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Research article

Tail-dependent lead-lag dynamics between fossil and sustainable assets: A Cross-Quantilogram approach

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Abstract: This study analyzed tail-dependent lead-lag linkages between fossil and sustainable assets using daily WTI crude oil futures, clean-energy equities, and the S&P Green Bond Index from August 3, 2015, to August 7, 2025. Unlike existing literature that typically studies oil-clean energy or green bond-equities in isolation, we embedded fossil fuel prices, clean-energy equities, and green bonds in a single tail-state lead-lag system and documented how transmission patterns reconfigure across downside and upside regimes. To condition the analysis on common uncertainty proxies, returns were regressed on the CBOE VIX and the (log) U.S. Economic Policy Uncertainty index, and the resulting residual-based series were examined with the cross-quantilogram (CQ) across target quantiles $\tau_1 \in \{0.10, 0.50, 0.90\}$, conditional on source states $\tau_2 \in \{0.10, 0.90\}$, with ~95% confidence bands. Heatmaps summarize average CQ signs (co-movement vs. stabilization) and the breadth of significance across lags. Two regularities emerged. First, dependence is state- and tail-contingent. In downside states ($\tau_2 = 0.10$), patterns of strong downside co-movement and rally suppression are evident, particularly between oil and renewables, with modest but persistent linkages to green bonds. Second, in upside states ($\tau_2 = 0.90$), the dominant pattern shifts toward stabilization and selective upside clustering, most visible within the "green block" and through lagged upside predictability from green bonds toward oil. Overall, conditional on controls for VIX and EPU, fossil and sustainable assets exhibit asymmetric, tail-driven interdependence: diversification weakens during distress, while stabilization and selective upside synchronization dominate in buoyant markets. These findings provide valuable insights for tail-aware portfolio design and state-contingent risk management.

Keywords: tail dependence; lead-lag linkages; cross-quantilogram; clean energy stocks; green bond index

JEL Codes: G15, C32, C58

Abbreviations: VAR: Vector Autoregression; CQ: Cross-Quantilogram; VIX: CBOE Volatility Index; EPU: Economic Policy Uncertainty

1. Introduction

The lead-lag relationship is critical to price discovery because it characterizes how quickly information is incorporated into prices across related assets, reflecting differences in trading frictions, liquidity, and market participation. This issue is especially salient for sustainable assets because clean-energy equities and green bonds are often exposed to policy-driven information shocks, episodic liquidity, and investor flow rebalancing that may be incorporated with delays rather than instantaneously. Accordingly, a lead-lag perspective is needed to determine whether sustainable assets respond to fossil-energy shocks with a lag, whether they transmit information back, and whether these dynamics become stronger in stress regimes, when downside risk management and diversification resilience are most relevant. Understanding the speed of asset adjustment enhances predictive market outcomes, improves investment decisions, and boosts market efficiency (Jambotkar & Raju, 2020; Výrost et al., 2019). However, financial markets cannot be separated from each other; major geopolitical risks, economic crises, and macroeconomic factors have the potential to influence price discovery processes and result in correlations that span asset classes (Sohag et al., 2022).

The COVID-19 pandemic added a layer of complexity to the relationship between lead and lag by augmenting financial contagion effects across markets and volatility spillovers (Rubbaniy et al., 2022). More broadly, stress regimes are environments in which diversification benefits are most likely to fail, because dependence structures tend to become nonlinear and asymmetric in the tails. For sustainable assets that are frequently marketed and held as diversifiers or hedges, the relevant empirical question is therefore not average co-movement but whether downside-tail dependence intensifies and whether adverse shocks propagate with lags. This tail-state perspective also aligns with risk oversight in green finance, where downside protection, drawdown control, and stress-scenario resilience are central concerns. The energy sector was one of the most affected by the COVID-19 pandemic, and the structure of the energy marketplace provided the backdrop for how traditional fossil fuel energy and new forms of sustainable finance instruments could interact with one another (Odilova et al., 2023). Given that ESG investments, green bonds, and renewable energy stocks are gaining prominence, it is critical for market participants to think about the relationship of these investments to fossil fuel markets. Academic literature has historically focused mainly on price fluctuations, and the oil price dependence on stock market fluctuations has dominated much of the academic attention; therefore, traditional lead-lag relationships need to be understood at a more nuanced level to support the integration of sustainable investments in financial systems (Mensi et al., 2023).

In order to address the changing nature of interdependencies and their interconnectedness, the cross-quantilogram (CQ) emerged as an advanced econometric technique for detecting nonlinear and asymmetric relationships in economic time series (Han et al., 2016). Unlike Granger-causality tests and VAR models, which are based primarily on mean-level dependence, the CQ allows us to identify directional predictability between quantiles (Bunditsakulporn, 2022). Crucially, CQ is well suited to our setting because it combines (i) tail dependence, which directly targets downside risk co-movement and stress-period diversification breakdown, with (ii) lead-lag dependence, which identifies delayed transmission and state-contingent price discovery patterns. This joint tail-and-lead-lag structure allows us to evaluate whether sustainable assets remain stabilizing during distress or instead exhibit tail clustering and delayed spillovers that erode diversification when it is most needed. More recently, this method has been used to study lead-lag relationships between commodity prices and stock-market volatility, often alongside common macroeconomic indicators, primarily across stock markets, commodities, and cryptocurrencies (Abakah et al., 2022; Tiwari et al., 2019). Furthermore, existing evidence suggests that directional predictability of commodity prices can significantly predict market volatility across major economies, including the United States and China (Mujtaba et al., 2024).

Although ESG investments and sustainable finance have gained significant traction in recent years, there remains a critical gap in the literature regarding their evolving relationships with traditional fossil fuel markets and renewable energy assets. Most existing studies examine these markets in bilateral settings (e.g., oil–clean energy, green bonds–equities) and therefore cannot identify whether green bonds act as a bridge, buffer, or amplifier between fossil and green equity segments, especially in the tails. A unified tail-based lead-lag system is needed to separate (i) within-green transmission (equities ↔ green bonds), (ii) fossil-to-green equity spillovers, and (iii) the cross-asset mediation role of green bonds that may reroute shocks across segments depending on market states. Our contribution is to formalize this three-market interaction as a single tail-dependent lead-lag system, so that "bridge vs. buffer vs. amplifier" roles are identified endogenously from directional predictability patterns rather than inferred from pairwise correlations. This study aims to fill this gap in the literature by:

- Placing fossil fuels (WTI), clean-energy equities (ICLN), and green bonds (S&P Green Bond Index) in a single tail-based lead-lag system, so that the fossil–green nexus is evaluated jointly rather than as separate bilateral extensions.
- Identifying whether green bonds behave as a transmission bridge or a stabilizer between fossil and green equity segments, and whether this role changes between distress (downside-tail) and buoyant (upside-tail) states.
- Examining nonlinear, quantile-specific, and regime-dependent dynamics using the CQ approach, which reveals tail behaviors and asymmetric shock transmissions that linear models like VAR or Granger causality fail to detect.
- Synthesizing lead-lag evidence across asset classes into dominant tail-state regularities (distress co-movement, rally suppression, stabilization, and risk-on clustering), instead of relying on isolated lag-by-lag patterns.
- Analyzing the role of market conditions, such as high volatility versus stability, on these interdependencies, to contribute to the literature on financial stability and systemic risk.
- Ensuring robustness through a pre-whitening procedure with VIX and EPU indices, so that the dependencies identified via CQ are interpreted as linkages conditional on these aggregate risk factors.
- Providing an integrated empirical map of downside and upside transmissions, combining detailed CQ lag evidence with heatmap visualizations to illustrate the depth, direction, and persistence of these linkages across markets.

These objectives are grounded in prior evidence highlighting the strong interconnections between energy and sustainable finance. Previous studies have presented evidence that the energy market's fluctuations tend to affect investment in renewable technologies, indicating there might be spillover effects amongst them (Dutta et al., 2020). Oil price uncertainty has been found to be a vital predictor of stock market volatility forecasts, supporting the established idea of how fossil fuel shocks create a ripple effect through the entire financial market (Qin & Bai, 2022). Furthermore, ESG factors combined with the growing penetration of clean energy finance into global portfolios have indeed altered risk-return profiles, thereby reshaping the European financial market (Lupu et al., 2022).

This study explores the lead-lag relationships among green bonds, clean-energy equities, and fossil fuel markets, utilizing the CQ approach as an integrated system of tail-states. The system-level structure produces a new perspective that is not available from bilateral assessments, i.e., the study identifies when green bonds move in unison with clean-energy equities as a “green block” and when green bonds transmit or dampen tail-risk to the fossil component with delays. The results will have implications for tail-aware portfolio optimization and state-contingent risk management while providing further information on how cross-market dependency structures reorganize as market conditions change. Thus, by closing a knowledge gap, the current study increases our understanding of these complicated linkages and provides applicable direction for researchers and investors in the area of sustainable finance.

This paper is organized as follows: Section 2 reviews the related literature; Section 3 introduces the data and variables; Section 4 details the methodology, including the CQ framework and the pre-whitening approach; Section 5 presents the empirical findings, exploring lead-lag dynamics across market regimes; and Section 6 concludes with key insights and implications for systemic risk, portfolio strategies, and policy considerations.

