequency phenomenon. At the short horizon (1–5 days), the TCI is only 0.12%, and all cross-market linkages are economically negligible, aside from a faint PRI↔TRI interaction (TRI → PRI = 0.30; PRI → TRI = 0.25). At the medium horizon (6–20 days), the TCI rises to 4.03%, with transmission largely confined to the policy/transition risk pair: TRI acts as a net receiver (Net = −0.95), and PRI as a net transmitter (+0.57), while equity and clean-energy volatilities remain largely decoupled. At the long horizon (≥ 21 days), the TCI increases sharply to 36.96%—accounting for about 90% of total connectedness—and the structure observed in the DY panel fully materializes. A dense, bidirectional network emerges among ICLN_Vol, DSI_Vol, and SP500_Vol, with ICLN_Vol remaining the dominant receiver (Net = −29.29) and SP500_Vol (+19.76) and DSI_Vol (+8.42) acting as the main transmitters. PRI and TRI continue to exhibit modest bilateral links (PRI → TRI = 4.69; TRI → PRI = 3.83) and only weak ties to equity markets.

Volatility spillovers across these markets are minimal at high frequencies, become modest at medium horizons—primarily within the policy and transition risk pair—and dominate at long horizons within the equity–clean-energy cluster. This pattern, consistent with the network visualizations, underscores that slower-moving, structural forces rather than short-lived shocks drive the cross-market transmission of volatility in our sample.

Table 4. Volatility Spillover Table

DY spillover results: TCI =						
	DSI_Vol	ICLN_Vol	SP500_Vol	PRI	TRI	From
DSI_Vol	43.22	16.08	40.27	0.09	0.34	56.78
ICLN_Vol	25.97	36.62	36.84	0.17	0.39	63.37
SP500_Vol	38.8	18.42	42.34	0.09	0.35	57.66
PRI	0.16	0.07	0.05	86.2	13.53	13.81
TRI	0.13	0.2	0.1	13.41	86.17	13.84
To	65.06	34.77	77.26	13.76	14.61	205.46
Net(=To-From)	8.28	−28.6	19.6	−0.05	0.77	

BK spillover results (Frequency 1-5 days): TCI = 0.12						
	DSI_Vol	ICLN_Vol	SP500_Vol	PRI	TRI	From
DSI_Vol	0.02	0.01	0.01	0.00	0.00	0.02
ICLN_Vol	0.00	0.00	0.00	0.00	0.00	0.00
SP500_Vol	0.02	0.01	0.03	0.00	0.00	0.03
PRI	0.00	0.00	0.00	2.95	0.25	0.25
TRI	0.01	0.00	0.01	0.30	3.17	0.32
To	0.03	0.02	0.02	0.30	0.25	0.62
Net(=To−From)	0.01	0.02	−0.01	0.05	−0.07	
BK spillover results (Frequency 6-20 days): TCI = 4.03						
	DSI_Vol	ICLN_Vol	SP500_Vol	PRI	TRI	From
DSI_Vol	0.88	0.27	0.67	0.00	0.00	0.95
ICLN_Vol	0.03	0.13	0.02	0.00	0.00	0.06
SP500_Vol	0.61	0.28	0.87	0.00	0.00	0.90
PRI	0.07	0.04	0.02	66.09	8.59	8.72
TRI	0.07	0.12	0.07	9.28	64.65	9.54
To	0.77	0.72	0.79	9.29	8.59	20.16
Net(=To−From)	−0.17	0.66	−0.12	0.57	−0.95	
BK spillover results (Frequency 21-infinity): TCI = 36.96						
	DSI_Vol	ICLN_Vol	SP500_Vol	PRI	TRI	From
DSI_Vol	42.29	15.84	39.59	0.08	0.34	55.85
ICLN_Vol	25.98	36.42	36.85	0.17	0.39	63.39
SP500_Vol	38.15	18.16	41.44	0.08	0.34	56.73
PRI	0.09	0.03	0.03	17.15	4.69	4.84
TRI	0.05	0.07	0.02	3.83	18.35	3.97
To	64.27	34.10	76.49	4.16	5.77	184.78
Net(=To−From)	8.42	−29.29	19.76	−0.68	1.80	

Note: The table reports the directional spillover matrix (percent) for five variables. The upper panel presents full-frequency results from the Diebold-Yilmaz (DY) framework, and the lower panel shows the Barun ŀk–Křehlík (BK) frequency decomposition into short (1-5 days), medium (6-20 days), and long (≥21 days) bands. Off-diagonal cells report spillovers from row i to column j; diagonal entries are own contributions. The rightmost From column gives the off-diagonal row sum (total sent by that market), and the bottom To row gives the off-diagonal column sum (total received). Net (= To − From) is the difference between the two (positive = net transmitter; negative = net receiver). Each block also reports the band-specific Total Connectedness Index (TCI): DY = 41.1; short = 0.12; medium = 4.03; long = 36.96. Row totals are approximately 100% (subject to rounding). The sum of TCIs across the three BK bands approximately equals the DY TCI, with small differences due to rounding. Both datasets, listwise deletion and forward-fill, can generate the similar table.

