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Asymmetric dependency among US national financial conditions and clean energy markets

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ABSTRACT

This paper examines the relationship between the US National Financial Conditions Index (NFCI) and the clean energy industry using quantile and frequency connectedness, cross-quantile, and wavelet quantile correlation (WQC) techniques. Results reveal (a) a stronger dependence between the NFCI and clean energy under bullish market states. Moreover, the total connectedness between the NFCI and clean energy mostly exhibits time-varying characteristics. In particular, clean energy has a greater spillover effect than the NFCI. (b) Dynamic frequency total connectedness at extreme quantiles provided a more comprehensive view of structural shocks in financial markets, and major crises, such as COVID-19, significantly amplified this connectedness. Overall, the WilderHill Clean Energy Index and the NASDAQ OMX Renewable Energy Index demonstrate substantial potential for hedging financial conditions. (c) The cross-quantile correlation results revealed an asymmetric dependency, demonstrating a sustained significant positive relationship between the NFCI and clean energy index (CEI) across the relative higher quantiles and middle quantiles. The WQC showed that the NFCI and specific CEIs tended to exhibit the strongest positive correlations in nonextreme quantiles and lower frequencies. These results can be of considerable interest to various financial market participants.

1. Introduction

Since the 19th century, human activities have emerged as a significant driver of climate change owing to the widespread and unregulated use of traditional fuels such as coal, oil, and natural gas for industrial production and daily life (Zhao, Benkraiem, Abedin, & Zhou, 2024). These activities have resulted in the release of greenhouse gases, which has accelerated global warming, unlike anything observed in the last two millennia.[1] Given the escalating global climate change and environmental concerns, clean energy is crucial in transitioning to a low-carbon economy. Clean energy adoption reduces greenhouse gas emissions significantly compared to conventional energy sources, making it critical to mitigating climate change (Chien, Hsu, Ozturk, Sharif, & Sadiq, 2022).

The US national financial landscape has a substantial impact on the world economy. As one of the world's largest economies

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[1] Source: United Nations, https://www.un.org/climatechange/what-is-climate-change.

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(Shahbaz, Gozgor, & Hammoudeh, 2019), the US boasts extensive and highly developed financial markets, giving it a critical position in the global economy and significant influence and authority in the financial sector (Naeem et al., 2022, bThe US has emerged as a pivotal center in the global financial arena, thanks to its large financial markets, robust financial institutions, capacity for innovation, and influential role in international financial governance. Consequently, previous studies have extensively studied and analyzed its role and impact on the global financial system (e.g., Abdou, Elamer, Abedin, & Ibrahim, 2024; Gomber, Kauffman, Parker, & Weber, 2018) and have also mentioned (e.g., Agoraki, Aslanidis, & Kouretas, 2022; Dhifaoui, Khalfaoui, Ben Jabeur, & Abedin, 2023; Hippler & Hassan, 2015) that the Chicago Fed's National Financial Conditions Index (NFCI) is a valuable resource for understanding the financial conditions of financial markets, bond and stock markets, and the banking system in the US. The NFCI is a composite indicator based on a weighted average of 105 financial operation indicators that provides insight into the overall state of the US financial markets.[2] Hence, the importance of our study extends beyond the borders of the US, as it is likely to provide valuable understanding of the state of international financial markets as well.

The study aims to investigate the relationship between the US national financial situation and the clean energy industry. The transition to clean energy is critical for climate governance, as the negative impacts of global warming caused by excessive fossil fuel consumption threaten both economically and environmentally sustainable development (Belaïd, Al-Sarihi, & Al-Mestneer, 2023; Juszczyk, Juszczyk, Juszczyk, & Takala, 2022). However, several factors, including market conditions, policy uncertainties, and financial market volatility, continue to affect the progress of clean energy transition. The economic policy orientation of the US government and the Federal Reserve is an important factor influencing clean energy financing because it directly impacts national financial conditions and macro-market expectations (Binder, 2020; Elsayed & Sousa, 2022; Rudebusch, 2019). Therefore, US national financial conditions and market confidence are critical in financing clean energy projects that attract investment and government support. The substantial involvement of US government bills and policies spanning a broad industry chain is particularly noteworthy (Porter & Kramer, 2018).

Considering these factors, the potential spillover transmission channels from the US national financial conditions to the clean energy market are as follows:

(1) *Energy price volatility*. Changes in the US financial conditions may impact the volatility of fossil fuel prices, such as natural gas and oil (Norouzi, 2021). Financial market instability or panic could affect traditional energy markets, causing price volatility, which in turn would affect the competitiveness of the clean energy market and investor confidence.

(2) *Changes in financial flows*. Tightening or loosening financial conditions may affect the flow of funds between markets (Alexander, Chen, & Ward, 2021; Angelopoulou, Balfoussia, & Gibson, 2014). Tightening financial conditions may lead investors to seek relatively stable and high-return assets, such as gold, thereby reducing investment in clean energy projects. Conversely, loosening financial conditions may encourage investors to seek riskier assets, potentially increasing investment in clean energy projects (Wu & Tian, 2022). According to recent research, a 1 % increase in the US financial conditions index resulted in a 10 % decline in the value of M&A transactions, impacting Wall Street's mechanics (Bergant, Mishra, & Rajan, 2023).

(3) *Changes in the policy environment*. Changes in financial conditions may impact government policies and regulations that support clean energy, which in turn may be influenced by government preferences, such as the Trump administration's focus on conventional energy sources (Cheung, 2020). Economic recessions, such as the COVID-19 pandemic, may reduce subsidies and support for the clean energy industry, consequently affecting market competitiveness (Yana, Nizar, Irhamni, & Mulyati, 2022; Zeng et al., 2024, b, c, d, e). Conversely, during an economic recovery, the government may increase support for clean energy, encouraging investment and development.

(4*) Investor confidence*. Volatile financial conditions may have an impact on investor confidence in the clean energy sector. As previously stated, unstable financial markets may cause investors to be cautious, resulting in lower investment in clean energy projects (Zeng et al., 2025). By contrast, stable financial conditions may increase investor confidence and attract capital flows to the clean energy industry. Thus, investigating the impact of the NFCI on the clean energy industry may provide valuable insights into the mechanisms by which the US financial market influences the clean energy industry. Therefore, empirically investigating this impact, which was previously understudied, could assist the US government in developing an appropriate policy framework to ensure the future stability of the clean energy sector.

To explore the impact of the asymmetric tail risk of the NFCI and clean energies in heterogeneous market states, we will first use a QVAR-based quantile connectedness method. This includes running regressions with different tails and fitting the VAR model at the extreme tail quartiles of 0.05 and 0.95 to better understand the quantile connectedness system for extreme negative and extreme positive shocks, respectively. Furthermore, we use Han, Linton, Oka, and Whang's (2016) cross-quantilogram (CQ) approach to evaluate the paired extreme dependency between the US's national financial conditions and the segmented clean energy index (CEI). Han et al. (2016) developed a methodology specifically for evaluating the predictability and dependence of the direction between two variables. In addition to capturing the dependency between variables, the CQ method can measure the lead–lag causal relationships for a given quantile, making it easier to assess the conditional variance distribution. The CQ technique can investigate dependency and predictability over specified lag periods by exploring various potential combinations within extreme quantiles. Finally, owing to investor heterogeneity, investors with varying risk preferences preferred different market conditions and investment horizons. For example, investors seeking stable investments frequently preferred short-term investments during rising market conditions because market risk was low and short-term returns were relatively stable (Bolton, Chen, & Wang, 2013). By contrast, investors who prefer high

[2] Chicago Fed, https://www.chicagofed.org/research/data/nfci/current-data.

risk and high returns may be more likely to invest long term during market downturns or fluctuations. This was because many high-quality assets' prices could become undervalued when the market fell, creating opportunities for long-term investors. Furthermore, high-risk investors can seek higher returns during market fluctuations using active investment strategies such as contrarian investing. As a result, using frequency connectedness and wavelet quantile correlation (WQC), which consider different quantiles (market conditions) and frequencies at the same time, the nonlinear, asymmetric, and multiscale correlations between the NFCI and the disaggregated CEIs across different time scales and quantiles can be effectively captured, addressing the aforementioned issues. The specific research questions we hope to answer are as follows: (a) what type of heterogeneity exists in the dependence framework between the NFCI and clean energies under heterogeneous market conditions? (b) What are the dynamic correlations between the NFCI and CEIs under various market conditions? (c) What is the direction and strength of spillovers between indices in different market states? Assessing the correlation and degree of spillover between the NFCI and CEIs can provide investors, policymakers, and other stakeholders with more accurate and comprehensive decision-making tools. (d) How do the frequency correlations between the NFCI and the price of specific clean energy sources manifest at each quantile? This is especially true for the dependence observed at the extreme quantiles of spillover.

This study contributes to the existing literature in several ways. To the best of our knowledge, this study was the first to examine the connection between the Federal Reserve Bank of Chicago's NFCI and US CEIs. This study discusses the relationship between the NFCI and CEIs and identifies which clean energy sources are least affected by financial conditions. Second, this is the first study to use a quantile method to analyze tail connectedness between the NFCI and the clean energy market, distinguishing between upper and lower quartiles ($q = 0.95$ and 0.05, respectively). This enables a comparison of the diverse and asymmetric patterns of spillover linkages between the NFCI and clean energy under various market conditions (tails). In addition to static connectedness analyses, this study conducts time-varying analyses to capture risk contagion across time periods and quartiles accurately. Major crises (e.g., COVID-19) were found to cause structural changes in the pattern of time-varying net spillovers between variables. Third, we examine the structure of short-term, long-term, and overall dynamic total connectedness index (TCI) at various quantiles. The dynamic frequency TCI at extreme quantiles provide detailed information about structural shocks in financial markets, especially during the COVID-19 period. Fourth, the study compares paired net spillover network graphs across quartiles. Market integration is particularly strong at the tails, increasing the likelihood of intranetwork risk contagion. Notably, the NFCI is a volatile recipient under any market conditions. Fourth, we investigate the predictive cross-interactions between NFCI and a particular CEI. The cross-quantification correlation results confirm the substantial spillover relationship between the NFCI and the CEI at both the relative upper and middle quantiles. These results are firm. In other words, when placed in both a bullish and normal state, NFCI significantly impacts clean energy. Fifth, the strength of the connection between the NFCI and the disaggregated CEIs varies with frequency and quantile. Furthermore, lower time frequencies demonstrate relatively stronger dependencies than higher time frequencies.

The remaining portion of the research is structured as follows. Section 2 provides a review of the literature. Section 3 describes the methodology and presents the dataset. Section 4 presents the primary empirical finding. Finally, Section 5 concludes the paper.

2. Literature review

Conventional energy sources not only contribute substantially to greenhouse gas emissions, but also cause serious environmental pollution, affecting the atmosphere, soil, and water (Wang, Liu, Abedin, & Lucey, 2024). Climate change has received increased global attention, and the development of clean energy markets is regarded as a critical strategy to address climate-related challenges and improve energy security (Andrijevic, Schleussner, Gidden, McCollum, & Rogelj, 2020). Song, Ji, Du, and Geng (2019) discovered a link between clean energy and fossil energy markets. Anton and Afloarei Nucu (2020) conducted an investigation focusing on 28 European Union member states between 1990 and 2015. Meanwhile, Nguyen, Naeem, Balli, Balli, and Vo (2021) examined the relationships between green bonds and other financial indices, including equities, futures, renewable energy, and conventional bonds. They found that the links between equity, futures, and renewable energy remained relatively strong after the crisis. Sweidan (2021) emphasized the role of geopolitical risk as a driver of renewable energy diffusion, with empirical results indicating a significant positive impact on clean energy deployment in the US during times of geopolitical uncertainty.

Clean energy is distinguished based on its diverse sources, such as solar, wind, hydro, and biomass, and it is well suited to humanity's long-term energy needs (DeAngelo et al., 2021). The benefits of clean energy over conventional sources are twofold. First, traditional energy sources have limited reserves, and their extraction and use seriously negatively affect the environment and human wellbeing. Second, adopting clean energy reduces reliance on external energy sources (Gozgor et al., 2022). Furthermore, clean energy is more reliable and stable than traditional sources, which are susceptible to geopolitical factors (Bratis, Laopodis, & Kouretas, 2020). Thus, promoting and advancing clean energy are critical for combating climate change and achieving a sustainable future (Sarker, Haque, Bhuiyan, Bruckard, & Pramanik, 2022; Wang, Su, & Umar, 2021). Furthermore, with the financialization of the clean energy industry, investments in clean energy have emerged as a significant funding source for its development (Mngumi, Shaorong, Shair, & Waqas, 2022). In 2022, the US market saw a $32.3 billion investment in clean energy. It has benefited from uncertainties surrounding the green stimulus package and renewable energy tax credits while attracting substantial venture capital and private equity financing (Azhgaliyeva, Beirne, & Mishra, 2023). This has made clean energy–related industries extremely appealing to investors. Meanwhile, it is critical to recognize the federal incentives implemented by the Biden administration and signed into law in August 2022. On March 31, 2023, more than $150 billion in capital investments were announced for utility-scale clean energy programs. This amount represents five years of clean energy investment in the US, demonstrating policymakers' high priority for the clean energy sector.[3]

Recent studies have explored the complex relationships between clean energy, various markets such as commodities, and pollution energy markets, revealing asymmetric, time-varying links and diversification opportunities. Ahmed, Cary, Shahbaz, and Vo (2021) found that, while increasing economic policy uncertainty helped reduce emissions, a reduction in economic policy uncertainty was the primary driver of the decrease in carbon dioxide emissions. Furthermore, there was no significant relationship between renewable energy R&D expenditure and carbon dioxide emission reductions. Farid, Naeem, Paltrinieri, and Nepal (2022) show that connectedness at extreme tails was stronger during the pandemic, indicating a significant transmission of return shocks between these commodity markets, with notable changes in connectedness over time. Green bonds showed asymmetric responses to different commodity groups, according to Naeem, Nguyen, Nepal, Ngo, and Taghizadeh-Hesary (2021). Green bonds, which have negative correlations with specific commodities, provided hedging and diversification benefits during periods of high market volatility. Farid, Karim, Naeem, Nepal, and Jamasb (2023) discovered weak short-term links and, in some cases, strong long-term links, indicating a substantial decoupling effect. During the pandemic, clean energy markets were relatively isolated from polluting energy markets, which improved portfolio diversification. Naeem, Peng, Suleman, Nepal, and Shahzad (2020) found that short-term correlations were generally stronger than long-term correlations during the global financial crisis and the shale oil revolution. Electricity futures were effective tools for risk diversification and hedging. Table 1 presents the summary of the literature discussed above.