2. Literature review

The use of lead-lag relationships in finance literature is concentrated on portfolio and risk management. Lead-lag relationships are used as forecasting and decision-making tools and for improving asset allocation and risk management processes. In the field of portfolio management, through the use of lead-lag relationships between large and small-scale portfolios/stocks, investment strategies that benefit from price changes can be developed (Drakos et al., 2015; Gruener & Finke, 2017); arbitrage opportunities obtained through these relationships can increase potential returns and facilitate the development of hedging strategies (Hayashi & Koike, 2019); and lead-lag relationships optimize portfolio management strategies and enable the prediction of market changes by facilitating the understanding of relationships between sector portfolios (Troster et al., 2021) and enable portfolio managers to respond quickly to observed phenomena (Huth & Abergel, 2014). In terms of risk management, the use of the lead-lag relationship can improve risk management strategies of portfolio managers (Sun et al., 2019). Through understanding the relationships between currency pairs, lead-lag relationships can reduce the foreign exchange risk exposure of portfolios (Basnarkov et al., 2020); additionally, the lead-lag relationships between indices can be used in the creation of well-diversified portfolios with reduced risk (Chiou, 2011).

Empirical literature examined lead-lag relationships between a variety of financial assets. Several studies aimed to explore lead-lag relationships between derivatives and stocks to predict stock value changes (Fung et al., 2015; Wang et al., 2024). Others aimed to develop actionable investment strategies by discovering lead-lag patterns in commodity prices (He et al., 2023; Okorie & Lin, 2020; Xu & Ye, 2023). Similarly, researchers have developed asset management strategies by uncovering the lead-lag relationships between stock price pairs (Curme et al., 2015; Huth & Abergel, 2014). Another part of the empirical literature includes studies that revealed the lead-lag relationship between bond and stock prices (Chordia et al., 2017; Tolikas, 2017) and the lead-lag relationships between CDS and bond yields (Nordén & Weber, 2009). Also, lead-lag relationships between volatility indices (Badshah et al., 2013) and between uncertainty indices and stock market returns (Albrecht et al., 2022; Amar & Carlotti, 2020) have been well-established in prior work. Moreover, green-finance studies indicate that these linkages are asset-class-specific and state dependent; Reboredo (2018) found that green bonds are more tightly coupled with corporate and treasury bond markets than with stocks or energy commodities, while Mensi et al. (2022) showed that spillovers between green bonds, WTI oil, and major equity markets are time-varying and crisis-sensitive. Focusing on extremes, Karim et al. (2024) further documented tail-driven dependence that can reconfigure in stress episodes.

Recent evidence has documented that green bonds exhibit state-dependent linkages with energy and financial markets and that these linkages can strengthen in extreme conditions, thereby challenging the safe-haven narrative. Tail-focused and nonlinear dependence studies highlighted that extreme co-movements and spillovers are not symmetric across market states, and that green assets can switch roles between hedges and transmitters depending on regimes. At the same time, much of the existing work remains pairwise, examining green bonds with a single counterpart (e.g., equities or commodities) and summarizing dependence without explicitly mapping directional lead-lag structure across a fossil-green-green triad.

Most studies on identifying lead-lag relationships have relied on the application of traditional, linear methods of assessment. One of the most common methods used to identify lead-lag relationships is the Granger causality test. This test was successfully applied by Demir et al. (2018) to investigate lead-lag relationships of the cotton market and by Alsakka & Gwilym (2010) to examine whether there were any lead-lag relationships between sovereign credit rating agencies. Vector autoregression (VAR) models are another technique used to investigate dynamic relationships within lead-lag assessments. Nordén & Weber (2009) successfully used VARs to investigate the interdependencies between credit default swaps (CDS), bonds, and stocks. Fonseca & Zaatour (2016) discussed an alternative model to analyze lead-lag relationships using the Hawkes process model, which provides a framework for analyzing both correlations and lead-lag relationships. Researchers have also applied cointegration techniques to assess longer-term relationships between various types of assets. Using error-correction models (ECM) to determine the nature of short-term adjustments relative to longer-term equilibrium relationships, these models allow researchers to gain a greater insight into the lead-lag dynamics, as seen in Chen et al.'s (2019) examination of the lead-lag relationships between sovereign credit ratings over time via time-series regressions. Linear regression models are similarly important tools for researchers to analyze lead-lag relationships. These models enable researchers to quantify the relationships between variables while simultaneously accounting for confounding factors. Huth & Abergel (2014) provided an example of the use of regression models to investigate the lead-lag relationship between futures contracts and stock returns, with a particular emphasis placed on the impact of variations in liquidity and trading volumes on the relationship. Threshold autoregressive (TAR) models, as employed by Chung et al. (2011), offer further insights into the nonlinear characteristics associated with lead-lag relationships. High-frequency data analysis has emphasized the importance of acknowledging asymmetries in financial time series. Through the methods of Bollerslev (2006), researchers can now study leverage effects and volatility feedback, thereby gaining additional insight into which assets may be leading others during high-volatility periods.

The paper contributes to the existing literature by employing the nonlinear CQ method to reveal tail-dependent lead-lag relationships. More importantly, it extends the green-finance dependence literature from bilateral linkages to a unified fossil-clean equity-green bond system, allowing us to assess whether green bonds act as a tail-state bridge, buffer, or amplifier between fossil and green equity segments. This system perspective is essential for interpreting sustainable assets not only as stand-alone diversifiers but also as components of a coupled transition-finance network, consistent with prior evidence on dynamic spillovers and extreme-risk dependence in green-bond settings (Mensi et al., 2022; Karim et al., 2024).

3. Data and variables

The study utilizes a database from August 3, 2015, to August 7, 2025, consisting of over 3400 daily observations for each series. The dataset covers five key financial variables: (1) WTI crude oil futures (CL = F), representing the fossil fuel sector; (2) ICLN ETF, as a near proxy for renewable energy stocks; (3) CBOE Volatility Index (VIX), representing global market uncertainty; (4) the U.S. Economic Policy Uncertainty (EPU) index, which reflects policy-related uncertainty; and (5) the S&P Green Bond Index, serving as a benchmark for the sustainable fixed-income market. Specifically, the crude oil price proxy is retrieved from Yahoo Finance as the front-month WTI crude oil futures series (ticker: CL = F), ICLN is retrieved as iShares Global Clean Energy ETF (NasdaqGM: ICLN), and VIX as the CBOE Volatility Index (ticker: ^VIX), all in USD. The S&P Green Bond series corresponds to the S&P Green Bond U.S. Dollar Select Total Return Index, downloaded from the official S&P Dow Jones Indices webpage using the *Export Data* function.

All asset and index return series are constructed as daily log-returns, $r_t = \Delta \ln(P_t)$. For the S&P Green Bond index, which is a total return index reported in level form, we compute log-returns as $\Delta \ln(TRI_t)$. For EPU, which is published as a daily level-based index on calendar days, we compute an analogous log-change series, $\Delta \ln(EPU_t)$, and then align it to the trading-day sample; zero log-changes are retained as zeros (no smoothing or adjustment is applied).

To ensure comparability across series, we merge the datasets by the intersection of dates and apply listwise deletion (i.e., we drop any date with a missing value in any series). Non-trading days are therefore not forward-filled; instead, the effective sample consists of the common trading days for which all variables are simultaneously observed.

Table 1. Descriptive statistics.

Variable	Min	Max	Mean	SD	Skewness	Kurtosis	JB	ADF
EPU	−2.635	3.032	−0.068	0.524	0.107	4.958	391.799*	−13.833*
GB	−0.024	0.023	0.000	0.004	−0.042	7.186	1770.304*	−12.560*
ICLN	−0.137	0.108	0.000	0.017	−0.411	9.861	4822.302*	−12.339*
VIX	−0.442	0.768	−0.001	0.081	1.325	11.403	7840.705*	−15.608*
WTI	−0.264	0.349	0.000	0.046	0.240	7.414	1990.763*	−12.703*

Source: Authors' calculations

* shows significance at 1%.

The descriptive statistics of the variables are presented in Table 1. The return series show near-zero means, consistent with stationarity in daily returns. Dispersion varies notably across markets, with the EPU index exhibiting the largest standard deviation, exceeding those of VIX, WTI, GB, and ICLN, reflecting its sensitivity to political events and policy shifts. The sharp daily fluctuations observed are not data errors but manifestations of uncertainty shocks typical of modern markets. VIX and WTI also show relatively high volatility compared with green assets. Skewness and kurtosis indicate strong deviations from normality, especially for EPU, ICLN, and VIX. Jarque–Bera statistics confirm non-normality at the 1% level, while ADF tests reject the unit root null, confirming stationarity and validating the data for quantile-based dependence analysis.

4. Methodology

To analyze nonlinear and asymmetric dependencies between energy-related financial assets, we adopt the CQ approach developed by Linton and Whang (2007) and further extended by Han et al. (2016). This technique discerns directional predictability of financial return series, such as clean energy and oil price shocks, at different parts of the return distribution, thus providing insights not available in traditional models that are based on means only.