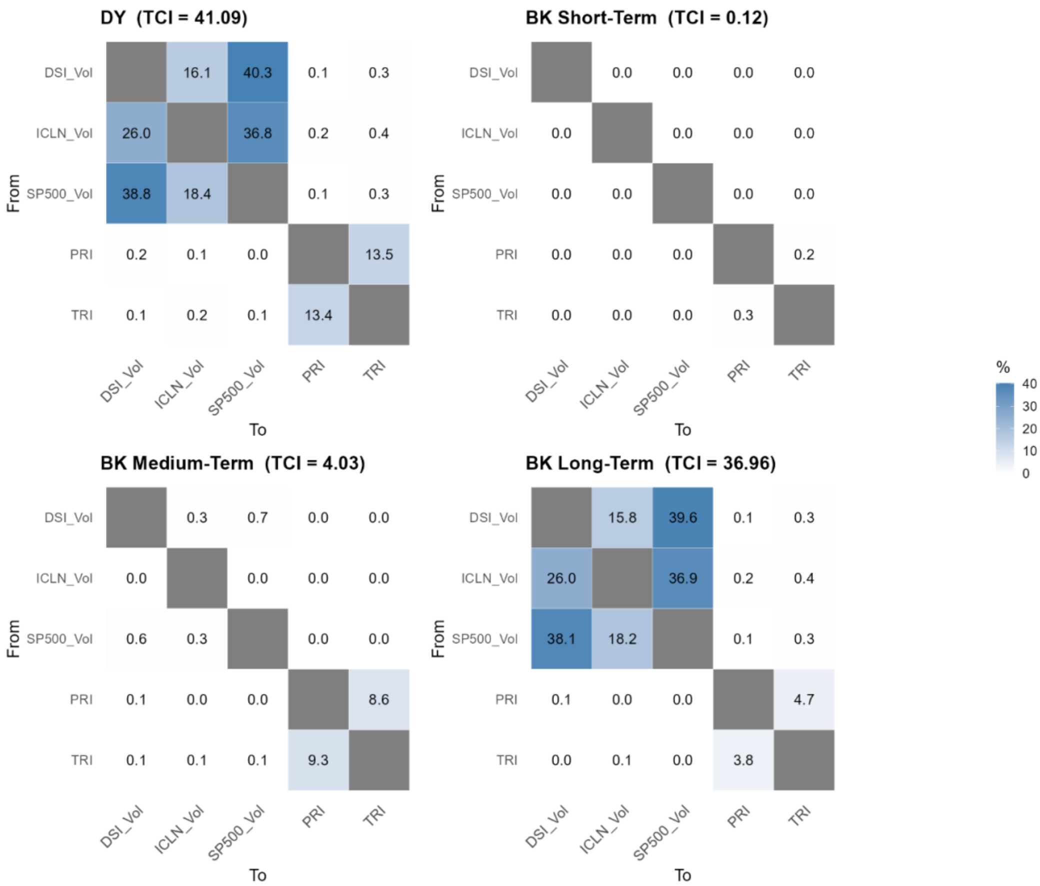

Figure 2. Volatility-spillover heatmaps at the full frequency (DY) and by frequency bands (BK)

Note: Each off-diagonal cell shows the share (%) of the forecast-error variance of the column market (To) explained by shocks to the row market (From). Diagonal (own) contributions are left blank for readability. Numbers inside cells are rounded to one decimal. A common color scale is used across panels to permit cross-band comparison. Total Connectedness Index (TCI): DY = 41.09; BK short = 0.12 (1-5 days), BK medium = 4.03 (6-20 days), BK long = 36.96 (≥21 days).

These findings highlight two key contrasts with the return-based results. First, volatility spillovers are predominantly a long-term phenomenon, in sharp contrast to return spillovers that are short-term and event-driven. This structural difference suggests that return connectedness reacts quickly to new information, while volatility connectedness reflects deeper and more persistent sources of uncertainty. Second, the BK decomposition reveals virtually no cross-market linkages at short horizons, limited interactions at medium horizons, and a well-defined, dense network only at long horizons. These results underscore the importance of frequency-specific analysis—without the BK framework, the long-run dominance of volatility spillovers would remain obscured within the aggregate DY measure.

Figure 2 visualizes the directional volatility spillovers based on the generalized FEVD at both the aggregate (DY) and frequency-specific (BK) levels. In the DY panel, equity volatilities (DSI_Vol, ICLN_Vol, SP500_Vol) are tightly interconnected—for example, DSI → ICLN = 26.0%, DSI → SP500 = 38.8%, ICLN → DSI = 16.1%, ICLN → SP500 = 18.4%, SP500 → DSI = 40.3%, and SP500 → ICLN = 36.8%—with the SP500 acting as the relatively stronger transmitter.

By contrast, the risk indices (PRI and TRI) form a distinct and self-contained block, displaying sizable bilateral linkages (PRI → TRI = 13.4%; TRI → PRI = 13.5%) but negligible connections with equity volatilities (mostly within the 0.0–0.4% range).

The BK decomposition reveals virtually no short-term transmission, moderate medium-term effects concentrated within the PRI–TRI pair (8.6–9.3%), and pronounced long-term spillovers that closely mirror the DY pattern—for instance, DSI

→ ICLN = 26.0%, DSI → SP500 = 38.2%, ICLN → DSI = 15.8%, ICLN → SP500 = 18.2%, SP500 → DSI = 39.6%, and SP500 → ICLN = 36.9%.