Furthermore, research has explored various aspects of the financial situation of the US nation, including the economic, financial, and policy spheres. Swiston (2008) emphasized the accuracy of the FCI as a leading predictor of the business cycle. Dibooglu, Erdogan, Yildirim, and Cevik (2020) used the NFCI to study its impact on US monetary policymaking and discovered that financial instability significantly increases the likelihood of transitioning from a smooth state to a stressed state. Dery and Serletis (2021) found a strong correlation between macroeconomic uncertainty, the nation's financial situation, and economic activity. Kwark and Lee (2021) used the quantile method to examine the impact of financial conditions in Korea and the US on future Korean GDP growth, revealing asymmetric effects across quartiles.

Despite the widespread interest in both clean energy and US national financial conditions, there is a lack of in-depth academic research on the quantile connection between the CEIs and the US NFCI. As a result, this study aims to conduct a systematic and comprehensive investigation into the spillover transfer mechanism between the NFCI and the clean energy market under various market conditions.

3. Methodology and data

Ando, Greenwood-Nimmo, and Shin (2022) use a quantile VAR model to develop quantile connectedness across different quartiles (market conditions). First, we show the quantile VAR, then describe the intermarket connectedness mechanism across quartiles.

3.1. Quantile vector autoregression

The quantile regression method shows the dependence of y_t on x_t after each extreme quantile $\tau(\tau \in (0,1))$, given that y_t/x_t is conditionally distributed. To estimate the quantile VAR process for the n variables, we compute it sequentially as follows:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), t = 1, \cdots, T \tag{1}$$

where y_t and $y_{t-i}(i = 1, \ldots, p)$ show the $n \times 1$-dimensional vectors of endogenous elements (N different markets), τ is the quantile we set with values within the range of 0 to 1, $c(\tau)$ denotes a constant vector with dimensions of $\mathrm{n} \times 1$, $e_t(\tau)$ is an error vector with dimensions of $\mathrm{n} \times 1$, and $B_i(\tau), i = 1, \cdots, p$ is an $\mathrm{n} \times \mathrm{n}$-dimensional matrix of lagged parameters evaluated from the quantile VAR, where $i = 1, \cdots, p$.

We assume that the residuals $\widehat{B}(\tau)$ and $\widehat{c}(\tau)$ satisfy the limits of the quantile most used and $Q_\tau\left(e_t(\tau) \middle| y_{t-1}, \cdots, y_{t-p}\right) = 0$. The market's estimated response y (conditional quantile τ) is calculated by applying the following equation to each quantile:

$$Q_\tau\left(y_t \middle| y_{t-1}, \cdots, y_{t-p}\right) = c(\tau) + \sum_{i=1}^{p} \widehat{B}(\tau) y_{t-i} \tag{2}$$

3.2. Connectedness estimates rely on quantile VAR

We transform the quantile VAR(p) estimate of Equation $Q_\tau\left(y_t \middle| y_{t-1}, \cdots, y_{t-p}\right) = c(\tau) + \sum_{i=1}^{p} \widehat{B}(\tau) y_{t-i}$ in the process of an infinite-order vector moving average as follows,

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau), t = 1, \cdots, T$$

[3] ACP, https://cleanpower.org/resources/clean-energy-investing-in-america-report/#form

Table 1
Related literature investigates the relationships between clean energy and various financial markets.

Author (s)	Year	Methods	Main findings
Ahmed et al.	2021	Asymmetric ARDL	Used symmetric and asymmetric autoregressive distributed lag models to study the nonlinear impacts of renewable energy R&D expenditure and economic policy uncertainty on carbon dioxide emissions. It was found that increasing economic policy uncertainty helped reduce emissions, whereas reducing economic policy uncertainty was the primary driver of the decrease in carbon dioxide emissions. Furthermore, there was no significant relationship between renewable energy R&D expenditure and carbon dioxide emission reductions.
Farid et al.	2022	QVAR Connectedness	We used a quantile connectedness method to analyze the relationships between energy, metals, and agricultural commodities in the context of COVID-19. Results showed that the connectedness at the extreme ends was stronger during the pandemic, indicating a significant transmission of return shocks between these commodity markets, with notable changes in connectedness over time.
Naeem et al.	2021	Cross-quantilogram Method	The trans-quantilogram technique was employed to look into the asymmetric relationships between green bonds and three major commodity groups. According to empirical findings, green bonds showed asymmetric responses to different commodity groups. Green bonds, which have negative correlations with specific commodities, provided hedging and diversification benefits during periods of high market volatility.
Farid et al.	2023	Rolling-window wavelet correlation and wavelet coherence	During COVID-19, we investigated the linkage structure between clean and polluting energy stocks. The study found weak short-term linkages and, in some cases, strong long-term linkages, indicating a significant decoupling effect. During the pandemic, clean energy markets were relatively isolated from polluting energy markets, which improved portfolio diversification.
Naeem et al.	2020	Diebold and Yilmaz (2012); Baruník and Křehlík (2018)	The spillover method examined the temporal and frequency correlation between electricity, carbon emission allowances, clean energy, and crude oil price shocks. During the global financial crisis and the shale oil revolution, short-term correlations were generally higher than long-term correlations. Electricity futures were effective tools for risk diversification and hedging.

$$
\begin{aligned}
\mu(\tau) &= \left(I_n - B_1(\tau) - \cdots - B_p(\tau)\right)^{-1} c(\tau), \\
A_s(\tau) &= \begin{cases} 0, s < 0 \\ I_n, s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \cdots + B_p(\tau)A_{s-p}(\tau), s > 0 \end{cases}
\end{aligned}
\tag{3}
$$

where y_t (the monetary policy rate) is given by the sum of the residuals $e_t(\tau)$.

According to Pesaran and Shin (1998), under the generalized forecast error variance decomposition (GFEVD), Eq. (4) will be used to estimate the GFEVD of a variable owing to spillover to heterogeneous indices when the forecast time horizon is H:

$$
\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} \left(e_i A_h \sum^{e_j}\right)^2}{\sum_{h=0}^{H-1} \left(e_i A_h \sum^{e_j}\right)} \tag{4}
$$

where $\theta_{ij}^{g}(H)$ reports the contribution of index j to the index i in period H. The error vector's variance matrix is represented by $\sum$. The jth diagonal parameter of matrix $\sum$ is denoted by σ_{ij}, and e_i is a vector with a value of 1 for the ith parameter and 0 for all the other elements. After normalizing every element in the variance decomposition matrix, we can obtain the following outcomes:

$$
\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{5}
$$

Subsequently, we create a fully normalized variance decomposition matrix, which will allow us to assess variance connectedness at the quantiles. The TCI is a parameter that measures the system's overall interconnectedness:

$$
TCI(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(\tau)} \times 100 \tag{6}
$$

The directional connectedness of variable i on other indices is as follows:

$$
TO_{ij}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ji}^{g}(\tau)}{\sum_{j=1}^{N} \widetilde{\theta}_{ji}^{g}(\tau)} \times 100 \tag{7}
$$

Total directional spillover in variable i from other markets:

$$
\mathrm{FROM}_{ij}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(\tau)} \times 100 \tag{8}
$$

The net directional spillover of variable i is as follows:

$$NET_i(\tau) = TO_{ij}(\tau) - FROM_{ij}(\tau) \tag{9}$$

According to previous research (e.g., Zeng et al., 2024, b, c, d, e), we use three quantile values of 0.05, 0.5, and 0.95 to indicate periods of extreme fall, average, and up market conditions, respectively.

3.3. Frequency base connectedness estimates of QVAR

A spectral analysis was used to distinguish between the various frequency profiles of tail risk connectedness across different variables. This process involved dividing the quantile connectedness into distinct frequency bands. As stated in Section 3.2, the primary focus was on the GFEVD, which is an important component of connectedness. Unlike the quantile variance decomposition, determined by the spillover impulse response, the variance decomposition spectrum depicted the frequency response caused by shocks. The frequency response framework $\Psi\left(e^{-i\omega};\tau\right) = \sum_h e^{-i\omega h}\Psi_h(\tau)$, which Ψ_h is evaluated by the Fourier transfer, and $i = \sqrt{-1}$, the causal spectrum at a certain band of frequency τ was generalized on quantile $\omega \in (-\pi, \pi)$ is described as follows:

$$(f(\omega;\tau))_{j,k} = \frac{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-i\omega};\tau\right)\Sigma\right)_{j,k}\right|^2}{\left(\Psi\left(e^{-i\omega};\tau\right)\Sigma\Psi'\left(e^{+i\omega};\tau\right)\right)_{j,j}} \tag{10}$$

where $(f(\omega;\tau))_{j,k}$ points out the section of the spectrum of the k at every band of frequency ω when the j asset meets a spillover.

Evaluating connectedness across a spectrum of frequency bands provided greater insight than analyzing connectedness on a single, specific band ω; hence, we compiled a generalized causal spectrum for band $B = (a,b) : a, b \in (-\pi,\pi), a < b$. Therefore, the framework of GFEVD on frequency B will be evaluated as follows:

$$\theta_{j,k}^{B}(\tau) = \frac{1}{2\pi}\int_{\varnothing}\Gamma_j(\omega;\tau)(f(\omega;\tau))_{j,k}d\omega \tag{11}$$

where $\Gamma_j(\omega;\tau)$ is a weighting structure, set on $\Gamma_j(\omega;\tau) = \frac{\left(\Psi\left(e^{-i\omega};\tau\tau\right)\sum\Psi'\left(e^{+i\omega};\tau\right)\right)_{jj}}{\frac{1}{2\pi}\int_{-I}^{\pi}\left(\Psi\left(e^{-ij};\tau\right)\sum\Psi'\left(e^{+\overline{i\pi T}\tau}\right)\right)_j d\lambda}$, pointing the power of the j at every frequency ω. Meanwhile, the GFEVD structure on the frequency B will be normalized to the following:

$$\widetilde{\theta}_{j,k}^{Q}(\tau) = \frac{\theta_{j,k}^{\infty}(\tau)}{\sum_{k=1}^{N}\theta_{j,k}^{\infty}(\tau)} \tag{12}$$

$\widetilde{\theta}_{j,k}^{g}(\tau)$ points out the pairwise connectedness from the k to j on a detail frequency B at τ^{th} quantile. Thus, data from multiple sources could be consolidated $\widetilde{\theta}_{j,k}^{\text{�}}(\tau)$ to get several quantile connectedness evaluates in band B. Furthermore, the TCI can be measured as band $B\left(\mathrm{TCI}^B\right)$:

$$\mathrm{TCI}^B(\tau) = \frac{\sum_{j,k=1, j\neq k}^{N}\widetilde{\theta}_{j,k}^{\mathscr{R}}(\tau)}{\sum_{j,k=1}^{N}\widetilde{\theta}_{j,k}^{\infty}(\tau)} \times 100 \tag{13}$$

overall, by defining band B as the pertinent interval, this study divided the TCI into high, medium, and low frequency ranges.

We used several quantile levels (0.05, 0.5, and 0.95) to show extreme falls, normal, and favorable market states based on previous studies (e.g., Zeng et al., 2024, b, c, d, e).

3.4. Cross-quantilogram

This study used Han et al.'s (2016) CQ method to assess the cross-quantile correlation between US financial conditions and clean energy. Compared to traditional correlation measures, the CQ method has a distinct advantage in detecting asymmetrical patterns within the cross-quantile dependency structure. The CQ correlation measures were visualized using heatmaps, considering various lag lengths, per established literature conventions. These heat maps depict a dynamic representation of the cross-quantile unconditional pair connection between two variables, providing an intuitive and visually appealing way to convey the overall dependence structure. Each heatmap depicts the quantile distribution of two specified variables on the horizontal and vertical axes. Including nine quantiles results in the representation of bivariate quantile combinations via 81 cells within each heatmap, where cells with a star symbol indicate the presence of significant correlation.

It is important to note that the CQ method assumes the underlying time series are stationary. This study examined a pair of time series, denoted as y_t and x_t, both of which adhere to stationary stochastic proceedings. Given that $y_t = \left(y_{1t}, y_{2t}\right)^T\mathscr{R}^2$ and $x_t = \left(x_{1t}, x_{2t}\right)^T\mathscr{R}^{d_1} \times \mathscr{R}^{d_2}$, a quantile framework with a conditional distribution will be defined as $F_{y_i|x_i}(\bullet|x_{it})$ and $q_{i,t}(\tau_i) = \{v : F_{y_i|x_i}(v|x_{it}) \geq \tau_i$ for every $\tau_i(0,1)$. There are two processes in the CQ approach. First, it estimates the "quantile-hit" steps, which fundamentally estimate the serial correlation between the two elements $y_{1t} \leq q_{1,t}(\tau_1)$ andy $y_{2,t-k} \leq q_{2,t-k}(\tau_2)$. The cross-dependency of dynamic “quantile-hit” will then be calculated.

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau 1}\left(y_{1,t} - q_{1,t}(\tau_1)\right)\psi_{\tau 2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi^2_{\tau 1}\left(y_{1,t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi^2_{\tau 2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}} \tag{14}$$

where $\psi_a = 1/[u < 0] - a$ defines that the quantile-hit steps that are estimated under moment $t - k$. Furthermore, k is the lead-lag ranges denotes to moment t, and $\rho_\tau(k)$ evaluates the quantile-hit steps.