The CQ framework depicts the quantile dependence structures, particularly in the tail parts, and is not bound by the limitations of such restrictive assumptions as normality, linearity, and finite higher-order moments. It is robust to monotonic transformations and only requires the strict stationarity of the time series, which makes it most suitable for financial data characterized by heavy tails and volatility clustering (Han et al., 2016). This makes it particularly valuable for analyzing financial markets under both stress and buoyant conditions.

4.1. Pre-whitening procedure

To enhance robustness, a pre-whitening procedure is applied using linear regression models. Specifically, WTI, ICLN, and S&P Green Bond Index returns are regressed on the VIX and EPU, and the resulting residuals are used to estimate CQs. This filtering step intentionally partials out the component of co-movement attributable to broad market volatility and policy-uncertainty conditions as proxied by VIX and EPU. Accordingly, the CQ results are interpreted as net (i.e., conditional on VIX and EPU) tail lead-lag dependence beyond these two common drivers, rather than as total spillovers in the raw returns. Because other common shocks and series-specific dynamics (e.g., autocorrelation or volatility clustering) may still remain in the residuals, we avoid causal interpretations and describe the findings as conditional interdependence.

Formally, the pre-whitening step can be expressed as follows:

$$WTI_t = \alpha_0 + \alpha_1 VIX_t + \alpha_2 EPU_t + \varepsilon_t^{WTI} \tag{1}$$

$$ICLN_t = \beta_0 + \beta_1 VIX_t + \beta_2 EPU_t + \varepsilon_t^{ICLN} \tag{2}$$

$$GREENBOND_t = \gamma_0 + \gamma_1 VIX_t + \gamma_2 EPU_t + \varepsilon_t^{GB} \tag{3}$$

Here, ε_t^{WTI}, ε_t^{ICLN}, and ε_t^{GB} denote the pre-whitened return series (residuals), which are subsequently employed in the CQ estimation.

4.2. Cross-quantilogram framework

Let $\{r_t^x\}$ and $\{r_t^y\}$ denote two strictly stationary return series, for example, the residual returns of ICLN and WTI. The unconditional α-th quantile of r_t^x is expressed as:

$$\pi_x(\alpha) = \inf\{z \in R: P(r_t^x \leq z) \geq \alpha\}, \quad \alpha \in (0,1) \tag{4}$$

Directional dependence between quantiles is established through the centered quantile-hit process defined as:

$$h_\alpha(u) = I[u \leq 0] - \alpha, \tag{5}$$

where $I[\cdot]$ is the indicator function. The CQ at lag l, for quantiles α and β, can be expressed as:

$$\kappa_{\alpha,\beta}(\mathrm{l}) = \frac{E\left[h_\alpha\left(r_t^x - \pi_x(\alpha)\right) \cdot h_\beta\left(r_{t-1}^y - \pi_y(\beta)\right)\right]}{\sqrt{E\left[h_\alpha^2\left(r_t^x - \pi_x(\alpha)\right)\right] \cdot E\left[h_\beta^2\left(r_{t-1}^y - \pi_y(\beta)\right)\right]}}, \tag{6}$$

This normalized measure indicating the quantile dependence from y to x at lag l takes values in [−1, 1], similar to a correlation coefficient. A zero value suggests no directional predictability between the two quantiles.

The empirical (sample) CQ is given by:

$$\hat{\kappa}_{\alpha,\beta}(\mathrm{l}) = \frac{\sum t = \mathrm{l} + 1^T h_\alpha\left(r_t^x - \hat{\pi}x(\alpha)\right) \cdot h\beta\left(r_{t-1}^y - \hat{\pi}y(\beta)\right)}{\sqrt{\sum t = \mathrm{l} + 1^T h_\alpha^2\left(r_t^x - \hat{\pi}x(\alpha)\right)} \cdot \sqrt{\sum t = \mathrm{l} + 1^T h_\beta^2\left(r_{t-1}^y - \hat{\pi}y(\beta)\right)}} \tag{7}$$

where $\hat{\pi}x(\alpha)$ and $\hat{\pi}y(\beta)$ are the empirical quantiles of the respective series.

In order to analyze the joint significance of quantile dependence across multiple lags, the portmanteau-type test of Han et al. (2016) is used:

$$\mathcal{K}\alpha, \beta^{(L)} = \frac{T(T+2)}{T-L} \sum \mathrm{l} = 1^L \widehat{\kappa_{\alpha,\beta}^2} \tag{8}$$

where T is the sample size, and L is the maximum lag order considered. This sort of testing parallels the Ljung–Box test for time-domain autocorrelation, which is adopted to quantify quantile dependence structures. The null hypothesis $H_0: \kappa_{\alpha,\beta}(\mathrm{l}) = 0$ for all l states that no directional predictability exists, and its rejection indicates significant dependence through different quantiles.

Most financial time series are characterized by serial correlation and heteroskedasticity; consequently, the stationary bootstrap of Politis and Romano (1994) is applied, which is robust to serial dependence and allows for constructing confidence intervals without strong parametric assumptions. The optimal block length is selected using the method of Politis and White (2004). Moreover, to handle potential multiple testing issues and to assess the joint significance of directional predictability across all lags simultaneously, we conduct a Bootstrap Portmanteau (Q) test. Following the same stationary bootstrap framework, we simulate an empirical null distribution of no lead-lag dependence by resampling the series independently. P-values are derived from 1000 bootstrap iterations, providing a robust joint evaluation of the CQs up to 20 lags.

In order to visualize dependence all along the distribution, heatmaps of $\widehat{\kappa_{\alpha,\beta}}(l)$ are generated over a fine grid of $(\alpha, \beta) \in \{0.05, 0.10, \dots, 0.95\}$. The generated heatmaps effectively display the strength of dependence, direction, and asymmetry, especially in the tails under both normal and extreme market conditions.

5. Findings

Figure 1 shows daily log-returns for GB, ICLN, VIX, and WTI, and daily log-changes for EPU, computed as $\Delta \ln(EPU_t)$, from the level-based daily index and then aligned to the trading-day sample via the common-date intersection. The figure illustrates the stylized facts that support a tail-sensitive perspective. All five series demonstrate robust evidence of volatility clustering, with calm periods interrupted by bursts of large moves, most notably during the onset of the COVID-19 pandemic around early 2020, when a simultaneous spike in volatility is clearly observable across all the panels. When interpreting the axis ranges across panels, a clear ranking emerges in the magnitude of swings: EPU and VIX show the widest ranges of log-returns (≈-2 to 3 for EPU; ≈-0.50 to 0.75 for VIX). Among the traded assets, the widest range of log-returns occurred in WTI (≈-0.20, 0.25), then ICLN (≈-0.12, 0.09), and the narrowest in GB (≈-0.02, 0.02). EPU exhibits frequent large jumps, both positive and negative, persisting into later years in the sample, which is consistent with its nature as a news- and policy-sensitive index. VIX shows recurrent large spikes during periods of stress and sudden negative spikes that were sharply reversed, reflecting the asymmetric response of VIX during turmoil. WTI exhibited one extreme negative outlier and several strong rebounds around 2020, followed by repeated but gradually attenuating swings, which is a typical pattern of commodities that experience abrupt shocks in supply and demand. ICLN shows similar patterns, with a steep drop in 2020, followed by a period of elevated turbulence, as well as some evidence of downside skew. In contrast, GB remains relatively low-variance across most of the sample but has isolated extremes, including one sharp negative observation in 2020 and a slight increase in variance thereafter. The synchronized spikes across the panels provide evidence of common shocks and time-varying interdependence between these assets, highlighting the need for a quantile-based framework such as the CQ to explore state-dependent transmission and asymmetric effects between markets.