Overall, volatility shocks propagate slowly and persistently across markets, with long-horizon linkages dominating both among equities and within the PRI–TRI pair. This suggests that while short-horizon diversification remains largely effective, long-horizon risk management and hedging strategies should account for substantial and asymmetric volatility spillovers.

5.2 Dynamic Analysis

It is well established that both returns and volatilities evolve over time, and that market connectedness tends to intensify during periods of financial stress. To capture these dynamics, we apply a rolling-window approach to estimate the time-varying Total Connectedness Index (TCI). The results reported below are based on a 200-day rolling window, though the findings remain robust when alternative window sizes of 150 and 250 days are employed.

Figure 3 illustrates the time-varying TCI of returns obtained from the Diebold–Yilmaz framework. The TCI fluctuates within a range of approximately 35–50% for most of the sample period but exhibits two distinct spikes. The first occurs around mid-2011, corresponding to the Libyan civil war, which sharply curtailed oil supply and pushed crude oil prices above USD 110 per barrel in the spring before retreating to around USD 90 by August. The second—and more pronounced—spike appears at the onset of the COVID-19 pandemic, when global equity markets declined abruptly, volatility indices such as the VIX surged, and overall uncertainty reached unprecedented levels.

Taken together, these results indicate that return spillovers are largely event-driven and transitory, with sharp increases in connectedness observed during major crises such as the 2011 oil shock and the 2020 COVID-19 pandemic.

Figure 4 displays the time-varying connectedness of returns based on the Baruník–Křehlík (BK) frequency decomposition. The results clearly show that spillovers are predominantly driven by short-term dynamics. The short-term component (orange line) accounts for the largest share of total connectedness, while the medium-term component (green line) plays a secondary role, and the long-term component (blue line) remains consistently subdued.

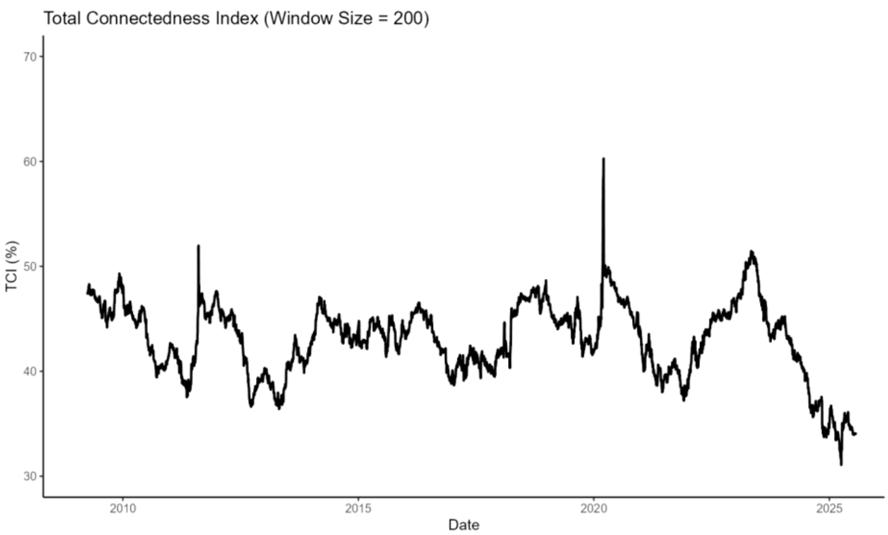

Figure 3. Time-Varying Total Connectedness Index of Returns (DY Approach)

Note: The figure shows the rolling Total Connectedness Index (TCI, %) computed within the Diebold-Yilmaz Framework using the generalized FEVD. Estimates are obtained from a VAR on the volatility of daily returns (lag length selected by AIC; forecast horizon H = 50) with rolling windows of w = 200. Higher values indicate stronger cross-market connectedness.

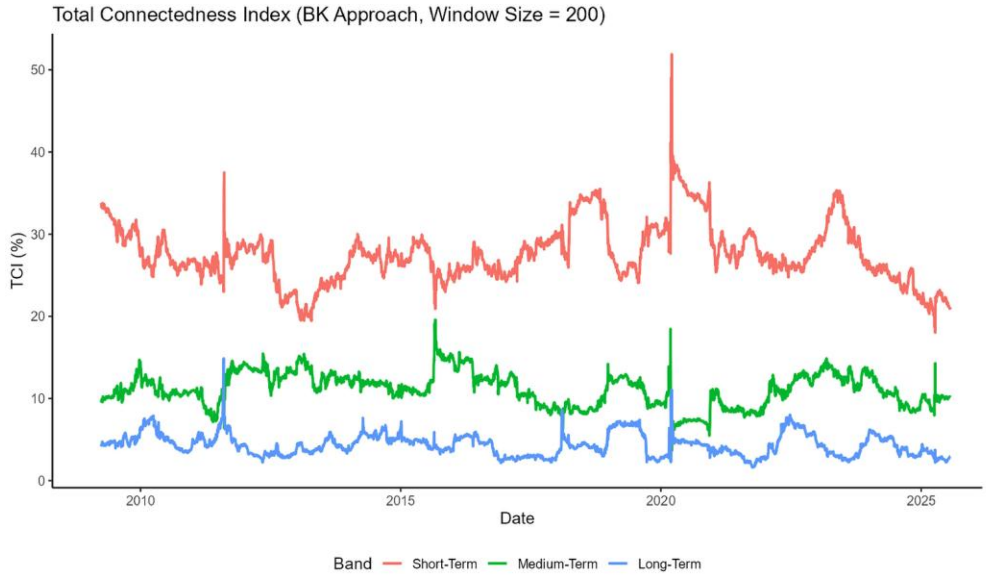

Figure 4. Time-Varying Total Connectedness Index of Returns (BK Approach)