Simultaneously, the CQ is an estimate of the presence of directional predictability across two markets, derived from the use of conditional quantiles. In the context of two given events denoted as $y_{1t} \le q_{1,t}(\tau_1)$ and $y_{2,t-k} \le q_{2,t-k}(\tau_2)$, the absence of directional predictability or cross-correlation is manifested when $\rho_\tau(k) = 0$ holds true. Furthermore, directional predictability or quantile correlation is observed when $\rho_\tau(k) = 1$ is met. Subsequently, the null hypothesis, positing that the conditional dependencies are markedly zero (referred to as H_0: $\rho_\tau(1) = \dots = \rho_\tau(p) = 0$), undergoes evaluation in contrast to an hypothesis of alternative suggesting a considerable deviation from zero (termed as $H_1 : \rho_\tau(k) \ne 0$ for any $k \in \{1 \dots\dots\dots p\}$). The Box–Ljung test is used to reach a statistical conclusion that supports the null hypothesis. The Box–Ljung test is defined as follows:

$$\widehat{Q}_t(p) = T(T+2)\sum_{k=1}^{p}\frac{\widehat{\rho}^2(k)}{T-k} \tag{15}$$

3.5. Wavelet quantile correlation

Kumar and Padakandla’s (2022) proposed that WQC represents a step forward from Li et al.’s (2015) initial QC methodology. This ground-breaking approach builds on the existing framework, allowing for a more detailed investigation into the interconnectedness of two variables, denoted as X and Y. In this setting, $Q_{\tau,X}$ corresponds to the τ^{th} quantile of X, while $Q_{\tau,Y}(X)$ corresponds to the τ^{th} quantile of Y, under the stipulation that X acts as the antecedent condition. Furthermore, X is defined as the independent series in this analytical construct.

The definition of quantile covariance is as follows:

$$\mathrm{q}_{cov_t}(\mathrm{Y},\mathrm{X}) = cov\{\mathrm{I}(\mathrm{Y} - \mathrm{Q}_{\tau,\mathrm{Y}} > 0, \mathrm{x})\} = \mathrm{E}(\varphi_\tau(\mathrm{Y} - \mathrm{Q}_{\tau,\mathrm{Y}})(\mathrm{X} - \mathrm{E}(\mathrm{Y})) \tag{16}$$

where $0 < \tau < 1$.

$$\varphi_\tau(\mathrm{w}) = \tau - \mathrm{I}(\mathrm{w} < 0). \tag{17}$$

Subsequently, establish the QC as follows:

$$\mathrm{q}cov_{\mathrm{t}}(\mathrm{Y},\mathrm{X}) = \frac{\mathrm{q}cov_{\mathrm{t}}(\mathrm{Y},\mathrm{X})}{\sqrt{(\mathrm{var}(\varphi_\tau(\mathrm{Y} - \mathrm{Q}_{\tau,\mathrm{Y}})var(\mathrm{X})}} \tag{18}$$

By integrating the maximal overlapping discrete wavelet transform, originally conceptualized by Percival and Walden (2000), Kumar and Padakandla (2022) extended the QC methodology to deconstruct variables X_t and Y_t. After this initial step, they proceed to break down the pairs X_t and $\mathrm{Y_t}$ at level j^{th}, employing specialized methods to determine the WQC for each individual level j. As a result, the following equation expresses Kumar and Padakandla’s (2022) WQC computation.

$$WQC_\tau(d_j[X], d_j[Y]) = \frac{qcov_\tau(d_j[Y], d_j[X])}{\sqrt{var\left(\phi_\tau\left(d_j[Y] - Q_{\tau,d_j[Y]}\right)\right)var(d_j[X])}}, \tag{19}$$

where X and Y denote independent and dependent markets, respectively.

Table 2
Variables definition.

Index name	Abbr.	Description
WilderHill Clean Energy	WILDER	WILDER monitors the top-performing clean energy firms listed on the NASDAQ exchange.
NASDAQ OMX Bio/Clean Fuels	BC	BC is an index that monitors the financial performance of companies engaged in the production of plant-based fuel.
NASDAQ OMX Renewable Energy	RE	RE is an index designed to gauge the success of companies involved in the renewable energy generation industries, encompassing geothermal, solar, fuel and wind cell technologies.
NASDAQ OMX Geothermal	GEO	GEO is an index that monitors the financial performance of firms engaged in the geothermal power generation sector.
NASDAQ OMX Fuel Cell	FC	FC is an index designed to gauge the success of companies involved in the energy sector of fuel cells.
NASDAQ OMX Solar	SOLAR	SOLAR is an index that monitors the financial performance of companies engaged in the solar energy generation sector.
NASDAQ OMX Wind	WIND	WIND tracks the performance of companies engaged in energy production through wind power.

3.6. Data

We rely on the Chicago Fed's NFCI to obtain critical information about US financial conditions. This index is meticulously crafted, considering a wide range of macroeconomic factors from money markets, debt and stock markets, and traditional and "shadow" banking systems. This invaluable tool allows us to effectively assess and respond to current financial conditions in the US while also providing an indicator for systemic financial risk (e.g., Afanasyeva, Jerow, Lee, & Modugno, 2024; Zeng et al., 2024, b, c, d, e). Then, drawing on the work of Zeng, Lu, and Ahmed (2023), we use the WilderHill CEI (WILDER) to assess the overall performance of the US clean energy industry. Furthermore, we look at six clean energy market indices: the NASDAQ OMX Bio/Clean Fuels (BC), the NASDAQ OMX Renewable Energy (RE), the NASDAQ OMX Geothermal (GEO), the NASDAQ OMX Fuel Cell (FC), the NASDAQ OMX Solar (SOLAR), and the NASDAQ OMX Wind (WIND). Table 2 provides a summary of the variables' definitions and abbreviations. The Datastream contains all of the return data for CEIs.

For our analysis, we use a dataset consisting of weekly data from January 1, 2013, to March 3, 2024, which includes major economic and political crises such as the 2016 UK Brexit, the 2018 US–China trade war, the COVID-19 crisis, and the 2022 Russo–Ukrainian war. The study utilized weekly data from 2013 to 2024 for two primary reasons. First, this period included significant economic and political events and critical stages in the clean energy industry's development. Second, the decision to use weekly data struck a balance between data frequency and sample size. To construct our weekly return series, we initially applied a first-order logarithmic transformation to the raw price series of all clean energy data and then computed the difference between logarithmic prices in adjacent weeks. This method captures short-term price fluctuations while minimizing potential nonstationarity issues. Furthermore, using return series provides several benefits, including improved statistical properties and direct reflection of relative changes in asset values. This strategy is consistent with investors' focus on relative gains rather than absolute price levels.

Examining the logarithmic return dynamics graphs for each variable in Fig. 1, we observe extreme volatility in the return series of all markets following the onset of the COVID-19 crisis in early 2020. Following the COVID-19 outbreak, the series of returns to the CEI became particularly volatile. This finding demonstrates the effectiveness of our methodology in capturing the impact of major events on market price volatility.

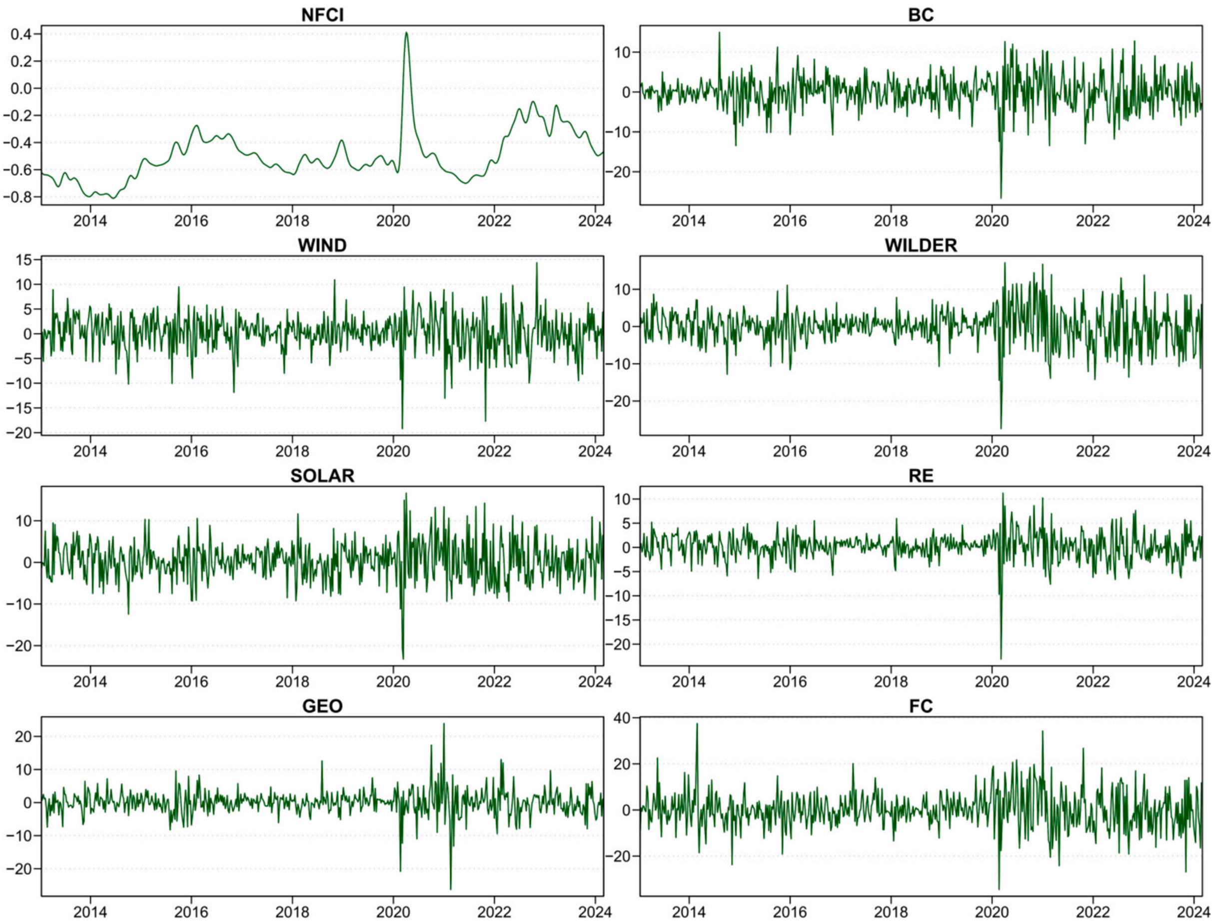


Fig. 1. Logarithmic return plot.

4. Empirical findings

Table 3 summarizes statistics from weekly returns for the NFCI and the seven CEIs. Except for NFCI and BC, their mean values are positive. SOLAR has the highest average return, while NFCI has the lowest average return. In particular, NFCI is the most volatile variable. In general, the CEIs are less volatile than the NFCI, as evidenced by the significantly lower standard deviation of the seven CEIs when compared to the NFCI. Skewness values indicate asymmetry in the distribution of return series, with most return series having negative skewness, indicating a left-skewed distribution. Kurtosis values indicate a non-normal price distribution across all markets. Only NFCI has kurtosis values greater than 3, indicating a departure from the expected behavior of a normally distributed series. The findings of the Jarque–Bera (JB) test strongly contradict the original hypothesis that all indices have a normal distribution. Furthermore, the Elliott–Rothenberg–Stock (ERS) unit root check indicates that all return series are stationary and suitable for subsequent time series analysis.

Panel A in Table 4 shows the pattern of connectedness in the presence of market depression (q = 0.05), indicating that the system is most strongly connected when the market is bearish. That the system's spillover linkage is highly dependent on market conditions, with the strongest linkage between markets occurring during a downtrend period. First, we observe TCI of 81.14 %, indicating a strong interconnection between these markets during severe recessions. Examining the NET row, we find that SOLAR (10.68 %) is the most significant net transmitter of spillovers in bearish (q = 0.05) market states, followed by RE (8.05 %). In particular, NFCI is the net recipient of spillover, becoming the system's largest net receiver (−21.95 %).

Panel B depicts the spillover between systems during normal market conditions (q = 0.5), with a TCI of 59.54 % (q = 0.5). Examining the net row, we find that RE (25.05 %) is the largest net sender of spillovers, closely followed by WILDER (22.56 %). Interestingly, as in extreme negative market conditions, the NFCI is the largest net receiver of connectedness across all indices (−36.1 %).

Panel C reports the condition during periods of extreme market optimism (q = 0.95). The observed TCI value is 80.53 %. Furthermore, we observe that the level of net spillovers between the segmented indices varies. In particular, the net row shows that SOLAR is the system's largest net sender of return connectedness (9.61 %), trailing only RE (7.901 %). According to Panel C, NFCI is the highest net receiver of shock from the system (−12.61 %), followed by GEO (−3.7 %). It is worth noting that the CEI dominates the spillover to the NFCI under all market conditions, as the NFCI consistently acts as a net receiver regardless of changes in market conditions, which suggests that clean energy has a significant impact on the economy.

In general, the system is most closely linked during bearish market conditions (q = 0.05). The interdependence between Clean Energy and NFCI varies during bullish, normal, and bearish periods. To deal with market uncertainty, protect asset values, and achieve stable returns, we briefly summarize the relevant findings: By going long Wilder under various market conditions, investors can effectively manage their risk exposure, reducing uncertainty and potential losses in their portfolios. Furthermore, the NFCI is consistently the system's largest net recipient regardless of market conditions.

Table 5 shows the net pairwise dynamic connectedness between the NFCI and the seven CEIs under various market conditions. In particular, the negative values in Fig. 2 represent the net receivers of the spillover links, while the positive values correspond to the net senders of the spillover, providing a comprehensive view. Notably, the dynamic net spillovers of the NFCI and the seven CEIs change roles over the sample period at different quantile levels.

Our findings in Table 5 confirm that the NFCI is consistently a net spillover taker for the CEIs for most of the study sample period. However, during a specific period (between 2018 and 2020), we observe that the NFCI appears to be a sender of spillover links to specific clean energy sources, such as the FC and GEO. This partially supports Selmi, Bouoiyour, Hammoudeh, Errami, and Wohar's (2021) conclusion that Trump's energy agenda has resulted in severe spillover shocks in RE markets. This leads us to the conclusion that the CEI consistently sends spillover shocks to the NFCI over the majority of the sample period in both the market's median and bearish periods, whereas the time-varying shocks exhibit greater temporal heterogeneity in the bullish periods.