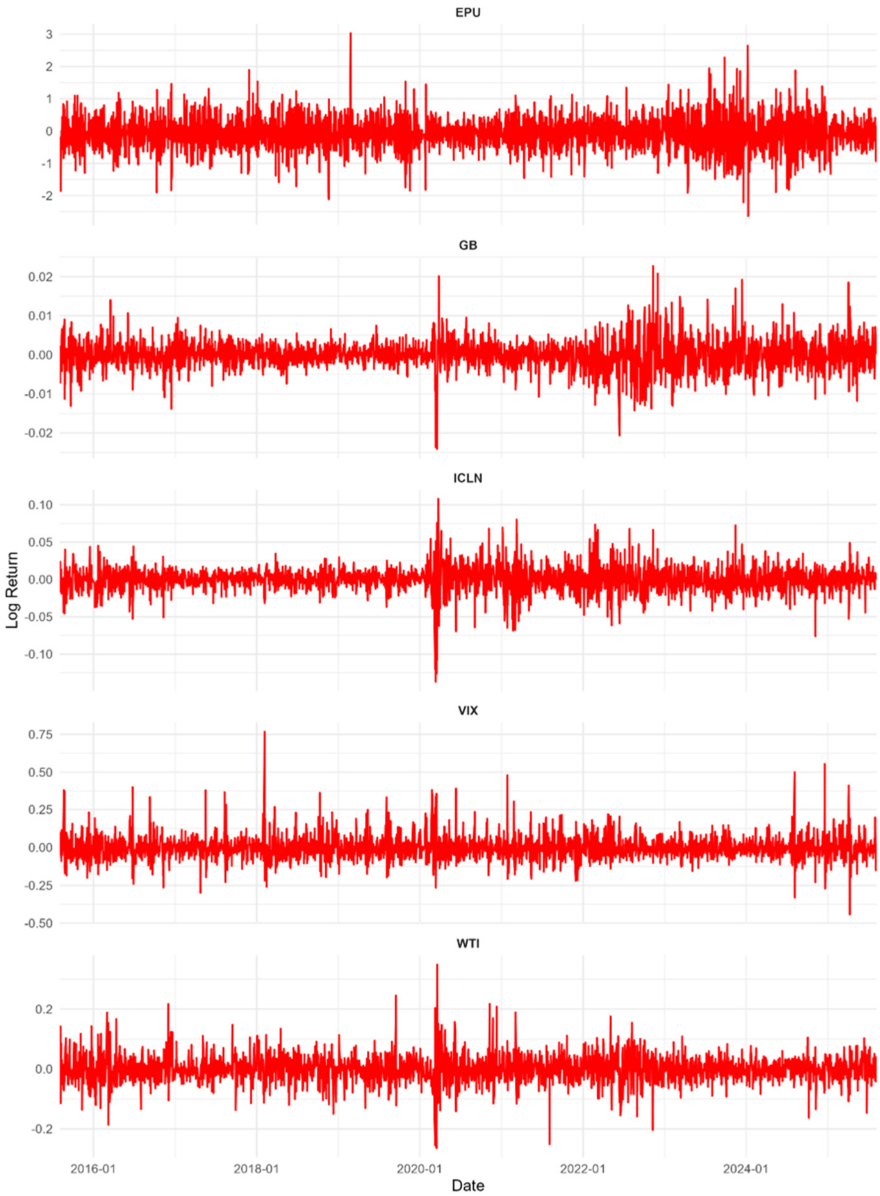

Figure 1. Log-return series of all variables.

5.1. Cross-quantilogram framework and setup

In the CQ framework, each panel shows the directional dependence between two markets. The horizontal axis represents the lag length, while the vertical axis reports the CQ coefficient that measures the predictive dependence. The conditioning quantile (τ_2) defines the source market's current state, while τ_1 denotes the target distribution segment: $\tau_1 = 0.10$ shows the downside tail, $\tau_1 = 0.50$ is the median, and $\tau_1 = 0.90$ indicates the upside tail.

Grey bands denote ≈95% bootstrap confidence under the null of no predictability. The bars within the band are treated as statistical noise, whereas the red-colored bars that exceed this area indicate significant predictive power. A shock from the source market at time *t* contains information about the probability that the target market will fall into a particular quantile at horizon *t+l*. Because we partial out VIX and EPU by construction, our CQ patterns should be interpreted as conditional dependence net of these uncertainty channels, not as total spillovers in the raw returns. To keep the discussion focused on the dominant economic messages (rather than isolated lags), we provide a short synthesis of the patterns that hold consistently across tails and asset classes in Section 5.3.1.

Before proceeding with detailed directional dependency analyses based on different quantiles and specific lags, it is crucial to assess the overall statistical validity (joint significance) of lead-lag relationships between markets. To this end, and to reduce concerns related to multiple testing, the Portmanteau (Q) test is applied as a joint inferential benchmark to evaluate total dependence over a 20-day lag period for each market case. The p-values of the test were obtained using the independent stationary bootstrap method (1000 iterations), which preserves the temporal dependency structure of the financial series. Table 2 presents the results of this joint significance test. The joint bootstrap results provide the primary basis for inference, whereas the lag-level CQ bars and heatmap cells are interpreted as descriptive tools for visualizing timing and asymmetry.

Table 2. Joint significance tests.

Relation	Quantile	Q statistics	p-value
WTI -> ICLN	0.1	61.3468	0.001***
WTI -> ICLN	0.5	13.2354	0.872
WTI -> ICLN	0.9	27.6111	0.147
ICLN -> WTI	0.1	25.4966	0.206
ICLN -> WTI	0.5	26.6142	0.117
ICLN -> WTI	0.9	26.1408	0.195
WTI -> GB	0.1	21.6009	0.373
WTI -> GB	0.5	17.5016	0.627
WTI -> GB	0.9	23.8729	0.301
GB -> WTI	0.1	39.0503	0.02**
GB -> WTI	0.5	36.4448	0.006***
GB -> WTI	0.9	32.9476	0.056*
ICLN -> GB	0.1	67.9223	0.002***
ICLN -> GB	0.5	22.8941	0.303
ICLN -> GB	0.9	63.377	0.000***
GB -> ICLN	0.1	91.3124	0.001***
GB -> ICLN	0.5	11.3001	0.929
GB -> ICLN	0.9	30.1167	0.106

Source: Authors' calculations

*, **, and *** shows significance at 10%, 5%, and 1%, respectively.

The joint bootstrap evidence in Table 2 shows that the relationships between markets are significantly asymmetric in terms of both direction and market conditions. Significant relationships that disappear in the median and upside tails are concentrated in the downside tails. This suggests that information transfer in financial markets is stronger during periods of stress and that information diffusion between assets weakens during positive market periods.

The results reveal a statistically significant directional predictability from the oil market to clean energy stocks. This aggregate dependence disappears in the median and upside tails. This suggests that negative shocks in the fossil fuel market are associated with a significantly higher conditional probability of distress in clean energy stocks, and the benefit of portfolio diversification between these two asset classes appears to weaken during times of crisis. This finding is consistent with the view that sharp declines in oil prices or increased uncertainty may prompt investors to reprice their energy-sector expectations. Conversely, the absence of a significant relationship in the opposite direction (clean energy → oil) suggests that the oil market may play a relatively stronger information role. This result is also consistent with the view that traditional energy markets remain an important reference point in energy pricing. The relationship between sustainable debt instruments and fossil fuels is noteworthy. While no significant predictability was found from WTI to GB under any market conditions, directional predictability from GB to WTI was statistically significant in both the downside and median tails. This asymmetry suggests a one-way directional dependence pattern from the green bond market to the oil market under certain market conditions. These results suggest that movements in the green bond market may provide an informative signal for subsequent energy-market outcomes, potentially reflecting information embedded in green bond pricing. The increasing interest of institutional investors in sustainable finance instruments may be strengthening the information relevance of this market. The connections between ICLN and GB exhibit the strongest and most sustained interactions in the system. In the downside tail, there is a reciprocal transmission of stress in both directions (ICLN to GB, $p = 0.002$; GB to ICLN, $p = 0.001$). Furthermore, in the upside tail, there is a statistically significant upside-tail directional predictability from ICLN to GB ($p = 0.000$).

In summary, the stationary bootstrap results show that lead-lag relationships between markets are jointly statistically significant, that the intensity of these relationships increases during downside periods, and that green bonds appear to function as a transmission channel rather than an isolated safe haven in the system.

To test whether the findings from the CQ analysis are sensitive to the data filtering process, the analyses were repeated using both the raw return series and the filtered residuals obtained after pre-whitening. Figure 2 shows that the CQ coefficients obtained from both data structures largely overlap. This high similarity between the raw and filtered series supports the robustness of the main CQ patterns to the filtering choice. However, this comparison should be interpreted as a robustness check only; it does not rule out the possible contribution of remaining serial dependence or conditional heteroskedasticity. Therefore, the similarity between the raw and filtered CQ profiles should not be taken as evidence of a “true” interdependence structure, but rather as support for the stability of the main dependence patterns across alternative data specifications.