Note: The figure shows the rolling Total Connectedness Index (TCI, %) by Baruník–Křehlík frequency bands, computed from a VAR on daily returns (lag length selected by AIC; forecast horizon H=50) using the generalized FEVD. Bands are defined as short (1-5 days), medium (6-20 days), and long (≥ 21 days). At each date, the sum across the three bands equals the total TCI (up to rounding); higher values indicate stronger cross-market connectedness.

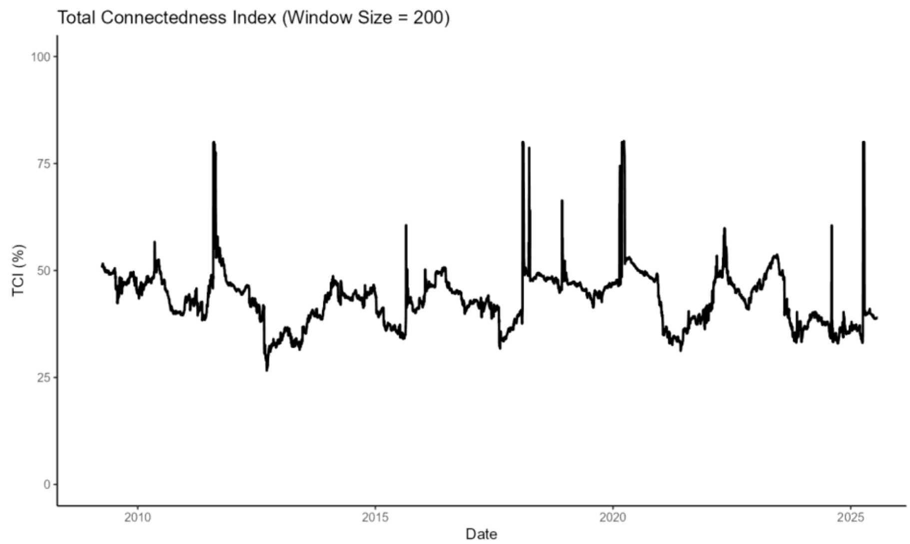

Figure 5. Time-Varying Total Connectedness Index of Volatility (DY Approach)

Note: The figure shows the rolling Total Connectedness Index (TCI, %) computed within the Diebold–Yilmaz framework using the generalized FEVD. Estimates are obtained from a VAR on the volatility of daily returns (lag length selected by AIC; forecast horizon H = 50) with rolling windows of w = 200. Higher values indicate stronger cross-market connectedness.

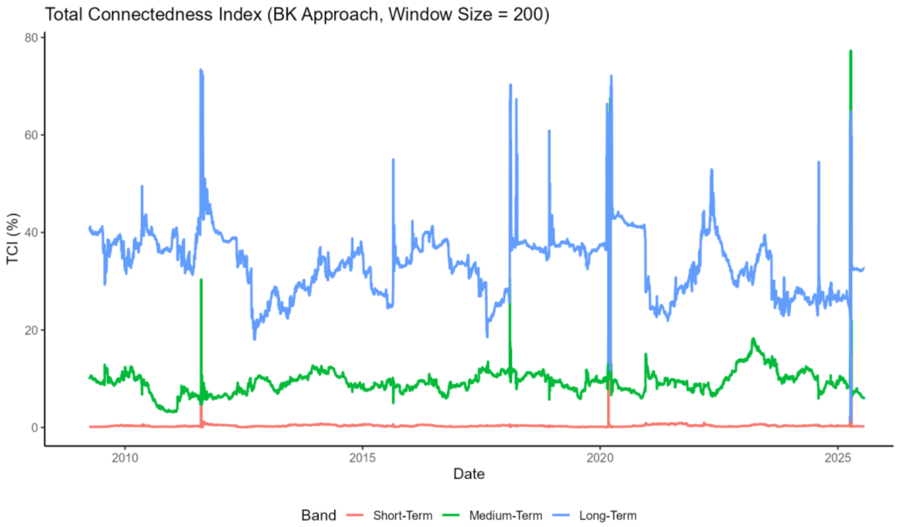

Figure 6. Time-Varying Total Connectedness Index of Volatility (BK Approach)

Note: The figure shows the rolling Total Connectedness Index (TCI, %) by Barunı́k–Křehlík frequency bands, computed from a VAR on the volatility of daily returns (lag length selected by AIC; forecast horizon H=50) using the generalized FEVD. Bands are defined as short (1–5 days), medium (6–20 days), and long (≥ 21 days). At each date, the sum across the three bands equals the total TCI (up to rounding); higher values indicate stronger cross-market connectedness.