The level of spillover in the system varies over time and across quartiles (market conditions), with the figure's warmer shading indicating higher system connectedness. Fig. 2 displays the results for the total dynamic connectedness of the systems across quartiles. Regarding the quartiles, the TCI shows an increase in the total spillover effect as market uncertainty increases. Similarly, extreme correlations within the system are stronger when the market is rising. However, spillovers may be asymmetric in terms of time and quartiles. In the time domain, notably, the TCI across quartiles sharply rises across the system in the early 2020s and the overall connectedness across the system strengthens significantly by the early 2022s, possibly because of the impact of the COVID-19 outbreak and the subsequent recovery period, suggesting that the connectedness of assets in the system is extremely sensitive to major crisis

Table 3
Summary statistics.

	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC
Mean	−0.497	−0.044	0.221	0.01	0.403	0.197	0.031	0.105
Variance	0.035	19.015	14.214	24.902	22.071	7.879	14.219	64.878
Skewness	1.217	−0.399	−0.579	−0.297	−0.107	−0.970	−0.220	0.233
Kurtosis	3.186	2.913	2.336	2.185	1.630	8.711	9.182	1.950
JB	389.859***	221.216***	164.877***	124.324***	65.549***	1931.564***	2049.281***	97.444***
ERS	−2.728***	−9.191***	−5.296***	−10.056***	−8.470***	−11.068***	−10.721***	−3.344***

Note: ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively. ERS: Elliott–Rothenberg–Stock unit root test. JB: Jarque–Bera goodness-of-fit test.

Table 4
Spillover matrix in NFCI and clean energy indices.

Panel A. Quantile (extreme lower, q = 0.05)									
	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC	FROM
NFCI	32.61	8.78	10.4	9.65	11.49	10	8.73	8.34	67.39
BC	6.66	16.62	12.7	13.46	13.02	13.53	11.87	12.14	83.38
WIND	6.7	11.77	16.43	13.38	13.37	14.33	11.73	12.29	83.57
WILDER	6.28	12.2	12.09	15.95	14.76	13.6	12.04	13.08	84.05
SOLAR	6.48	11.4	12.52	14.11	17.95	14.34	11.42	11.78	82.05
RE	6.28	11.71	13.43	13.46	14.31	15.96	12.41	12.44	84.04
GEO	6.59	11.88	11.93	12.91	12.75	13.34	17.71	12.88	82.29
FC	6.44	11.91	11.88	13.76	13.02	12.93	12.4	17.65	82.35
TO	45.44	79.65	84.95	90.72	92.72	92.09	80.59	82.95	649.12
NET	−21.95	−3.73	1.38	6.67	10.68	8.05	−1.7	0.6	TCI = 81.14 %
NPDC	0.00	2.00	3.00	5.00	6.00	7.00	1.00	4.00	

Panel B. Quantile (median, q = 0.50)									
	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC	FROM
NFCI	51.13	9.43	6.22	8.62	7.58	7.89	5.1	4.03	48.87
BC	2.76	43.74	7.55	12.73	8.34	12.42	5.6	6.85	56.26
WIND	1.63	7.16	40.76	10.72	8.95	19.44	4.69	6.64	59.24
WILDER	1.76	9.6	7.62	30	16.4	15.36	6.48	12.79	70
SOLAR	1.88	6.64	7.27	18.41	34.64	18.84	4.71	7.61	65.36
RE	1.49	8.87	14.13	15.01	16.47	29.04	7.27	7.72	70.96
GEO	2.17	6.07	5.92	9.81	6.53	12.09	50.7	6.72	49.3
FC	1.07	6.88	6.37	17.26	9.01	9.98	5.71	43.7	56.3
TO	12.77	54.66	55.08	92.57	73.28	96.02	39.56	52.36	476.29
NET	−36.1	−1.6	−4.15	22.56	7.92	25.05	−9.75	−3.94	TCI = 59.54 %
NPDC	0.00	3.00	3.00	6.00	5.00	7.00	1.00	3.00	

Panel C. Quantile (Extreme upper, q = 0.95)									
	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC	FROM
NFCI	32.64	10.14	9.67	8.63	9.83	8.98	10.63	9.47	67.36
BC	7.59	18.11	11.86	12.77	13.31	13.45	11.07	11.83	81.89
WIND	7.84	12.14	17.94	12.35	12.33	14.14	11.42	11.84	82.06
WILDER	7.63	11.82	11.46	16.3	14.78	13.79	11.29	12.94	83.7
SOLAR	7.57	11.61	11.39	13.81	18.28	14.7	10.97	11.67	81.72
RE	7.25	12.04	12.79	12.88	15.02	17.1	11.34	11.58	82.9
GEO	8.56	11.55	12.33	11.85	12.7	12.8	18.21	12	81.79
FC	8.31	11.46	11.68	13.67	13.35	12.96	11.37	17.2	82.8
TO	54.75	80.75	81.18	85.97	91.32	90.81	78.09	81.33	644.21
NET	−12.61	−1.13	−0.88	2.27	9.61	7.91	−3.7	−1.46	TCI = 80.53 %
NPDC	0.00	3.00	2.00	5.00	7.00	6.00	1.00	4.00	

Notes: "TCI" denotes the total connectedness index. The rolling-window is set to 100 days.

events and that market integration is unlikely (Furuoka, Yaya, Ling, Al-Faryan, & Islam, 2023). This finding is consistent with those of Cheng, Deng, Liang, and Cao (2023).

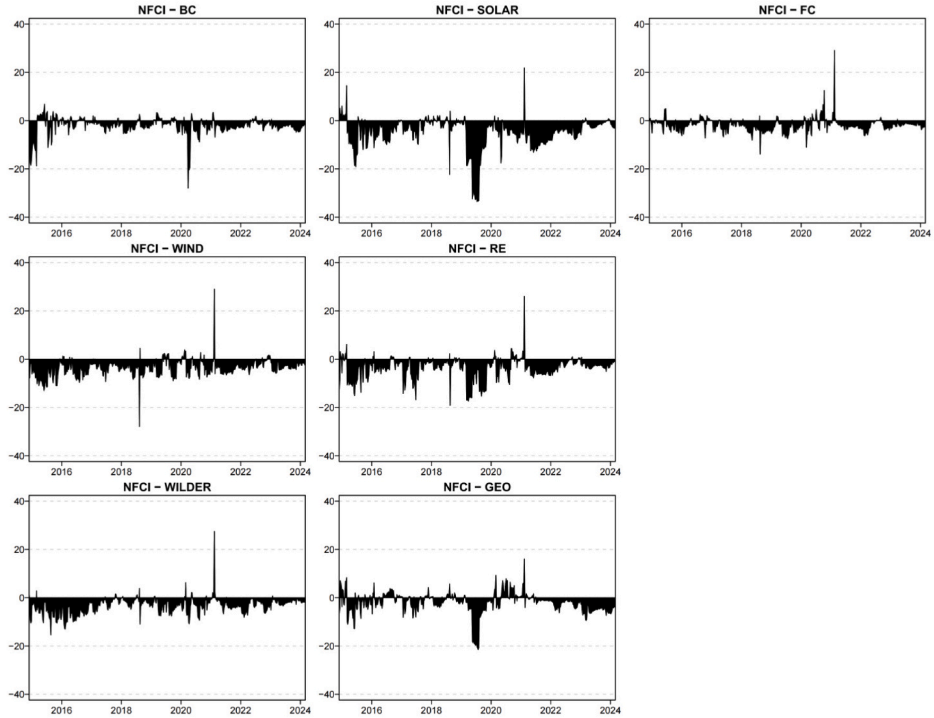
The next step was to calculate the net spillovers of all the variables in the system. The analysis used various quartiles to sensitively identify the net spillover transfer mechanism in financial markets. Investigating net spillovers in markets across time and quartiles presented an intriguing challenge. The TCI was calculated using 100 rolling-window observations, with the X and Y axes representing the time component and relative quartile, respectively. Importantly, variables with warmer colors were considered net spillover senders, whereas variables with cooler shades were considered net shock recipients.

The heatmap in Fig. 3 depicts the time-varying spillover effects between the NFCI quartiles. Throughout the sample range, the NFCI consistently acts as a net receiver. Notably, the dark blue color band between early 2020 and 2022 catches our eye, suggesting that the NFCI experienced significant shocks from clean energy sources during COVID-19 and recovery. This is consistent with the results of earlier studies, which show that the COVID-19 outbreak substantially impacted global financial markets, making them highly vulnerable (e.g., Lu, Xu, Zeng, & Zhou, 2023). Furthermore, the Trump administration's policy decisions may have contributed to the deep blue band observed in the median quartile at the start of 2019–2020, creating uncertainty and challenges for the clean energy industry (Mayer, 2019).

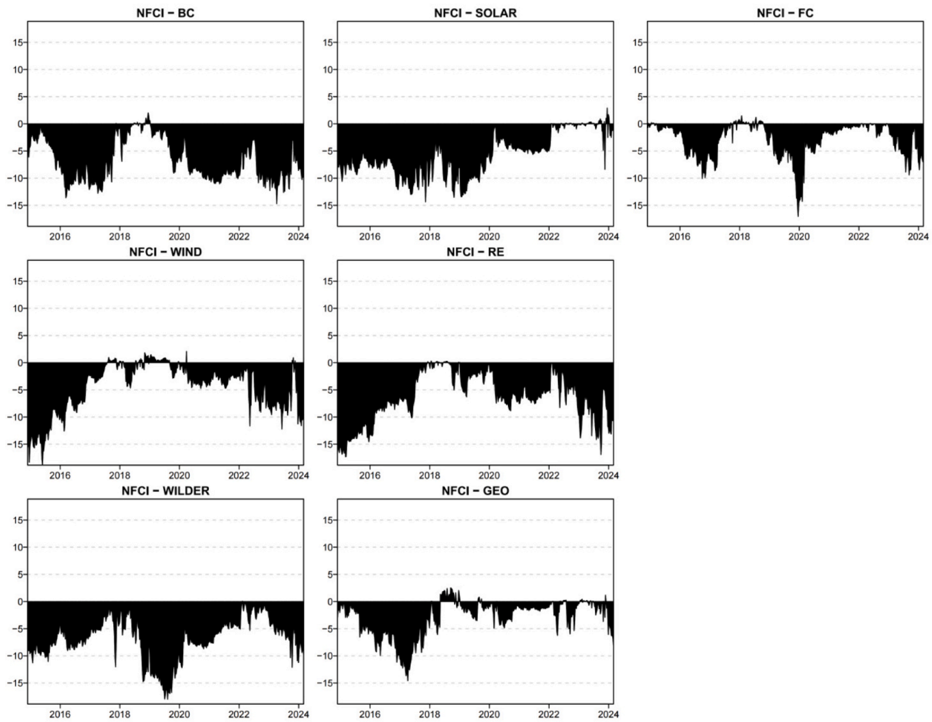
Table 6 shows a diagram of the paired spillover network at various quartile levels, with yellow circles representing spillover receivers and dark blue circles representing spillover transmitters. The arrows indicate the direction of spillover transfer. Furthermore, the scale of the circles quantifies the amount of spillover transfer or receipt, while the thickness of the lines indicates the intensity of the

Table 5
Dynamic net pairwise direction connectedness between NFCI and CEIs.

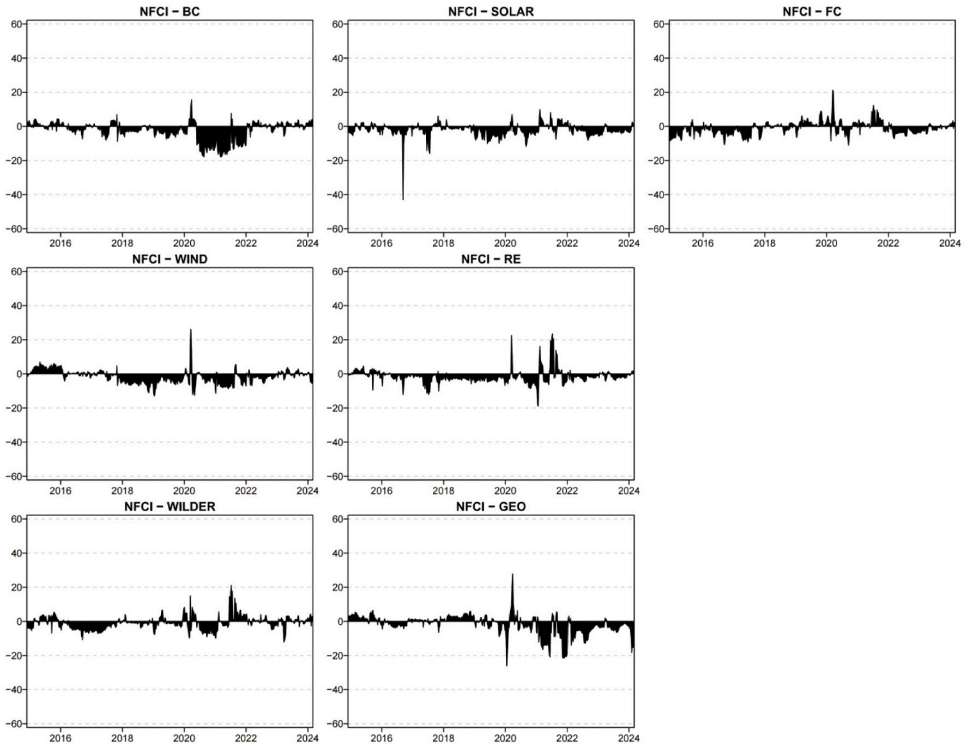
Panel A. Quantile (extreme lower, q = 0.05)



Panel B. Quantile (median, q = 0.50)



Panel C. Quantile (Extreme upper, q = 0.95)



transfer. The paired spillover network diagram visually and drastically depicted the direction and intensity of transmission. A comparison of the network plots in the three panels revealed that the NFCI was subject to all market conditions and received the most spillover from the other variables. By contrast, WILDER, SOLAR, and RE were net senders of spillovers across quartiles. Furthermore, the three network plots showed that the pattern of pairwise spillovers varied under market conditions. Specifically, the direction and intensity of the paired spillovers varied significantly depending on market conditions. Under the bear market condition ($q = 0.05$), the FC and WIND became system-wide spillover senders. Furthermore, pairwise spillovers between variables were reduced in the bear market scenario. Spillover effects were primarily specific to individual variables, with WILDER, SOLAR, and RE serving as net senders, transferring spillover to specific variables, most notably the NFCI, which received massive net spillover from the other variables' delivery. In particular, shock from other variables affected BC and GEO, which is consistent with the previous findings presented in Table 4. These results support the empirical findings of Tiwari, Aikins Abakah, Gabauer, and Dwumfour (2022), who observed that CEIs were strong net spillover senders in the network, whereas WIND primarily served as a spillover receiver. To expand on the results of the quantile connectedness method, the cross-quantile plot approach was used. This method allowed for a more in-depth investigation of the cross-predictive relationship between the NFCI and the specific CEI at specified quantiles.