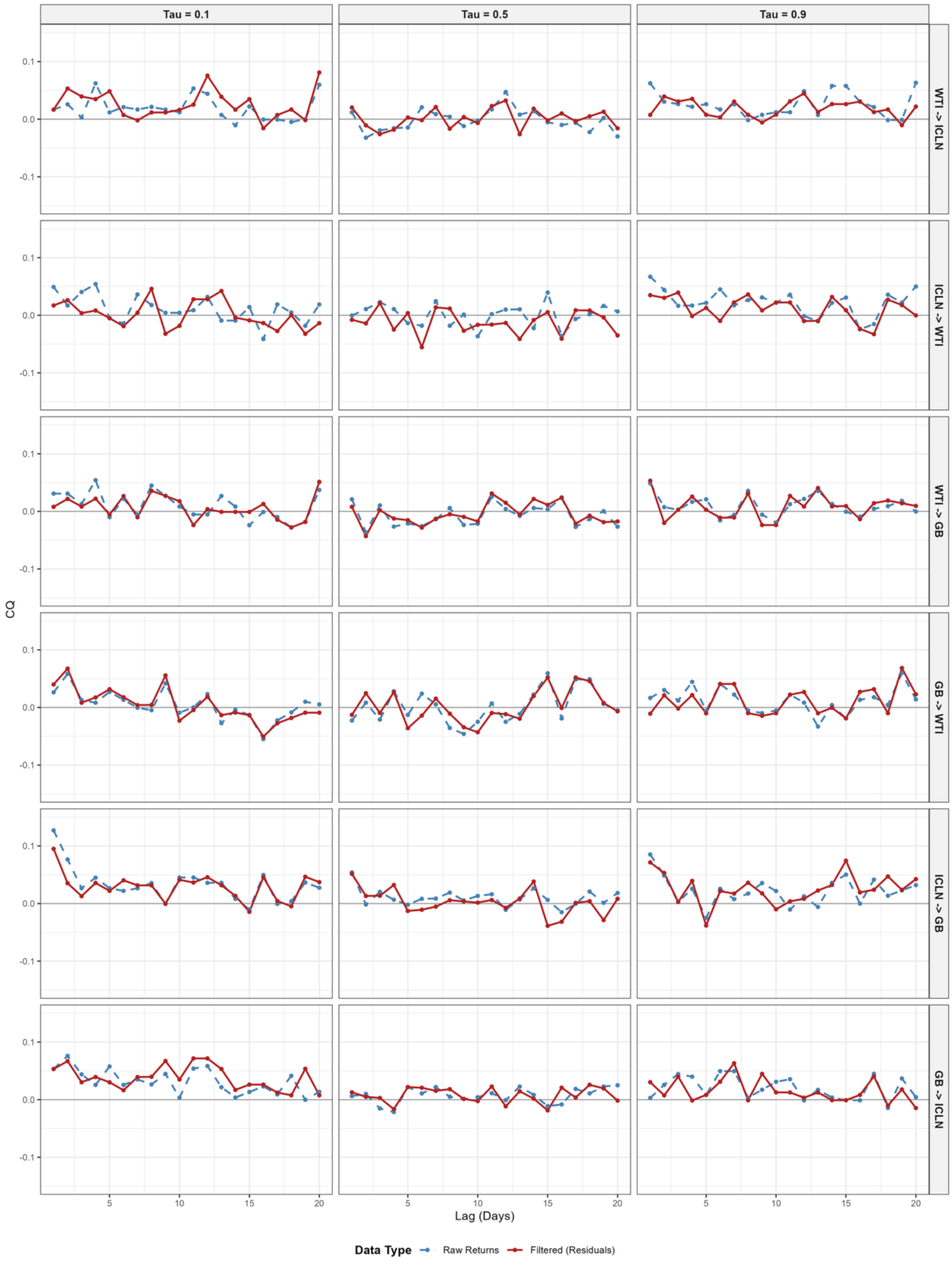

Figure 2. Robustness of CQ estimates under raw returns and filtered residuals.

5.2. Results under τ_2 = 0.10 (source in downside tail)

Figure 3 presents the results when the source market is conditioned on its lower tail (τ_2 = 0.10). Here, the focus is on how distress propagates. We use the term *contagion* to denote state-contingent co-distress in which downside shocks increase the probability of downside outcomes elsewhere beyond what is implied by average co-movement. Rally suppression refers to the weakening of upside-tail probabilities following negative shocks, consistent with margin constraints, de-risking, and reduced risk-bearing capacity during stress. Stabilization captures cases where tail risk in the target is dampened, consistent with state-contingent rotation or hedging-motivated reallocation that reduces adverse-tail probabilities even in stressed environments. The following lag-by-lag discussion serves as a descriptive map of where predictability clusters across quantiles and horizons; overall inferential weight rests on the joint bootstrap tests reported in Table 2. Positive coefficients at $\tau_1 = 0.10$ imply downside co-movement (contagion of bad news), consistent with risk-off shifts in investor behavior that trigger de-risking and synchronous sell pressure across fossil and green exposures. Negative coefficients at the same quantile indicate stabilization, which is consistent with state-contingent rotation or hedging-motivated reallocation toward the target asset in stress states, reducing its probability of entering the downside tail. At $\tau_1 = 0.90$, the negative coefficients account for rally suppression, which is consistent with rebalancing and risk aversion in stress episodes that can compress upside realizations even when the target does not fully co-crash. On the contrary, the positive coefficients imply rare decoupling effects.

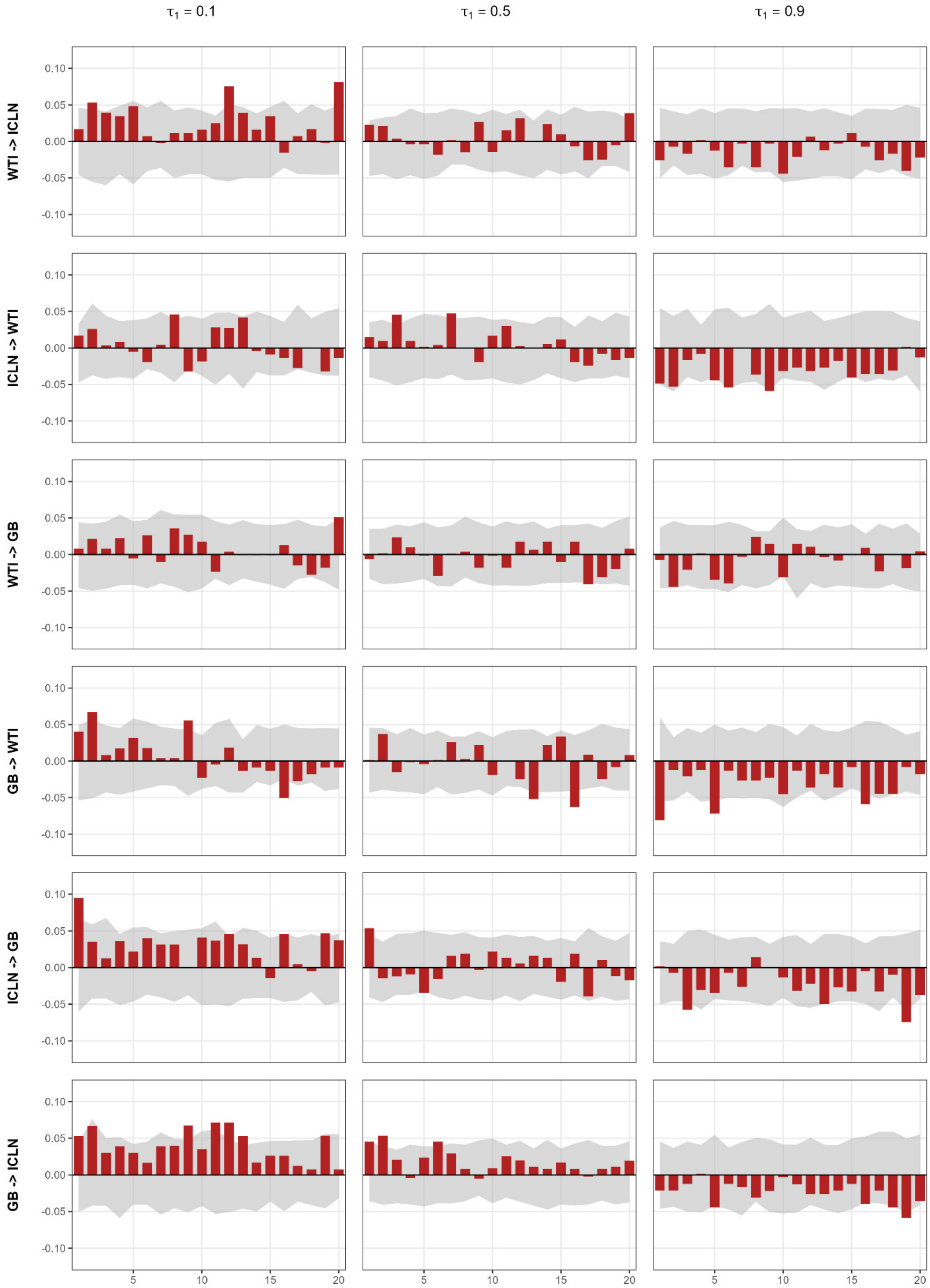

Figure 3. CQ results when the source market is in the downside tail ($\tau_2 = 0.10$).

The interpretation focuses on how distress spreads when the source market is in its lower tail ($\tau_2 = 0.10$). When the coefficient is positive and significant at $\tau_1 = 0.10$, there is downside co-movement, meaning the target market is more likely to also be in its downside tail (contagion). The negative and significant coefficient at $\tau_1 = 0.10$ implies a stabilizing influence, meaning the target is significantly less likely to fall into its lower tail despite the distress in the source. The negative and significant coefficient at the upper tail of the target ($\tau_1 = 0.90$) indicates rally suppression, i.e., downside shocks in the source have a significant negative effect, decreasing the likelihood that the target will experience unusually high returns. In contrast, a positive and significant coefficient at $\tau_1 = 0.90$ suggests a rare but noteworthy decoupling effect, in which the target continues to experience upside extremes despite the source being distressed.