Two major spikes emerge in 2011 and 2020. In both episodes, the short-term component rises most sharply, confirming that returns respond immediately to sudden shocks. The medium-term component increases modestly during crises, but its magnitude is far smaller than that of the short-term component. The long-term element remains relatively flat throughout the sample period.

Overall, these findings suggest that return spillovers are primarily a short-term phenomenon. Returns react rapidly to climate-related news and global shocks, reflecting high market liquidity and the quick adjustment of investor sentiment.

Figure 5 presents the time-varying connectedness of volatilities using the Diebold–Yilmaz (DY) framework. Compared with returns, the volatility-based TCI remains higher on average (around 50%) and exhibits four distinct spikes corresponding to major global events: the 2011 Libyan civil war and European debt crisis, the 2018 U.S. trade policy shocks (tariffs on steel, aluminum, and Chinese imports), the COVID-19 pandemic in 2020, and renewed U.S. trade measures in 2025.

Unlike return spillovers, which are concentrated in the short term, volatility spillovers are more persistent and primarily reflect long-run structural factors. They rise not only in response to short-lived financial shocks but also during broader geopolitical and policy disruptions.

For comparison with earlier figures, the 2011 oil price shock and the 2020 pandemic have already been discussed in Figure 3. Here, we emphasize the two tariff-related episodes. In March 2018, the United States imposed tariffs of 25% on steel and 10% on aluminum, citing national security concerns, while temporarily exempting certain countries such as Canada and Mexico. Later that month, the U.S. announced tariffs on approximately USD 60 billion of Chinese goods in response to alleged unfair practices in technology and intellectual property. Both measures generated substantial uncertainty in global trade and financial markets, as reflected in the spike in volatility connectedness. Finally, the 2025 episode shows another pronounced increase linked to renewed tariff measures, again contributing to elevated volatility transmission across markets.

Figure 6 illustrates the frequency decomposition of volatility connectedness obtained from the BK method. In contrast to returns, where spillovers are dominated by the short term, volatility spillovers are largely driven by the long term. The blue line (long term) is clearly dominant, and nearly all spikes occur in this band. The green line (medium term) exhibits moderate increases during crises, whereas the red line (short term) remains close to zero throughout.

This pattern suggests that volatility spillovers are primarily shaped by persistent, structural forces such as monetary policy shifts, trade disputes, and geopolitical tensions. Short-term shocks exert minimal influence, while long-term movements capture enduring forms of systemic risk. Most of the major spikes in 2011 (oil price shock and Libyan conflict), 2018 (U.S. tariffs and trade war), 2020 (COVID-19 pandemic), and 2025 (renewed tariff measures) appear in the long-term component. Although short-term elements show limited responses—mainly to oil and pandemic shocks—the medium- and long-term components capture all four episodes, underscoring their role in propagating persistent uncertainty.

Taken together, the contrast with returns is striking. Return spillovers are short-lived and event-driven, whereas volatility spillovers are long-lasting and rooted in structural uncertainty. While the DY framework captures the overall level of interdependence, the BK decomposition reveals that volatility connectedness emerges predominantly at longer horizons, exhibiting a distinct "long-term bias" relative to return spillover. (The time variation in the net spillovers for returns and volatilities is presented in Appendix B.)

6. Discussion

Our findings provide several insights into the transmission mechanisms of climate-related risks across financial markets. Unlike previous studies that emphasize strong spillovers from ESG indices and green finance to broader markets, we find that the news-based climate risk indices—PRI and TRI—show only limited interaction with equity markets. This indicates that media-driven attention to climate risks has not yet been fully reflected in equity spillover dynamics. This distinction does not contradict earlier evidence but instead highlights a difference in timing and integration: sentiment related to physical and transition risks, as measured by news analytics, may spread more gradually through financial systems than asset-based sustainability measures, such as ESG indices or green factor portfolios, which are already incorporated into institutional investment strategies.

Another key contribution of our analysis is the distinction between return and volatility transmission channels. The predominance of short-term return spillovers indicates rapid, event-driven responses to shocks—whether from climate events or geopolitical tensions—aligning with the view that equity markets react quickly but often only temporarily to new information. In contrast, the strong long-term dominance of volatility spillovers suggests that deeper uncertainty persists, reflecting the gradual accumulation of structural risks. This asymmetry supports the argument that volatility-based connectedness offers a more reliable perspective for identifying systemic and policy-induced uncertainty than return-based measures alone.

Finally, the heterogeneous roles of DSI and ICLN—where DSI consistently acts as a net transmitter of shocks and ICLN serves as a net receiver—highlight the importance of distinguishing between broad ESG indices and specialized clean energy benchmarks. DSI's larger market capitalization, higher liquidity, and closer integration with mainstream financial flows likely explain its function as an information source. In contrast, ICLN's narrower sectoral focus and greater sensitivity to capital inflows make it more reactive to external shocks. These differences indicate that climate-aligned investment vehicles are not homogeneous; their spillover dynamics depend on factors such as index composition, market depth, and investor base characteristics. Future research should examine these aspects more explicitly.