Fig. 4 depicts a heat map of the correlations between the NFCI and the CEIs. In this case, an alternate lag length of one week was considered when determining cross-quantile correlations between variables. The Ljung–Box test was used to determine the significance of the CQ at different levels to achieve this. Fig. 4 shows that, in addition to the negative correlation between the NFCI's lower tail and the BC, there was a strong paired dependency relationship between the NFCI and specific CEIs, as evidenced by the significant correlation within the median region of the diagonal heatmap. In particular, for the NFCI with WIND, WILDER, SOLAR, and RE, significant values in the relative upper quantiles (greater than 0.5 on two specific sides) indicated extreme correlations within the quantile. It was important to note that the strong correlations highlighted the impact of US national financial conditions on the progression and concerns of clean energy initiatives, whereas the subtle dependencies highlighted the gradual growth of clean energy projects (Zeng et al., 2024, b, c, d, e). In conclusion, the general consensus was that there was significant cross-predictability between the NFCI and the CEIs in the upper and middle quantiles. This was consistent with previous findings of connectedness, highlighting the strong dependence between the NFCI and the CEIs in the relatively high quantiles. Simultaneously, these findings addressed a gap in connectedness research, as the connectedness analysis failed to capture the cross-dependency between the NFCI at specific quantiles and the clean energy sector. In contrast, the results of the cross-quantile approach undoubtedly visualized this critical aspect.

This study then employed WQC to assess the dependency structure between the NFCI and specific clean energies across different

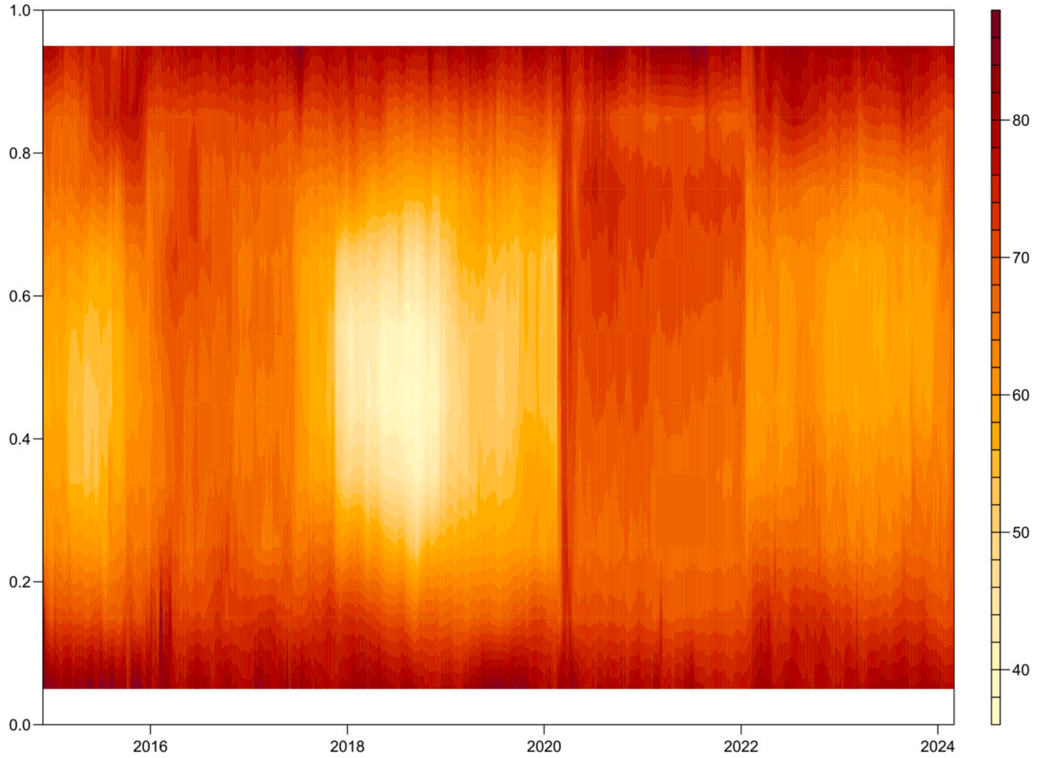


Fig. 2. Total connectedness across quartiles and time domains.

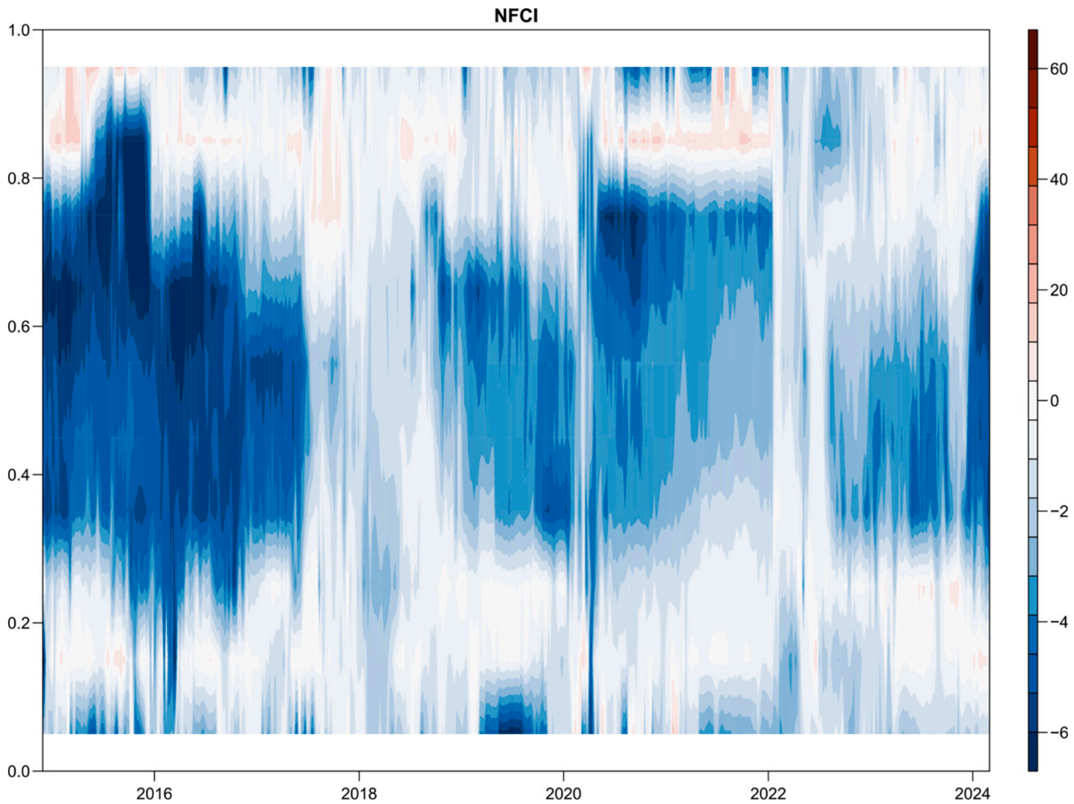
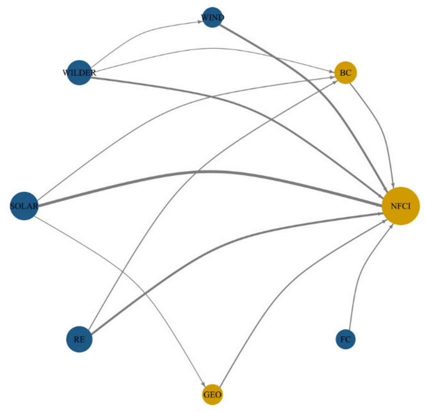


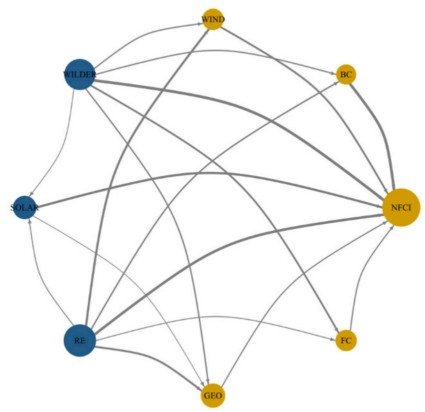
Fig. 3. NET connectedness of the NFCI.

Table 6
Network of net pairwise direction connectedness between the NFCI and CEIs.

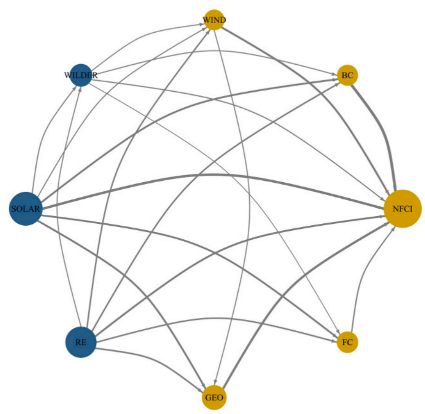
Panel A. Quantile (extreme lower, q = 0.05)



Panel B. Quantile (median, q = 0.50)



Panel C. Quantile (Extreme upper, q = 0.95)



time frequencies and quantiles. This addressed the shortcomings of previous methods, which could not examine the impact of different frequencies (investment horizons) on the quantile correlation structure between the NFCI and clean energies. Before delving into the empirical results of the WQC, it is worth noting that all of the WQC-based results in Fig. 5 are presented as heat maps. Each heatmap's left side represented different time–frequency bands, indicating the shift from short- to long-term frequency domains. The color bar on the right side of the figure shows the strength of the correlation between the NFCI and the disaggregated CEIs. For example, colors less than 0.0 indicated negative correlations, colors greater than 0.0 indicated positive correlations, and colors equal to 0.0 indicated no

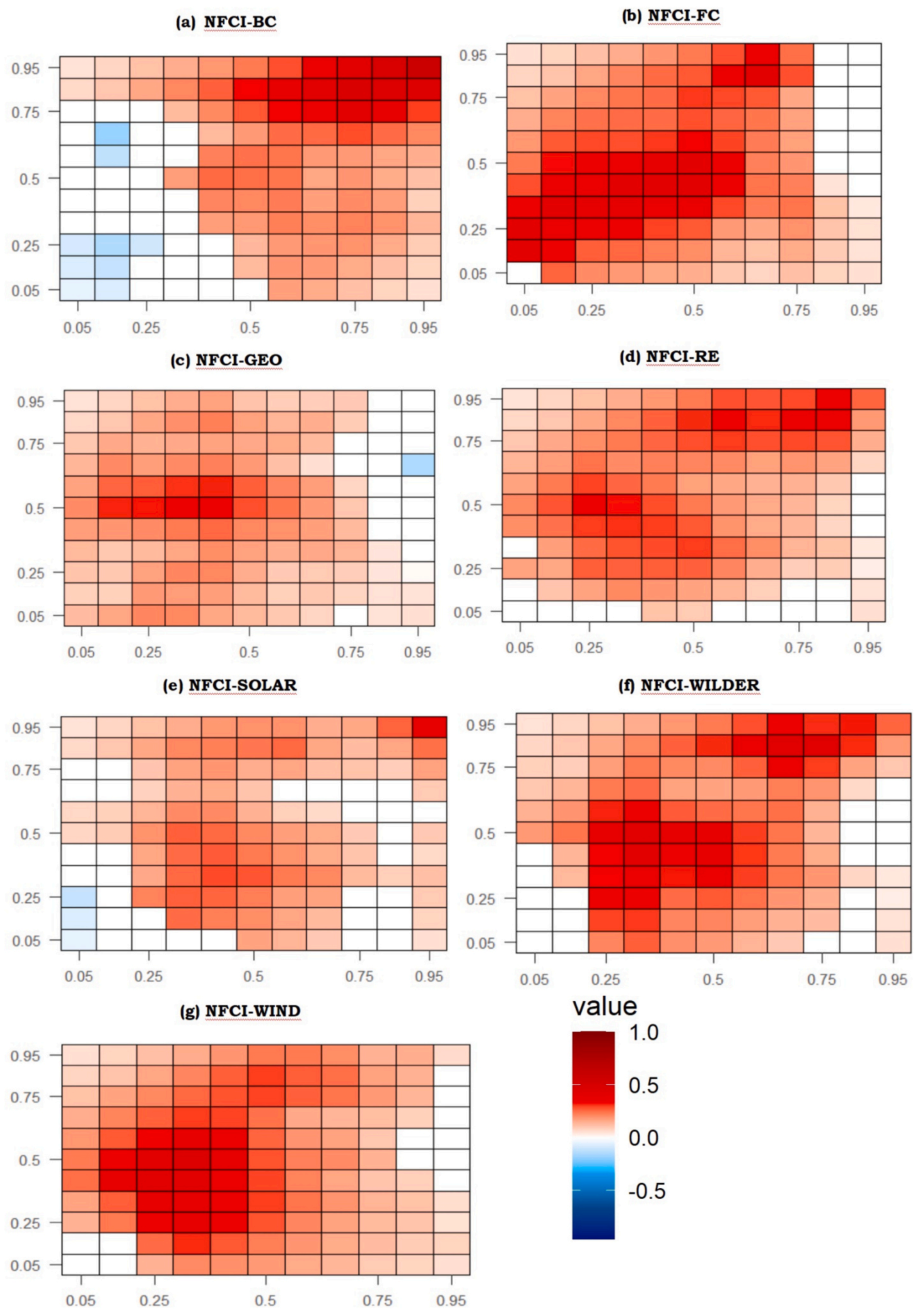
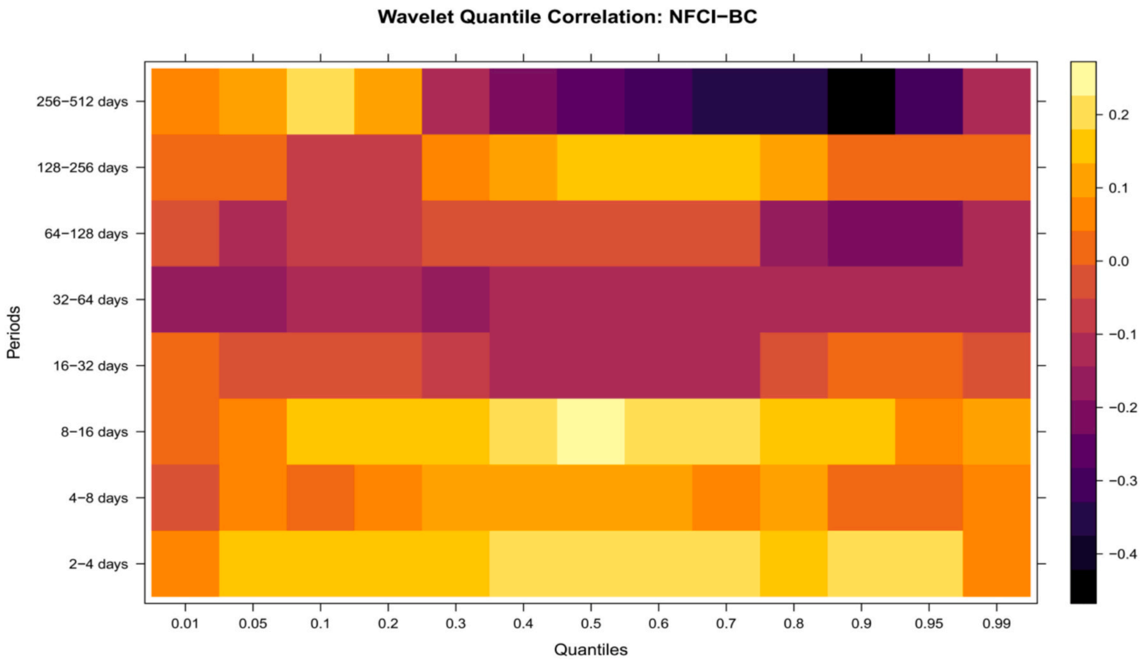