Based on this framework, the empirical findings at $\tau_2 = 0.10$ indicate asymmetric yet statistically significant spillovers across the three linkages. In WTI → ICLN, the strong positive at $\tau_1 = 0.10$ and lags 2, 12, and 20 imply that there is both short-horizon and long-horizon downside co-movement, where oil sell-offs are significant predictors of the increased likelihood of renewable equities also experiencing distress. The median quantile ($\tau_1 = 0.50$) indicates a marginally significant effect at only lag 20, whereas the upper quantile ($\tau_1 = 0.90$) shows no significant effects, which indicates the lack of systematic upside transmission. In the reverse direction, ICLN → WTI, the best results are found at the upper quantile ($\tau_1 = 0.90$), where there are significant negative coefficients at lags 6 and 9 that indicate rally suppression, i.e., renewable sell-offs have a significant negative effect on the probability of oil entering its upper tail. At the median ($\tau_1 = 0.50$), there are significant positive coefficients at lags 3 and 7, indicating short-run spillovers into the central distribution of oil, whereas the lower tail ($\tau_1 = 0.10$) indicates only a marginal and non-persistent positive at lag 8.

In the WTI → GB context, there is limited significance. The positive coefficient at $\tau_1 = 0.10$, lag 20, indicates a possible delayed downside echo, while the negative coefficient at $\tau_1 = 0.50$, lag 17, indicates there is significant dampening at the median. At $\tau_1 = 0.90$, no significant findings indicate that oil distress does not systematically affect green-bond rallies. On the other hand, the distribution in the reverse GB → WTI direction is much larger. At $\tau_1 = 0.10$, there are significant positives at lags 2 and 9, which indicate downside co-movement immediately and in the short run, while the negative at lag 16 indicates that prolonged green-bond stress significantly decreases the probability for oil itself to go into its downside tail. At $\tau_1 = 0.50$, the significant negatives at lags 13 and 16 at the median indicate some dampening of oil's center distribution. Finally, at $\tau_1 = 0.90$, the significant negatives at lags 1, 5, and 16 indicate persistent rally suppression and are consistent with sell-offs in green bonds being associated with lower upside potential over the short to medium horizon.

Turning to the ICLN-GB nexus, the ICLN → GB direction demonstrates immediate contagion: $\tau_1 = 0.10$, lag 1 shows significant positive evidence of instant downside co-movement, while marginally significant positives at lags 16 and 19 capture delayed transmission. At $\tau_1 = 0.50$, the significant positive at lag 1 again captures the short-lived nature of the at-median spillover. In contrast, $\tau_1 = 0.90$ shows significant negatives at lags 3, 13, and 19, consistent with rally suppression, and that distress in clean energy is associated with a lower probability of green bonds going into their upside tail. The reverse GB → ICLN direction is even clearer. In the $\tau_1 = 0.10$ case, a cluster of significant positives over lags 9–13 suggests downside co-movement persisting into the mid-horizon, while at the median $\tau_1 = 0.50$, the significant positives at lags 1, 2, and 6 indicate that spillovers into ICLN's central quantile occur quickly. In the upper tail case, $\tau_1 = 0.90$, the significant negatives at lags 5, 16, and 18, and a particularly robust negative at lag 19, are consistent with persistent rally suppression, suggesting that GB is associated with lower clean-energy upside potential.

Taking everything into consideration, $\tau_2 = 0.10$ conditions show that the most dominant factors are rally suppression and downside co-movement. Oil shocks are associated with distress predictability in both the short and long run, while distress in the renewable sector is associated with lower upside probability in oil. In the WTI–GB pair, oil distress shows limited directional predictability for green bonds, but green-bond distress is associated with broader and more persistent downside co-movement in oil, particularly by limiting its upside potential. In the green block, patterns consistent with immediate tail co-movement are visible in both directions, with rally suppression especially strong from green bonds toward renewables. Overall, the common picture is that diversification is least effective during downturns: market declines trigger spillovers that concentrate on the downside, while chances for upside steadily fade.

5.3. Results under $\tau_2 = 0.90$ (source in upper tail)

Figure 4 shows the respective results when the source market is in its upside tail ($\tau_2 = 0.90$). In this case, positive and significant coefficients at $\tau_1 = 0.90$ indicate upside co-movement (risk-on clustering), consistent with improved risk appetite and pro-cyclical flows into fossil and green assets that raise the probability of joint upside outcomes. Negatives at the same quantile imply divergence, which is consistent with state-contingent rotation across segments, where strength in one market coincides with weaker performance in the other. At $\tau_1 = 0.10$, negative and significant coefficients show stabilization (rallies suppress downside risk in the target), consistent with risk-on recoveries and volatility compression that reduce downside tail realizations. Significant positives imply fragility (rallies perversely increase downside risk), which can reflect rebalancing and positioning imbalances that increase tail vulnerability despite contemporaneous strength. As in Section 5.2, the lag-level bar patterns below are interpreted as descriptive indicators of timing and asymmetry, with inferential weight resting primarily on the joint bootstrap results in Table 2.

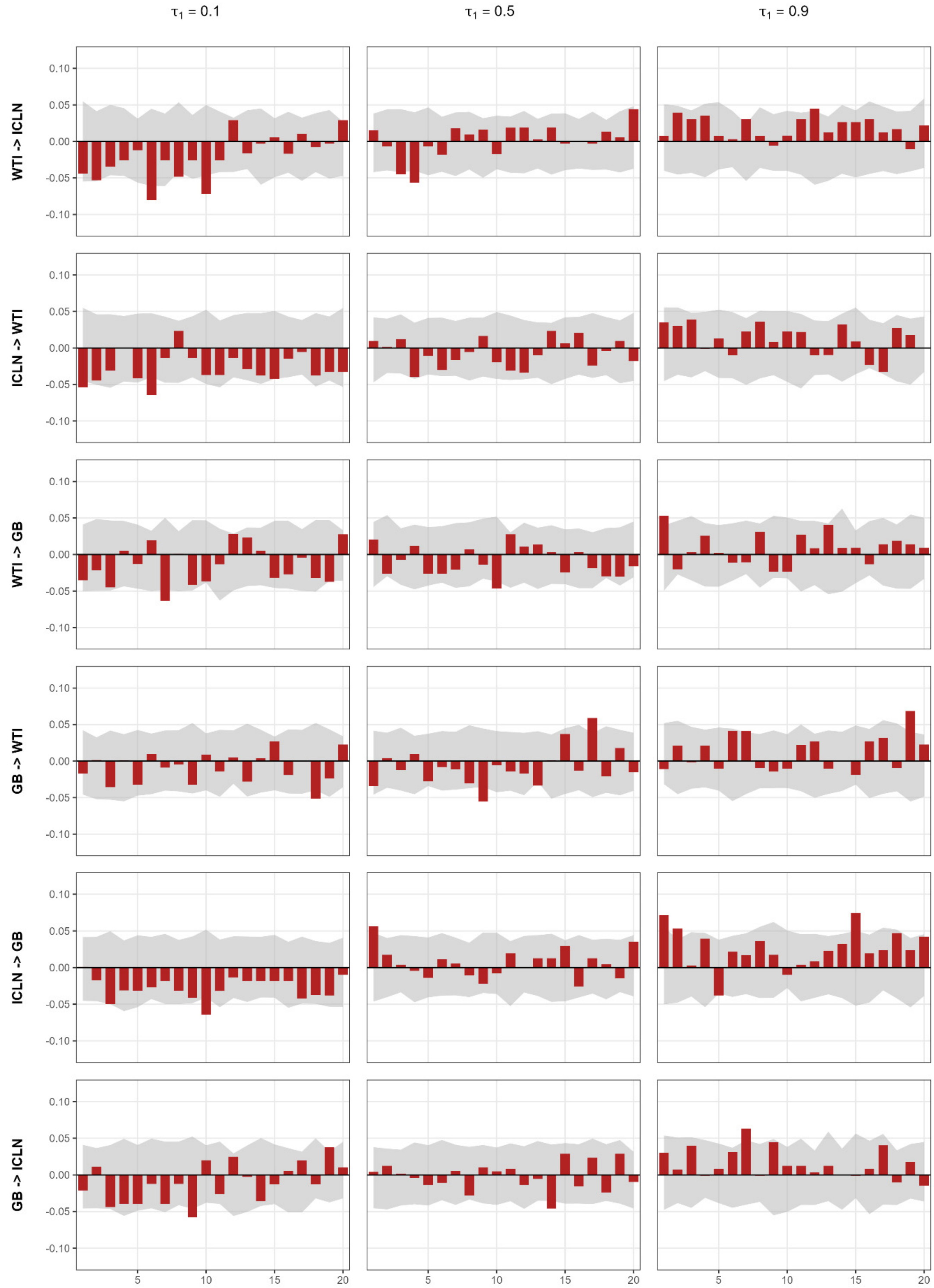

Figure 4. CQ results when the source market is in the upside tail ($\tau_2 = 0.90$).