7. Concluding Remarks

This study examined the spillover effects of economic uncertainty between equity markets—represented by the SP500, DSI, and ICLN—and news-based climate risk indices, PRI and TRI, across time and frequency domains using the Diebold–Yilmaz (DY) and Barunǩ – Křehlík (BK) frameworks. By using PRI and TRI as proxies for climate-related uncertainty and combining them with three key equity benchmarks representing the U.S. large-cap, ESG-focused, and clean energy markets, we analyzed the magnitude and direction of spillovers between climate risk attention and financial market dynamics. The rolling-window approach enabled us to capture time-varying relationships during major global episodes, such as the Libyan conflict, U.S. tariff shocks, and the COVID-19 pandemic.

First, PRI and TRI exert only limited influence on equity spillovers. This finding contrasts with previous studies that emphasized strong interconnectedness between ESG indices, green finance, and the broader market (Zeng et al., 2025; Mensi et al., 2022; Dogan et al., 2025). In our framework, the two climate risk indices primarily interacted with each other rather than with equities, suggesting that news-based measures of physical and transition risks have not yet been fully priced into equity markets. This difference indicates that sentiment extracted from textual analysis evolves more gradually than financial indicators based on ESG or clean energy portfolios already integrated into institutional investment strategies.

Second, our results reveal a clear asymmetry between return and volatility spillovers across time horizons. Short-term spillovers are dominated by returns, indicating that equity markets respond quickly but only temporarily to shocks. In contrast, long-term spillovers are driven by volatilities, reflecting deeper and more persistent uncertainty related to structural or policy risks. This pattern supports earlier evidence on time–frequency asymmetry (Dogan et al., 2025) and reinforces the view that volatility-based connectedness offers a more comprehensive measure of systemic uncertainty than returns alone.

Third, the time-varying analysis of returns identified two significant spikes: one during the 2011 Libyan conflict and related oil price surge, and a larger spike at the onset of the COVID-19 pandemic in 2020. These findings indicate that return spillovers are strongly event-driven and typically dissipate rapidly after crises end. This observation is consistent with broader literature showing that market connectedness increases sharply during periods of acute stress, then stabilizes (Mensi et al., 2022).

Fourth, the dynamic volatility analysis identified four major episodes of heightened spillovers: the 2011 Libyan conflict, the 2018 U.S. tariff shocks, the COVID-19 crisis in 2020, and renewed tariff shocks in 2025. Compared with returns, volatility spillovers showed more frequent and persistent spikes, highlighting volatility's central role as the main channel for long-term uncertainty transmission. Unlike earlier studies that emphasized return spillovers, these findings indicate a structural shift toward volatility-driven contagion during global crises.

Taken together, these results indicate that return spillovers reflect short-lived, event-driven reactions, whereas volatility spillovers represent deeper and more persistent aspects of financial uncertainty.

Beyond their technical implications, these findings contribute to the broader discourse on sustainable finance and climate-related market dynamics. By integrating news-based climate risk indices with ESG and clean energy benchmarks, this study connects social awareness with financial market responses. Because PRI and TRI are derived from textual data, they capture real-time shifts in public attention, indicating that investor sentiment is influenced by both economic fundamentals and societal concern over environmental risks. The limited integration of these climate risk measures into equity spillovers suggests that financial markets continue to underreact to climate-related news—a gap that may narrow as sustainability considerations become more embedded in global investment practices.

From a policy and investment perspective, the dominance of volatility spillovers highlights the importance of long-term risk management strategies aimed at mitigating persistent uncertainty. Reducing climate risks through effective policies and transparent transition frameworks can decrease volatility and promote greater market stability, thereby supporting long-term economic resilience.

Finally, several avenues for future research remain. Although this study examined spillovers in returns and volatilities, recent studies have begun to examine higher-order moments, such as skewness and kurtosis (He and Hamori, 2021; He and Hamori, 2024). Extending the current framework to include these higher-moment dynamics would provide a deeper understanding of how climate and financial uncertainties propagate across markets and over time.

Authors' contributions

Conceptualization, Y.H. and S.H.; investigation, K.H. and S.H.; data curation, K.H.; writing—original draft preparation, K.H.; writing—review and editing, Y.H. and S.H.; supervision, Y.H.; project administration, S.H. All authors have read and agreed to the published version of the manuscript.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval

The Publication Ethics Committee of the Redfame Publishing.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

Not commissioned; externally double-blind peer reviewed.

Data availability statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Data sharing statement

No additional data are available.

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Appendix A

Results of ARMA model

Variable	ARMA - GARCH	JB test	LB test	LB2 test
DSI_Return	ARMA(1,4) -GARCH(1,1)	941.630 (0.000)	8.777 (0.553)	8.390 (0.591)
ICLN_Return	ARMA(5,0) -GARCH(1,1)	575.917 (0.000)	5.315 (0.869)	8.885 (0.543)
SP500_Return	ARMA(1,0) -GARCH(1,1)	1158.657 (0.000)	8.789 (0.552)	7.483 (0.679)

Note: ARMA-GARCH indicates the selected orders of the ARMA and GARCH components of the model. JB test reports the Jarque–Bera test statistic and its corresponding p-value. LB test reports the Ljung–Box test statistic for residuals and its corresponding p-value. LB2 test reports the Ljung–Box test statistic for the squared residuals and its corresponding p-value.