Fig. 4. Heatmap depicting the cross-correlations between the NFCI and specific CEIs.
Note: The diagram depicted a lagged one-week cross-quantilogram (CQ) dependency between the National Financial Conditions Index (NFCI) and clean energy sources. Every cell in the heat map corresponded to the CQ for a specific pair of quantiles. The color legend at the bottom indicated the CQ amounts. Any nonsignificant CQs were set to zero, while the colored rectangles represented statistically significant predictability regions as determined using the Box–Ljung test. The vertical axis in each heatmap denoted the NFCI quantiles, while the horizontal axis represented the quantiles for each CEI.

correlation.

Concerning the results in Fig. 5, some interesting general phenomena were observed between the NFCI and the disaggregated CEIs. WQC estimates confirmed that the NFCI and most CEIs had cross-quantile positive correlations in the short- and medium-run frequency domains (up to 32 days). However, only minor correlations between the NFCI and these CEIs were found at some quantile levels. In contrast, in most quantile spaces of the medium- and long-term frequency bands (greater than 32 days), the empirical results clearly



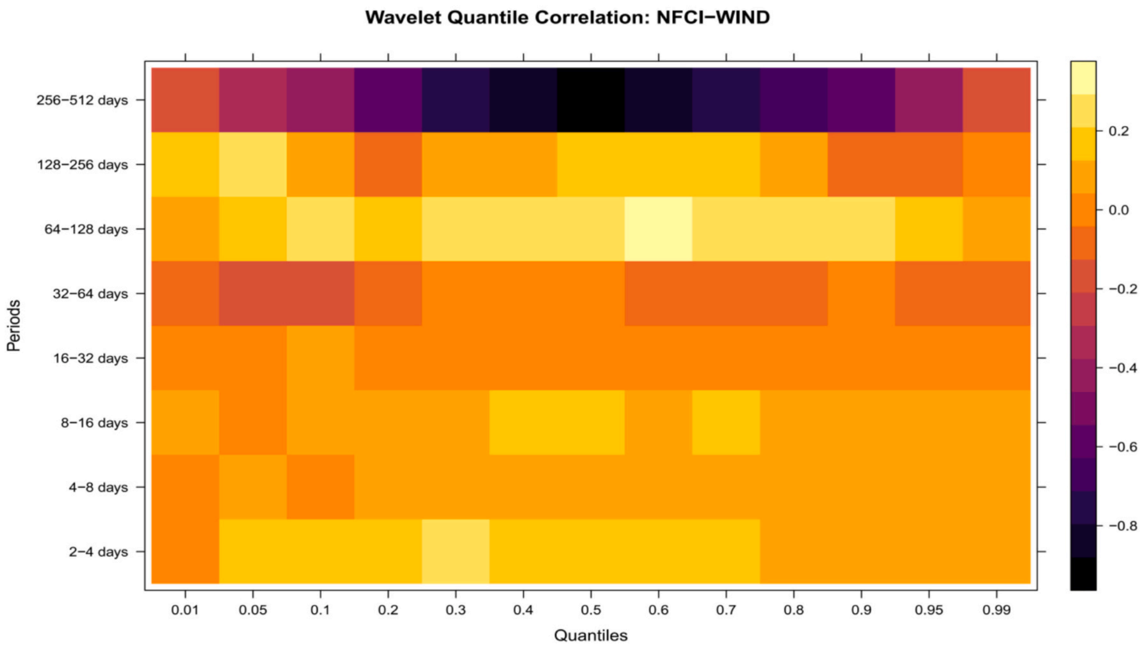
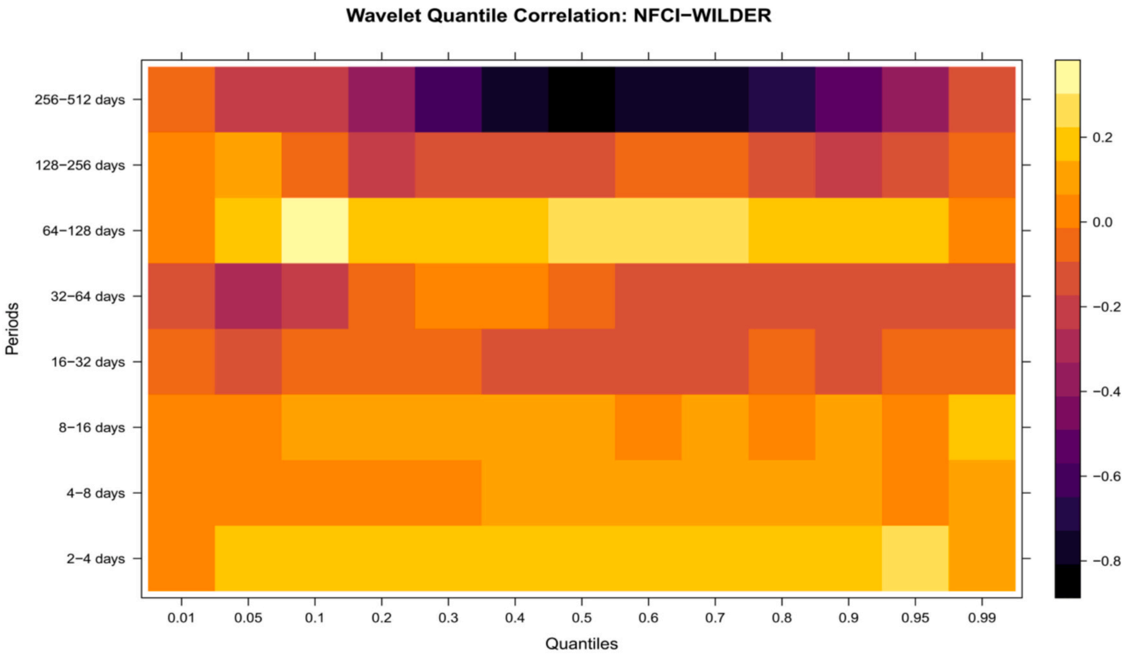


Fig. 5. Results for wavelet quantile correlation (WQC).



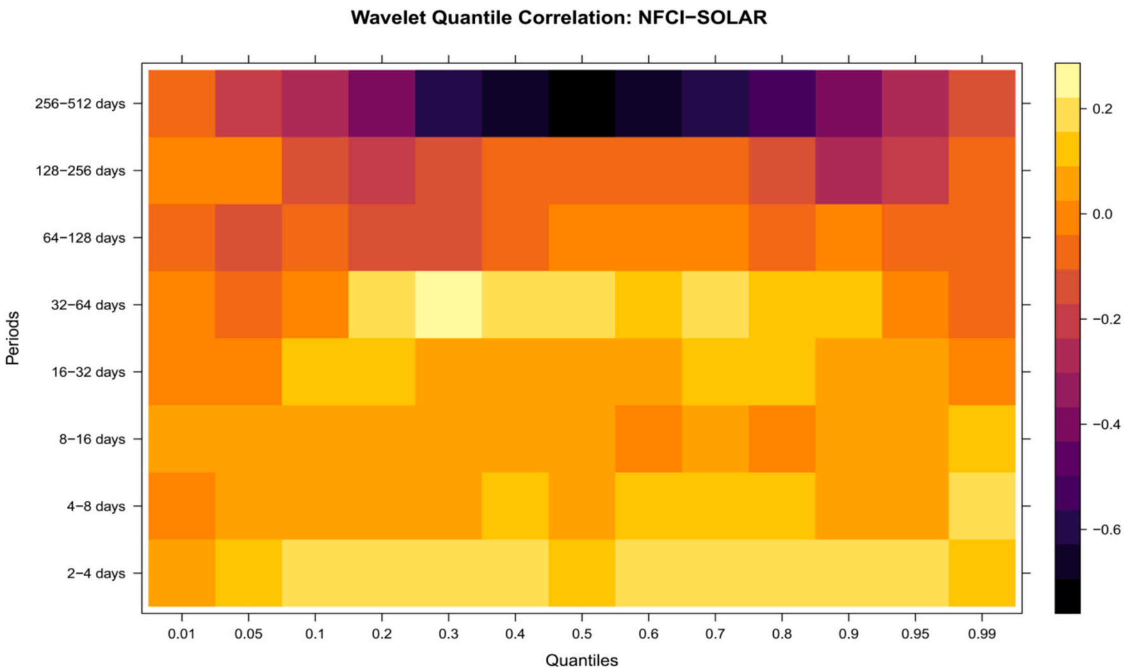
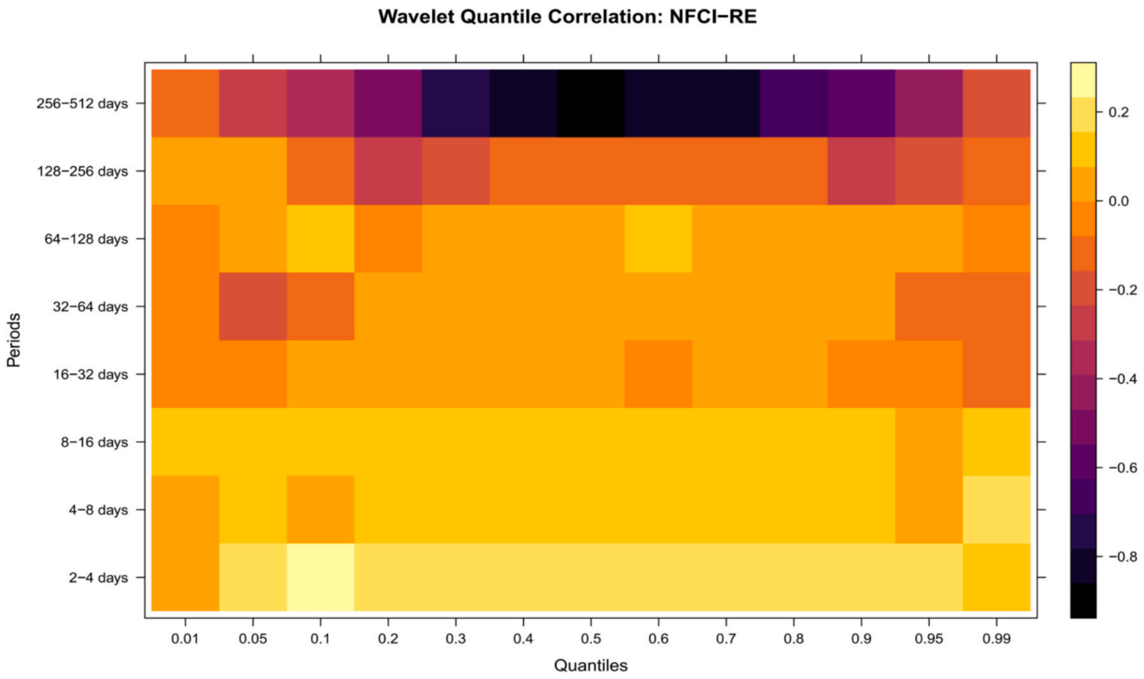


Fig. 5. (*continued*).