When the source market is in its upper tail ($\tau_2 = 0.90$), the focus shifts to how rallies spread. A positive and significant coefficient at $\tau_1 = 0.90$ shows upside co-movement, meaning that a rally in the source makes it much more likely for the target market also to reach its upper tail. This joint movement is often called synchronized rallies or risk-on clustering. By contrast, a negative and significant coefficient at $\tau_1 = 0.90$ points to divergence, where rallies in the source actually lower the chance of extreme gains in the target. Looking at the lower quantile of the target ($\tau_1 = 0.10$), a negative and significant coefficient signals stabilization, since rallies in the source cut the downside risk for the target. In comparison, a positive and significant coefficient at $\tau_1 = 0.10$ suggests fragility, where gains in the source are linked with a higher chance of downside events in the target.

For WTI → ICLN, the clearest signals come in terms of the downside and median quantiles; $\tau_1 = 0.10$ (lags 6, 10) and $\tau_1 = 0.50$ (lags 3–4) are significantly negative, indicating that oil rallies lower the probability that renewables enter their downside or median states, thus pointing to a stabilizing channel. At $\tau_1 = 0.90$, there are marginally significant positives (lags 7, 12), suggesting that any upside reinforcement is limited. Considering the reversed direction, ICLN → WTI, $\tau_1 = 0.10$ shows a marginal negative at lag 1 and a clearly significant negative at lag 6, consistent with renewable rallies being associated with a lower conditional probability of oil entering its downside tail. Beyond lag 6, the ICLN → WTI quantiles remain generally benign, as the median and upper quantiles show no notable effects. Overall, looking at the pair as a whole, upper-tail shocks operate mainly as downside protection rather than upside amplification.

WTI → GB shows complementary channels. In WTI → GB, $\tau_1 = 0.10$ (lag 7) and $\tau_1 = 0.50$ (lag 10) are both significantly negative, suggesting that there is a strong, stable effect. However, at $\tau_1 = 0.90$, there is a clearly significant positive at lag 1, suggesting that at that lag, green-bond returns may rise following extreme oil rallies, which do not persist beyond lag 1. In the GB → WTI, stability was also noted at $\tau_1 = 0.10$ (lag 18) and $\tau_1 = 0.50$ (lag 9), indicating a strong green bond response that lessened downside and median outcomes for oil. At the same time, there is robust evidence of a risk-on channel: $\tau_1 = 0.50$ (lag 17) and $\tau_1 = 0.90$ (lags of 7 and 19) are significantly positive, indicating that green-bond rallies indicate delayed upside spillovers into oil. This asymmetry suggests that, while oil's upper-tail episodes contribute mostly as short-run downside protection for sustainable debt, green-bond rallies are associated with delayed upside predictability in oil at longer horizons. This is consistent with a common liquidity and risk-appetite factor.

For the green block, for the ICLN → GB direction, the evidence shows both stabilization and risk-on clustering. Under $\tau_1 = 0.10$, lag 10 is significantly negative, meaning renewable rallies lower the probabilities of green bonds experiencing distress. Under $\tau_1 = 0.50$, lag 1 is significantly positive; under $\tau_1 = 0.90$, there are positives at lags 1 and 2. A persisting signal at lag 15 suggests that immediate renewable strength feeds to green-bond rallies, but re-emerges at longer horizons. In the inverse GB → ICLN direction, $\tau_1 = 0.10$ (lag 9) and $\tau_1 = 0.50$ (lag 14) are significantly negative, signaling once again stabilization. $\tau_1 = 0.90$, however, shows a significant positive signal at lag 7, indicating a short-run upside co-movement. Thus, downside suppression appears asymmetric (notably stronger from GB toward ICLN), and upside clustering is bidirectional, suggesting that there is a common "green risk-on factor" linking equities and fixed income in the sustainable finance space.

All of these results show that, under $\tau_2 = 0.90$ conditions, cross-market linkages function globally through downside stabilization; in other words, the possibility of distress in one market is lessened by rallies in the other market. There is some evidence for synchronized upside co-movement, though it is less robust than downside stabilization; furthermore, upside co-movement appears most clearly within the green block and through green bond-to-oil delayed spillovers. These results reflect two main ideas: (i) upper-tail shocks in fossil fuel assets act chiefly as protective hedges, providing downside support to both renewables and green bonds; and (ii) upper-tail shocks from green assets are associated with delayed upside predictability for fossil fuels, consistent with shared liquidity and risk sentiment channels. This interaction highlights that in buoyant states, oil is stable while green assets lead, signaling a common liquidity and risk sentiment channel that joins conventional and sustainable markets.

5.3.1. Synthesis of dominant empirical patterns

Over both downside ($\tau_2 = 0.10$) and upside ($\tau_2 = 0.90$) regimes, the economic messages are robust to changes in lag levels. The key findings of this analysis are as follows: First, dependence is extremely tail-driven, with both low → low and high → high same-tail cell types dominating, and cross-tail cells capturing economically intuitive suppression or stabilization effects. Second, in distress regimes, there was significant downside contagion and rally suppression, indicating that diversification benefits decrease at times when stress hedging is most critical. Third, in buoyant regimes, the primary transmission mechanism shifted from rally transmission to downside stabilization, with only limited support for "risk-on" clustering, and that support being almost exclusively within the "green" segment. Fourth, there are also strong asymmetries in how asset roles vary across asset classes; the green block (ICLN – GB) exhibited the most frequent and longest-lasting linkages, and green bonds most frequently showed directional predictability toward oil rather than the reverse, whereas oil's influence appeared to be episodic and more concentrated in extreme states. The above system-level regularities represent the primary takeaways of the empirical section, and the individual lag-by-lag CQ bar plots serve as descriptive diagnostic tools for the timing of these phenomena.

5.4. Cross-quantilogram heatmap evidence

Figure 5 presents the CQ heatmaps that summarize the state-dependent relationships between pairs of markets using the residual series adjusted for VIX and EPU. The y-axis (τ_2) represents the quantile of the source market, while the x-axis (τ_1) represents the quantile of the target market. The orange shaded areas represent positive dependence (co-movement), the blue regions indicate negative dependence (stabilization or suppression), and the size of the markers indicates the proportion of significant lags at ≈ 95% confidence. Three main bilateral linkages are presented and discussed below.

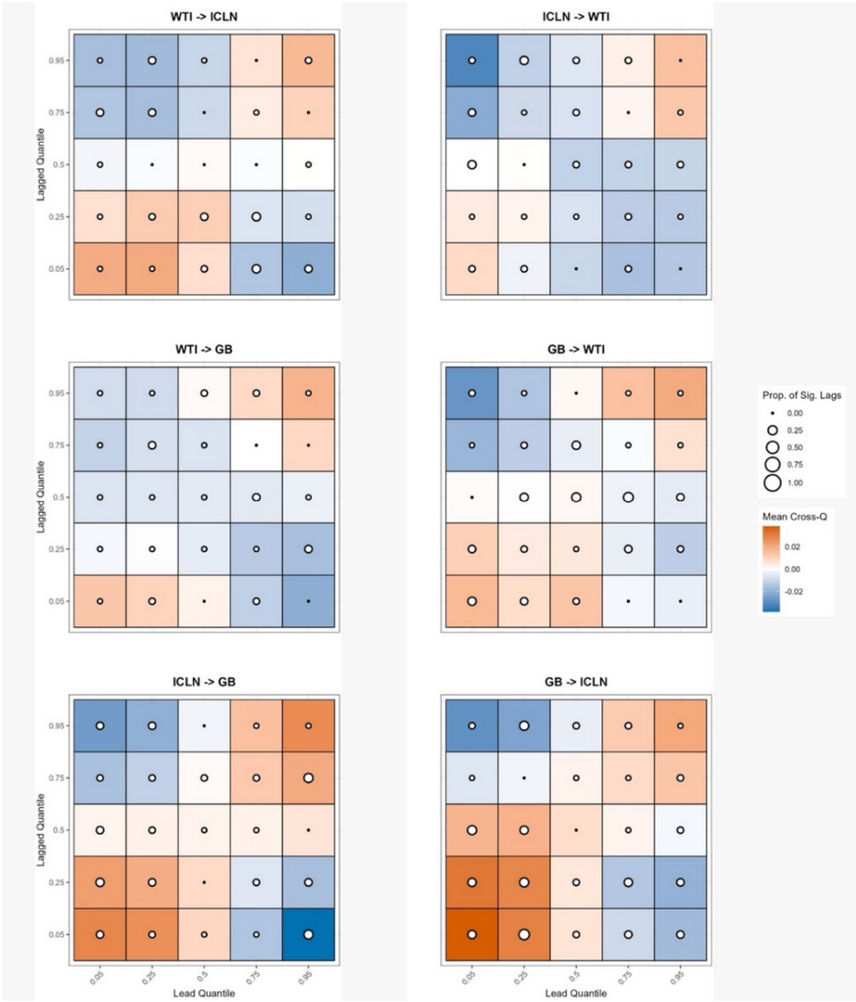

Figure 5. CQ heatmaps.