Appendix B

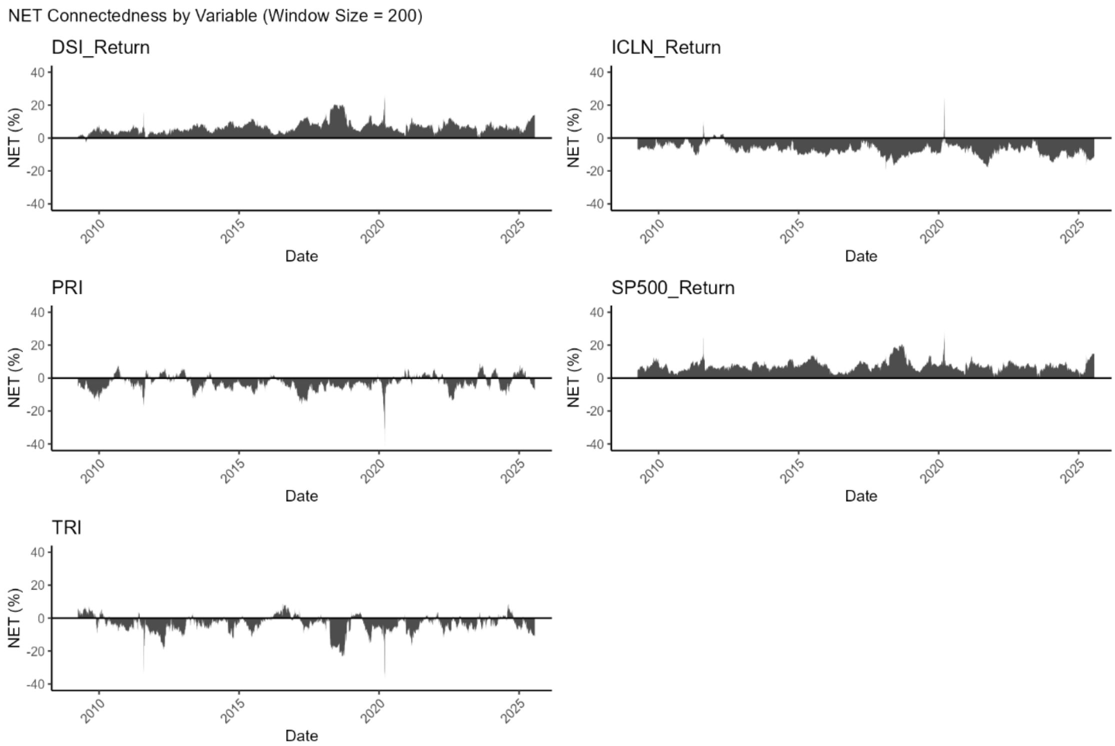

Figure B1. Time-Varying Net Connectedness Index of Returns (DY Approach)

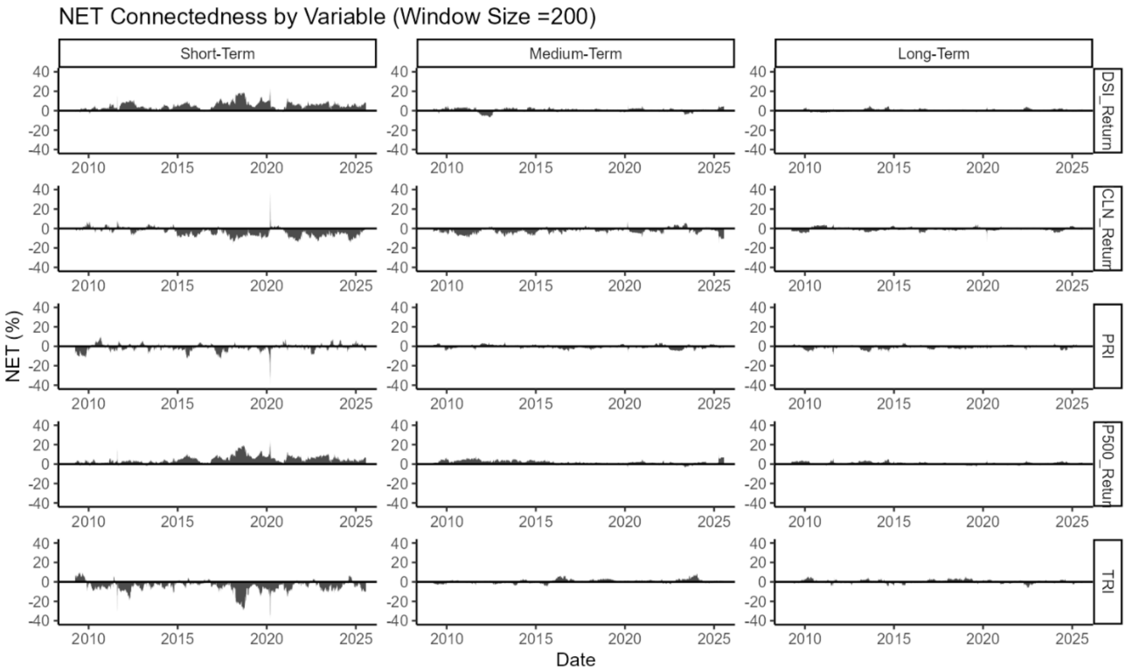

Figure B2. Time-Varying Net Connectedness Index of Returns (BK Approach)