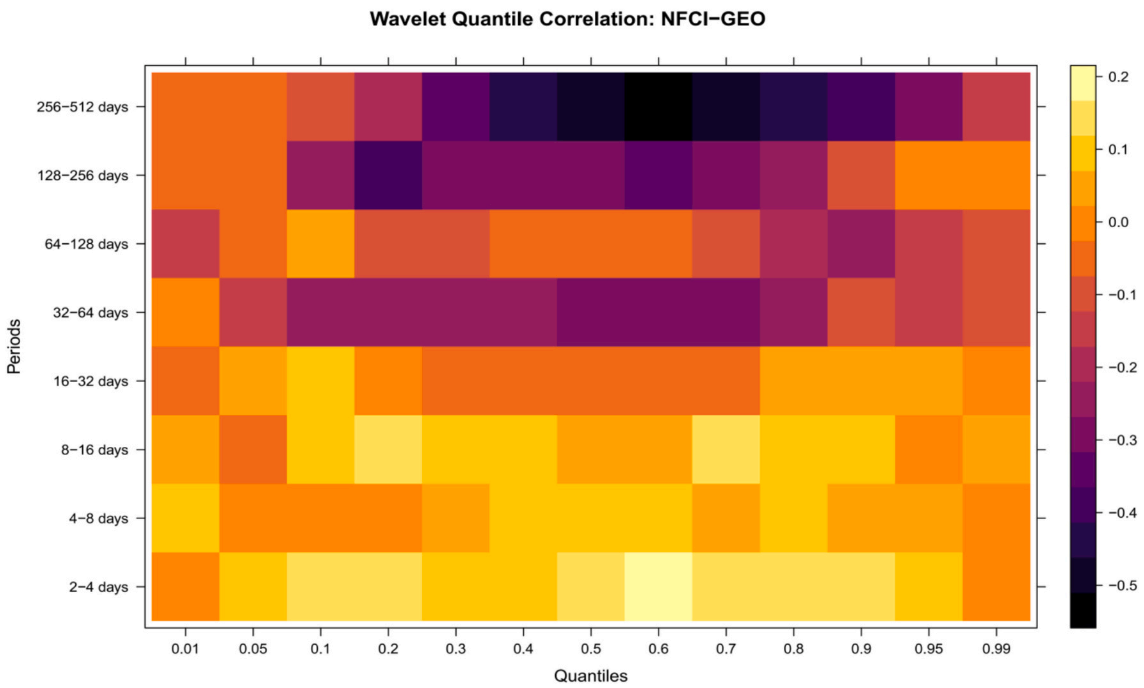


Fig. 5. (*continued*).

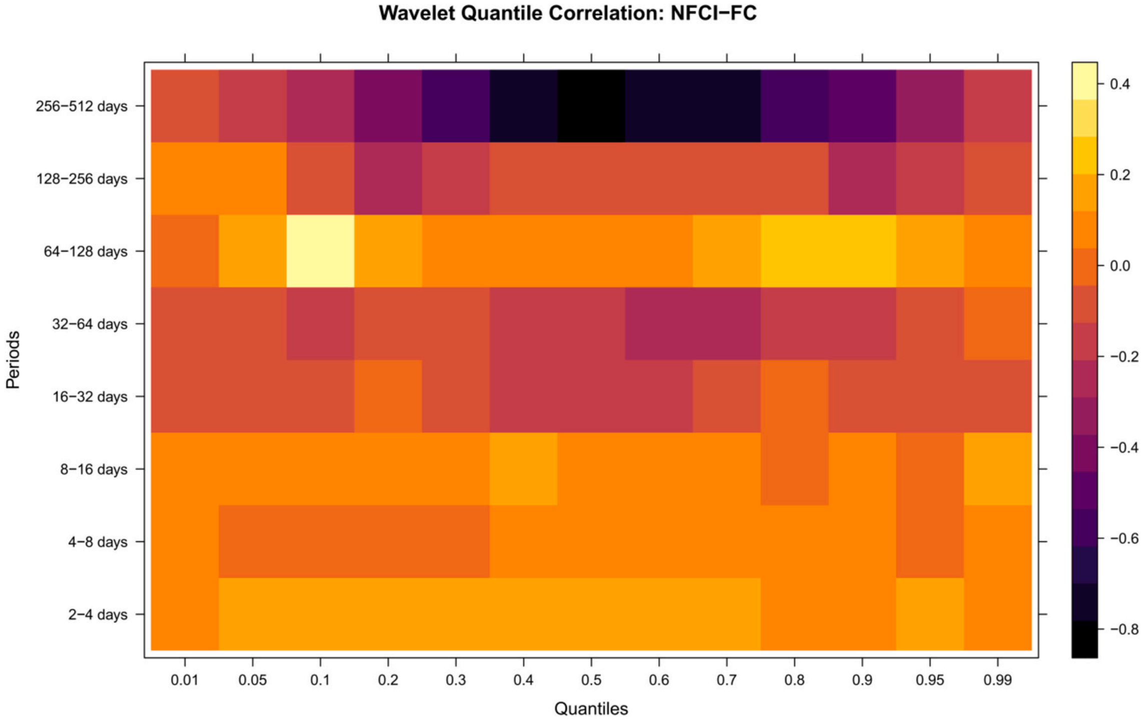


Fig. 5. (*continued*).

showed significant and negative connections between the NFCI and the CEIs.

Although previous general results showed stronger cross-quantile dependency characteristics between the NFCI and clean energies in the short and medium term, the WQC estimates confirmed heterogeneity in the time–frequency–quantile dependency structure between the NFCI and each CEI. For example, at frequencies up to 256 days (one trading year), the NFCI showed a positive influence on WIND at nearly all quantiles, except for negative correlations at the 0.05–0.1 quantile levels in the medium-term frequency range (32–64 days). In contrast, GEO responded negatively to NFCI shocks in almost all quantile spaces after the medium-term frequency (32–64 days).

Finally, when focusing on the specific quantile spaces of the connection between the NFCI and the disaggregated clean energies in Fig. 5, the WQC estimation results confirmed that the dependency between the NFCI and CEIs was asymmetric across the quantile space. Fig. 5 showed that in nonextreme quantiles (0.05–0.95) and lower frequencies (2–16 days), the NFCI and disaggregated CEIs had the strongest positive correlations compared to those in other spaces. This implied that short-term shocks to the NFCI would have a greater impact on the clean energy sector under stable market conditions. This was because the clean energy industry was more sensitive to economic and financial changes than the traditional energy industry (Guo, Zhang, & Iqbal, 2024).

4.1. Robustness test and further analysis

We double-checked the connectedness between the NFCI and the eight clean energies to ensure its robustness. To do so, we increased the rolling-window size to 150 days. This is an important issue to consider because the time-varying characteristics of spillovers may necessitate a change in rolling-window size selection. Fig. 6 depicts our robustness check findings. When the size of the rolling-window is changed, there is no sensitivity to dynamic total spillovers, which confirms the robustness of the main findings of this investigation.

The findings regarding the frequency transmission capacity of TCI dynamics are significant in connectedness studies (Naeem et al., 2023, b). In this section, we will look at the structure of short- and long-term, as well as overall dynamic TCI. We focus on dynamic frequency TCI at extreme quantiles, which describes system spillover transmission during extreme market or economic conditions. Fig. 7 shows the frequency connectedness results.

Panels A, B, and C of Fig. 7 show the dynamics of TCI in the time and frequency domains under various market conditions (0.05, 0.5, and 0.95 quantile levels). In Fig. 7, we first observe the time axis of the TCI at different quantiles. After 2020, we see a significant increase in the overall TCI under median market conditions (0.5 quantile). However, the long-term frequency TCI results show that long-term TCI did not exhibit the same persistent linkage as overall and short-run TCI, but rather showed a distinct fluctuation pattern throughout the sample period. As a result, the frequency estimate revealed that the increase in overall TCI during median market conditions was primarily due to short-term dynamics rather than long-term ones. This emphasized the importance of analyzing short- and long-term dynamics separately, as focusing solely on overall TCI may obscure the causes of these fluctuations.

Another noteworthy finding is the apparent asymmetry between short- and long-term spillover results in the time and frequency domains. Spillover effects are more pronounced in extreme lower- and upper-tail conditions (0.95 and 0.05 quantiles) than in regular market conditions (0.5 quantile). Furthermore, from a dynamic standpoint, under extreme tail conditions, a decrease in short-term frequency spillovers is frequently followed by an increase in long-term frequency spillovers. By contrast, under normal market conditions, spillover patterns at various frequencies tend to move in tandem, particularly for short-term frequency and overall TCI. Finally, understanding the short-term and long-term TCI dynamics across all quantiles revealed that short-term dynamics dominated overall TCI, which were more volatile than long-term dynamics.

These findings suggest that while the TCI in the median quantile is relatively low, it provides useful information on the evolution of systemic risk over time and across different frequencies under varying market conditions. This is especially important for observing how financial markets react to structural shocks caused by global crises, such as COVID-19 in 2020. TCI results at various frequencies obtained using the quantile framework provide more detailed insights into market dynamics (Naeem & Arfaoui, 2023; Zeng et al., 2024, b, c, d, e).

Finally, we conducted an additional robustness assessment to conduct a thorough investigation into the nature of variable connectedness and provide a comprehensive explanation of the impact of NFCI and the clean energy market on structural shocks and major crises. Specifically, by comparing pre-COVID-19 data to full sample data, we were able to better understand the operational patterns of NFCI and the clean energy market during relatively calm periods. This also improved our understanding of how major market crises affect the dynamics of market connectedness.

We chose COVID-19 as the tipping point for a major crisis. Our reasoning is as follows. First, COVID-19 triggered a global health crisis and economic recession, significantly affecting the market performance of clean energy (Naeem et al., 2022, b). Second, the pandemic caused unprecedented market volatility and uncertainty, significantly changing market participants' behavior. Finally, policymakers' pandemic-related measures, such as lockdowns and economic stimulus policies, significantly impacted financial conditions and clean energy investments (Naeem et al., 2023, b). As a result, we believe that the onset of COVID-19 caused a unique and comprehensive structural shock to financial markets.

At the implementation level, we defined the sample for the relatively stable period preceding COVID-19 as January 1, 2013–January 23, 2020. The latter date corresponds to the Wuhan lockdown, widely regarded as the beginning of the global impact of COVID-19. Furthermore, many previous studies used a similar timeline (e.g., Ashraf, 2020; Lu & Zeng, 2023). Various factors influenced our decision to choose this date. First, the Wuhan lockdown marked the Chinese government's unprecedented strict measures, which drew immediate attention from global financial markets. Second, owing to this event, international financial markets

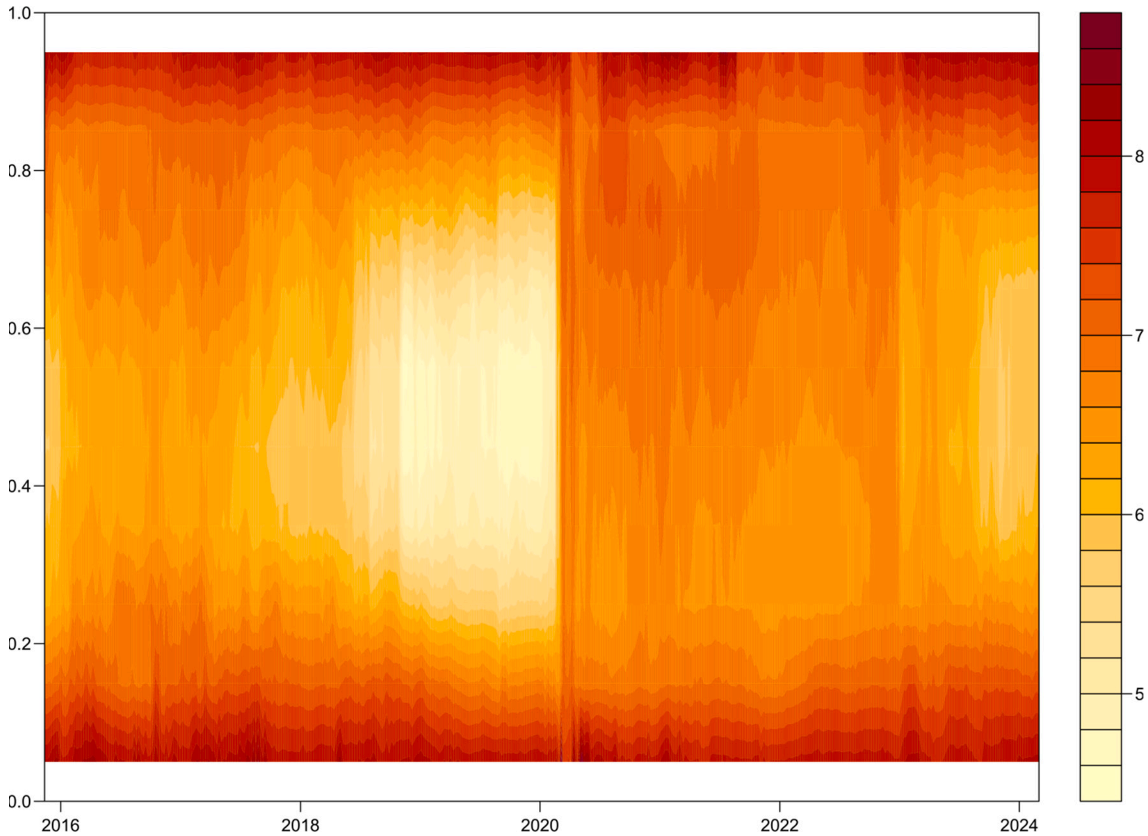
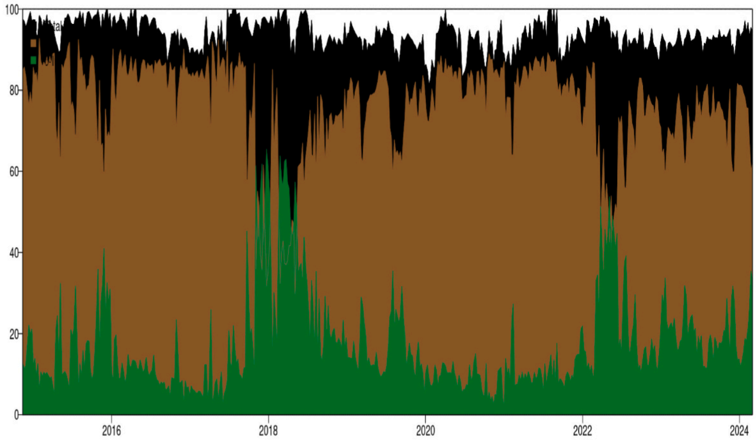
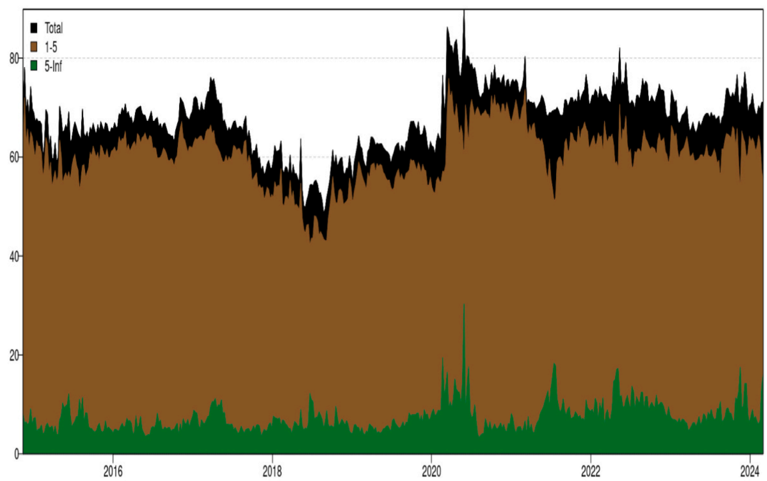