5.4.1. WTI ↔ ICLN (oil ↔ clean-energy equities)

The bilateral linkages exhibit the classic "same-tail co-movement/cross-tail suppression". When WTI exhibits downside ($\tau_2 \approx 0.05$–0.25), the leftmost column block ($\tau_1 \approx 0.05$–0.25) is light-orange with small non-zero circles, representing downside contagion into ICLN. The low→high corner is blue with circles, indicating ICLN rally suppression in an oil stress state. When WTI exhibits buoyancy ($\tau_2 = 0.95$), the arrangement is flipped: high→high cells turn orange, indicating risk-on clustering, and high→low cells are blue (downside stabilization). The ICLN median column ($\tau_1 = 0.50$) remains muted (near-white, small circles), so the oil → renewables transmission is predominantly tail driven. In the reverse ICLN → WTI panel, the sign pattern is generally consistent (blue on cross-tails), except that high→high shows light orange with small markers (only weak upside reinforcement); the stronger signal appears near the WTI median column (bluish cells), consistent with mid-quantile dampening.

5.4.2. WTI ↔ GB (oil ↔ green bonds)

Both directions show the expected tail asymmetry, orange on the same tails and blue on the cross-tails, but the robustness varies by direction. In WTI → GB, signal strength is modest: same-tail cells (low→low, high→high) are mostly light-orange, and the circles are smaller, indicating fewer significant lags; cross-tail cells are blue with little significance, implying episodic stabilization/suppression rather than a pervasive channel. By contrast, GB → WTI is noticeably stronger. The low→low block in GB → WTI is orange with larger circles (downside contagion from GB into oil), high→high is orange as well (risk-on clustering), and cross-tails are blue with circles (GB stress suppresses oil rallies; GB rallies stabilize oil downside). Thus, shocks from green bonds appear to transmit more clearly into oil assets than the reverse, especially in the tails.

5.4.3. ICLN ↔ GB (clean-energy equities ↔ green bonds)

The green-to-green nexus is the tightest in Figure 5. For ICLN → GB, the low→low cells are orange with large circles (downside contagion), while the low→high corner is deep blue with a large marker, indicating strong rally suppression in GB when renewables are under stress. When ICLN is in its upper tail, high→high turns orange (immediate risk-on synchronization) and high→low is blue (stabilization). The reverse GB → ICLN is equally robust: low→low is orange (bond-market stress pulls renewables down), low→high is blue (equity rallies are suppressed under GB stress), and high→high is orange (synchronized upswings), with circles generally larger than in the WTI links. This indicates strong two-way transmission inside the green block, propagating distress and rallies in both directions.

Overall, after pre-whitening with VIX and log-EPU, the three themes emerge. (i) Tail-state dependence: across all pairs, same-tail (low→low, high→high) cells are orange and often significant, distress co-moves with distress; rallies cluster with rallies, while cross-tails are blue, distress suppresses rallies; rallies stabilize downside. (ii) The strongest linkages are in the green block (ICLN–GB), and green bonds transmit into oil. (iii) The impact of oil is mostly limited to extreme situations, while green assets have a broader and more persistent influence. For portfolio allocation and risk management purposes, this implies diversification is weakened in bad states (downside contagion and rally suppression dominate). Risk-on clustering and downside stabilization are most evident in good states within the green block and from green bonds into oil.

5.5. General evaluation based on CQ analysis and heatmaps

Because all CQ estimates are computed on VIX/EPU-filtered residuals, the heatmaps and significance shares summarize net dependence conditional on the uncertainty environment, not the full dependence structure that includes VIX/EPU-driven channels. The CQ outcomes illustrated in Figures 3 and 4, as well as the heatmaps in Figure 5, convey an integrative view of state-dependent linkages. The bar-by-bar CQ plots show where significance clusters in downside ($\tau_2 = 0.10$) and upside ($\tau_2 = 0.90$) states, while the heatmap additionally identifies average CQs across lags and the share of ≈95% significant lags via marker size (breadth of significance). As the series are residualized with respect to VIX and EPU, both CQ outputs provide measures of net dependence rather than dependence induced by common volatility or policy shocks. Across all pairs, a clear tail-state dependence emerges: the modal pattern is same-tail co-movement (low-low, high-high) and its counterpart is cross-tail suppression or stabilization (low-high, high-low). In downside states ($\tau_2 = 0.10$), the signature is contagion plus rally suppression as co-varying targets are more likely to enter their lower tail and less likely to reach their upper tail when the source is distressed.

In upside states (τ_2 = 0.90), the signature flips to downside stabilization with selective risk-on clustering, as targets' downside probabilities drop, while high–high co-movement appears in some cases, although generally weaker. Median-to-median connections exist (e.g., in ICLN → WTI and GB → WTI) but subordinately so, reaffirming that predictability principally lies in extremes rather than around the median.

The second regularity is that the green block (ICLN–GB) has broad and persistent linkages that enhance the green block's connective role in the broader system. In both the CQ bars and the heatmaps, green–green linkages exhibit the clearest version of the same-tail/cross-tail template with immediate and delayed spillovers. Beyond this block, green bonds transmit more persistently into oil, including median effects, while the oil's effects on others are more episodic and concentrated in extreme states. Overall, the evidence indicates that dependence across fossil and sustainable assets is state-contingent and tail-driven, conditional on controlling for aggregate uncertainty via VIX and EPU. Specifically, diversification weakens in distress as downside contagion and rally suppression dominate, whereas in buoyant states, stabilization and selective risk-on clustering prevail, most visibly within the green block and, with lags, from green bonds into oil.

6. Conclusions

The CQ analysis demonstrates that interdependence among oil, renewable equities, and green bonds is strongly state- and tail-dependent. Under distress (τ_2 = 0.10), markets exhibit pronounced downside co-movement and rally suppression. Oil crashes are associated with short- and long-horizon distress predictability in renewables, while renewable sell-offs are associated with lower upside probability in oil. In the oil–green bond channel, oil distress weakly predicts weakness in sustainable debt, but stress in green bonds is associated with broad and persistent downside co-movement and lower upside-tail probabilities for the counterpart market. These effects are most visible in the green-bond→oil and green-to-green relations, implying that the green segment has become an integrated cluster with state-dependent diversification limits within the broader energy–finance ecosystem. After controlling for VIX and EPU, the persistence of these linkages suggests that the documented tail-state patterns are not solely driven by the common uncertainty component captured by these proxies. However, the results should be read as conditional interdependence, as other shared shocks may remain. An important implication of our design is that uncertainty-related transmission captured by VIX and EPU is filtered out by construction; therefore, our findings complement (rather than replace) evidence on total spillovers in unfiltered returns. Patterns consistent with contagion in the green block are immediate and bidirectional, especially from green bonds to renewables, suggesting that diversification benefits weaken during periods of distress: downside shocks propagate rapidly, while upside potential fades.

When the source market lies in its upper tail (τ_2 = 0.90), transmission shifts from contagion to stabilization. Rallies in oil and green assets reduce the probability of adverse outcomes elsewhere, acting as short-term stabilizers. Oil's upper-tail shocks offer only temporary protection, whereas green-bond rallies are associated with delayed upside predictability in oil and short-run upside predictability in ICLN, reflecting a common "green risk-on factor". This indicates that oil buffers downside risk in buoyant phases, while green assets synchronize rallies through shared liquidity and sentiment channels.

Three key insights emerge. First, tail dependence is asymmetric: downside shocks are associated with stronger directional predictability than upside shocks. Second, asset roles are distinct; oil acts as a transmitter of distress, green bonds act as a prominent transmitter of tail-state dependence in downturns and as risk-on leaders in recoveries, while clean-energy equities remain intermediaries, sharing co-distress with both sides. Third, contagion and rally suppression during stress reveal negative lead-lag dynamics, whereas green-bond rallies in buoyant markets form positive lead-lag clusters. Together, these findings establish a tail-dependent, regime-conditional lead-lag structure that linear methods fail to detect, offering a tail-aware allocation and conditional hedging perspective for investors.

For investors, diversification between fossil and green assets is least effective in downturns; hedging should therefore target tail risks rather than average correlations. In buoyant phases, stabilization and selective clustering dominate, with green bonds showing upside predictability for oil with a lag and for ICLN in the short run. Given that our evidence is based on market-level return dynamics, the implications are best interpreted as investor-oriented: they inform tail-aware portfolio construction and conditional hedging rather than regulatory oversight claims. Future work should extend the analysis to higher-frequency data, structural breaks, and portfolio-level optimization to strengthen the link between the documented tail-state lead-lag patterns and practical risk management.

Author contributions

Ahmet Furkan Sak conceptualized the study, designed the research framework, and supervised the overall project. Mustafa Çelik was responsible for data collection, preprocessing, and validation. Faruk Temel performed the empirical analysis and contributed to model implementation in R. Ismail Celik reviewed the literature, contributed to result interpretation, and assisted in manuscript editing. All authors discussed the findings, contributed to the final version of the manuscript, and approved the submitted version.

Use of AI tools declaration

The authors declare that AI tools were used only for language editing and stylistic improvements.

Acknowledgments

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Conflict of interest

The authors declare that they have no competing interests.

Data Availability Statement

The data that support the findings of this study are publicly available from Yahoo Finance, policyuncertainty.com, and the official S&P Dow Jones Indices webpage. Detailed variable definitions, transformations, and sample-construction procedures are provided in the manuscript.

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