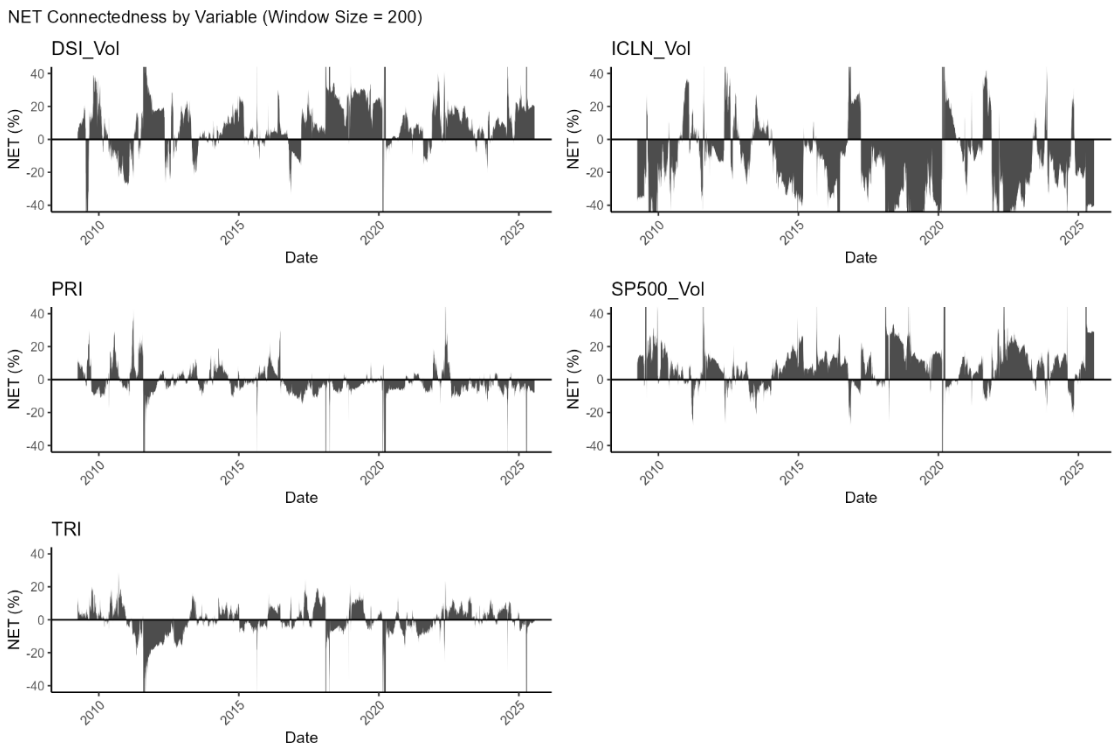

Figure B3. Time-Varying Net Connectedness Index of Volatilities (DY Approach)

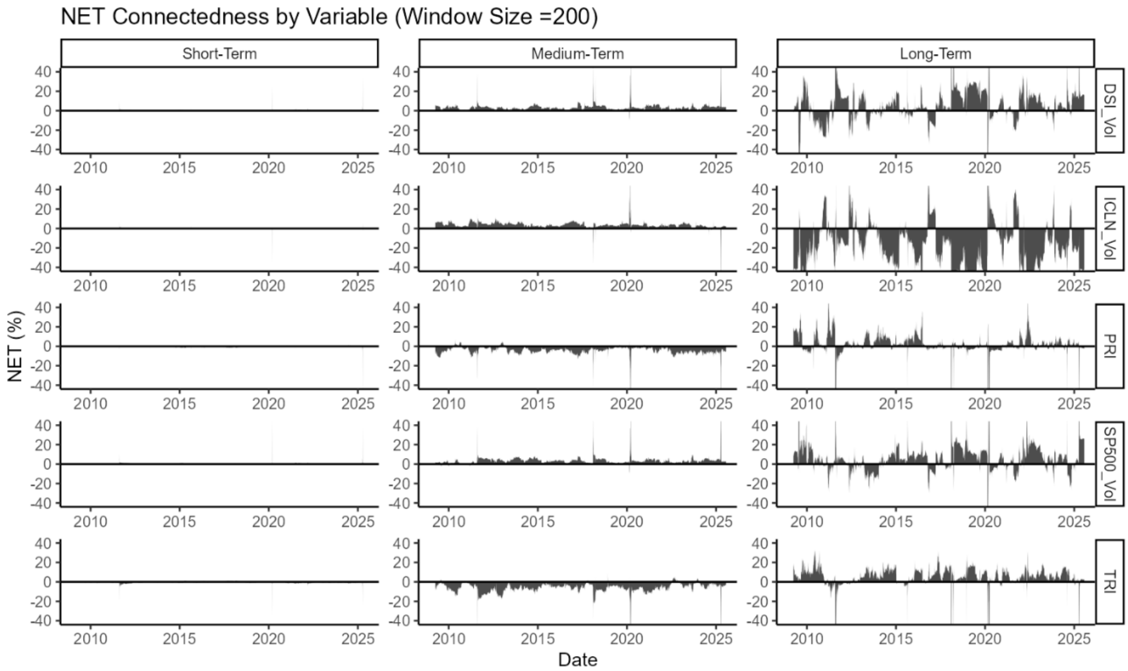

Figure B4. Time-Varying Net Connectedness Index of Volatilities (BK Approach)