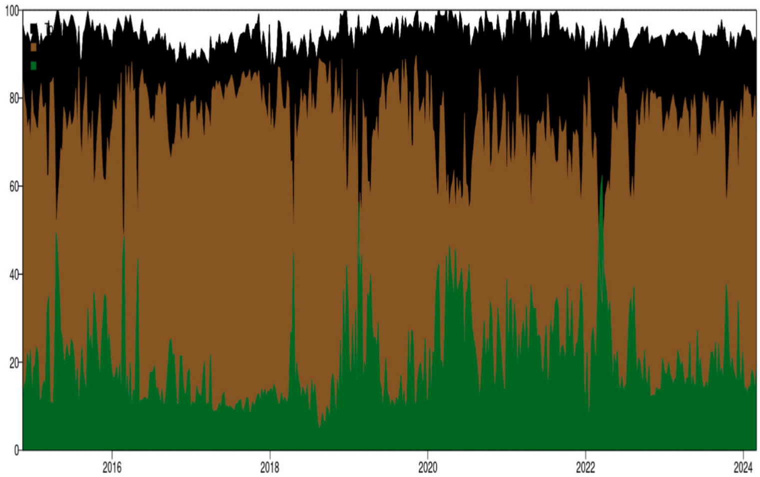
Fig. 6. Robustness test for dynamic total connectedness.



(A). Extreme low quartile (q=0.05)



(B). Median quartile (q=0.5)



(C). Extremely high quartile (q=0.95)

(caption on next page)

Fig. 7. Dynamic total connectedness across quantile and frequency.
Note: Building on previous research (e.g., Zeng et al., 2024, b, c, d, e), we used three quantile levels (0.05, 0.5, and 0.95) to distinguish extreme bear, normal, and extreme bull market states. According to Chatziantoniou, Abakah, Gabauer, and Tiwari (2022), the short-run frequency ranges from 1 to 5 days, whereas the long-run frequency ranges from 5 to infinity days. The black part represents the total TCI, the brown part represents the short-term TCI, and the green part represents the long-term TCI.

experienced significant volatility, and investors' risk preferences and behavior patterns changed noticeably (Engelhardt, Krause, Neukirchen, & Posch, 2021). Finally, this time period occurs just before the widespread outbreak of the pandemic, allowing us to capture the critical moment when markets transitioned from a relatively normal to a crisis state.

Our robustness analysis yielded some intriguing key findings. Before the COVID-19 outbreak, the differences in TCI between various quantiles were negligible compared to the entire sample period, according to the results in Table 7. Extreme low quantile TCI > extreme high quantile TCI > median TCI, as observed in Table 2, persisted. This suggests that, despite external shocks from the market crisis, NFCI and the clean energy market maintained a high and stable level of connectedness, with its structure remaining relatively stable. This pattern reflects a uniform response by market participants to extreme events, implying that the market structure may have had shock-absorbing mechanisms prior to the crisis.

It is also worth noting that we observed subtle but significant structural changes, particularly in the extremely low quantile. Table 7 shows that, prior to the COVID-19 outbreak, WIND became a net spillover receiver, whereas GEO became a net spillover transmitter. This finding sheds light on how structural shocks and major crises affect clean energy market subindices, highlighting how the COVID-19 crisis altered the dynamic connections between clean energy subindices. Consequently, our results also reveal the differentiated performance of specifying clean energy when faced with market downturn risks, which is important for understanding industry

Table 7
Spillover matrix across the NFCI and clean energy indicators before COVID-19.

Panel A. Quantile (extreme lower, q = 0.05)									
	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC	FROM
NFCI	25.92	9.06	11.59	10.84	11.95	11.33	9.65	9.67	74.08
BC	7.4	15.87	12.13	13.38	13.89	13.47	12.38	11.48	84.13
WIND	7.26	11.45	15.6	13.61	14.52	14.24	11.98	11.33	84.4
WILDER	6.87	11.54	11.11	16.1	16.05	13.32	12.72	12.27	83.9
SOLAR	6.59	10.46	12.36	14.05	18.29	14.78	12.22	11.24	81.71
RE	6.79	10.97	12.43	13.33	15.88	16.24	12.96	11.39	83.76
GEO	7.26	11.64	10.85	13.11	14.09	13.2	17.99	11.86	82.01
FC	7.39	11.54	10.91	13.73	14.02	12.61	12.68	17.12	82.88
TO	49.56	76.67	81.38	92.06	100.41	92.95	84.59	79.25	656.86
NET	−24.52	−7.47	−3.02	8.16	18.7	9.19	2.58	−3.63	TCI = 82.11 %
NPDC	0.00	2.00	2.00	6.00	7.00	5.00	4.00	2.00	
Panel B. Quantile (median, q = 0.50)									
	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC	FROM
NFCI	48.46	7.11	6.43	9.61	10.31	7.62	6.15	4.31	51.54
BC	1.86	48.69	7.85	11.15	8.04	12.45	5.27	4.7	51.31
WIND	1.83	7.34	46.25	9.55	8.37	18.65	3.5	4.5	53.75
WILDER	1.47	8.45	6.61	33.69	18.38	14.81	6.16	10.44	66.31
SOLAR	1.85	5.83	5.93	19.44	35.47	21.39	4.51	5.59	64.53
RE	1.43	8.67	13.19	14.24	19.55	31.93	6.28	4.7	68.07
GEO	2.21	5.2	4.64	9.38	6.57	10.65	57.66	3.68	42.34
FC	1.08	5.51	4.64	16.23	8.48	6.83	3.89	53.35	46.65
TO	11.73	48.11	49.29	89.6	79.7	92.41	35.75	37.92	444.51
NET	−39.81	−3.2	−4.46	23.29	15.17	24.33	−6.59	−8.74	TCI = 55.56 %
NPDC	0.00	2.00	4.00	6.00	5.00	7.00	3.00	1.00	
Panel C. Quantile (Extreme upper, q = 0.95)									
	NFCI	BC	WIND	WILDER	SOLAR	RE	GEO	FC	FROM
NFCI	35.91	9.19	9.19	8.99	9.99	8.91	7.94	9.88	64.09
BC	7.83	18.25	11.76	12.16	13.75	13.75	11.27	11.24	81.75
WIND	7.76	12.49	18.92	12.18	11.59	14.11	11.25	11.7	81.08
WILDER	7.35	11.37	11.38	16.61	15.01	13.87	11.87	12.54	83.39
SOLAR	7.39	11.75	10.98	13.59	18.38	15.44	11.22	11.24	81.62
RE	6.76	12.17	12.41	12.63	15.86	17.7	11.53	10.95	82.3
GEO	8.3	11.54	12.3	12.24	12.77	13.19	18.12	11.55	81.88
FC	8.15	11.28	11.32	13.64	13.63	13.16	11.34	17.49	82.51
TO	53.53	79.79	79.34	85.43	92.59	92.43	76.41	79.11	638.62
NET	−10.57	−1.96	−1.74	2.04	10.98	10.13	−5.48	−3.4	TCI = 79.83 %
NPDC	1.00	4.00	2.00	5.00	7.00	6.00	0.00	3.00	

Notes: "TCI" denotes the total connectedness index. The rolling-window is set to 100 days.

resilience and formulating targeted policies.

Finally, these insightful results provide new evidence about NFCI and the clean energy market's response to structural shocks and major crises. We found that even during the relatively stable period preceding the crisis, the market maintained a high level of connectedness, particularly under extreme conditions. This inherent structural characteristic may have made the NFCI and the clean energy market less vulnerable to future major market crises. However, it is worth noting that the COVID-19 crisis appears to have exacerbated certain preexisting market vulnerabilities and reshaped the risk-transmission dynamics in the clean energy market. This is most evident in the role reversal of wind and geothermal energy. These valuable findings highlight the importance of developing flexible policy frameworks to account for the diverse performance of clean energy subindices under changing market conditions.

5. Conclusions and policy remarks

This study presents practical findings on the correlation between the US Chicago Fed Financial Condition Index and eight CEIs using Ando et al.'s (2022) quantile connectedness framework. In contrast to mean-based connectedness approaches used in previous studies, our method emphasizes the significance of tail spillovers between markets, enabling us to observe spillover patterns under various market conditions. Furthermore, this study investigated the structure of frequency TCI. In both normal and extreme market fluctuations, the varying cross-dependency of paired quantiles was observed between the NFCI and CEI. To extend the results of our connectedness analysis, we used Han et al.'s (2016) cross-quantile correlation framework. This framework employs a nonparametric measure of cross-quantile correlations between two markets. This "quantile-hit" method does not rely on any moment conditions, making it suitable for heavy-tailed time series. Furthermore, the cross-quantile plot captures the nonlinearity and asymmetry of the interdependence of the indices, allowing us to calculate the degree of dependency between the NFCI and CEI under different market conditions. Finally, the WQC method was used to characterize the dependency between the NFCI and specific clean energy markets under various market conditions, revealing the multiscale characteristics of the correlations. The data set spans weekly data from January 1, 2013, to March 3, 2024, and includes critical crises such as the COVID-19 pandemic and the Russia–Ukraine war.

The main findings are as follows. Aggregate connectedness is more prominent in extreme tail market scenarios than in median cases, particularly in the upper tail. The dynamic total connectedness increases significantly following the onset of the COVID-19 crisis in the early 2020s. Most clean energy markets, except for the SOLAR index, contribute more to market shocks following COVID-19 in the upper and median quartile. By contrast, the NFCI experiences significant spillovers from other markets following COVID-19. The network pairwise connectedness results show that WILDER, SOLAR, and RE are spillover senders in all market scenarios, whereas the NFCI is a net receiver across all the quartiles. These insights enable market participants to better understand the direction and strength of connectedness and the relationship between clean energy markets and financial conditions. Furthermore, the cross-quantile correlation results revealed that the associated NFCI and CEI spillovers were asymmetric and heterogeneous. There was a statistically significant relationship between the relative highest and middle quantiles. Finally, the WQC showed that the short-term frequency dependence structure of the NFCI and disaggregated CEIs was more significant than the long-term frequency. Furthermore, in non-extreme quantiles (within the 0.05–0.95 range) and lower frequencies (2–16 days), the NFCI and disaggregated CEIs exhibited the strongest positive correlation compared with that in other spaces. Our additional robustness checks on pre-COVID-19 data revealed similar connectedness patterns, with some structural changes occurring under extreme market conditions. These findings emphasize the inherent interconnectedness of the NFCI and specific clean energy sources and its evolution during market crises.

Given the extreme events during the studied period, it was important to investigate the connectedness between tail risks, as these findings have direct policy implications today. Policymakers could use our empirical results to apply appropriate policy tools to mitigate negative impacts on the clean energy market during periods of market stress. Different types of spillover effects under varying market conditions necessitate targeted responses to ensure the clean energy market runs smoothly even in extreme conditions. The results also revealed differences in feedback on spillover effects between various CEIs, necessitating different policies under specific emergency conditions. Based on this study's findings, we propose the following policy recommendations: 1). Under market stress, policymakers should use appropriate policy tools to mitigate negative impacts on the clean energy market. Targeted measures are required to address various types of spillover effects under varying market conditions to ensure that the clean energy market operates smoothly during extreme conditions. 2). Given the disparities in feedback on spillover effects across CEIs, policymakers should develop differentiated policies under specific emergency conditions, paying special attention to the WILDER, SOLAR, and RE markets owing to their potential impact on national financial conditions. 3. Policymakers should establish robust risk monitoring and early warning mechanisms, paying close attention to the risk-transmission channels and mechanisms between the US financial market and the global clean energy market, particularly during extreme market conditions. Strengthening international cooperation is critical for jointly addressing global financial risks. 4). Investors should be encouraged to use the WILDER, SOLAR, and RE markets, which are the least sensitive to changing market conditions, as potential safe havens for other clean energy assets, attracting risk-averse investors. Investors should be guided in developing robust, diversified investment strategies based on the paired risks in the clean energy market during periods of relative market stability. 5). Policymakers should increase their support for green finance and the clean energy industry by improving relevant laws, regulations, and standards; creating a favorable policy environment; and strengthening the clean energy market's resilience to external shocks.

Because the US is the world's largest economy and the sole superpower of our time, it is critical to emphasize the significance of its financial situation. Understanding the linkages and interconnections of international financial markets is critical, as risks originating in the US financial market can quickly spread to other countries and regions, impacting the operation of the global financial system. Therefore, future research should focus on better understanding the risk-transmission channels and mechanisms of the Chicago Fed's NFCI and the global clean energy industry, with a particular emphasis on green financial markets.

Declaration of generative AI in scientific writing

No generative AIs were used in the preparation of this manuscript.

Ethics approval and consent to participate

Not applicable.

Consent for publication

All authors are very positive to publish this manuscript on this journal.

Availability of data and materials

Our data will be available on request.

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Hongjun Zeng: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mohammad Zoynul Abedin:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Investigation, Conceptualization. **Ran Wu:** Writing – review & editing, Writing – original draft, Resources, Formal analysis, Conceptualization. **Abdullahi D. Ahmed:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation.

Declaration of competing interest

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.

Data availability

Data will be made available on request.

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