Measuring the extreme linkages and time-frequency co-movements among Artificial Intelligence and Clean Energy Indices

Abstract

This is the first study analyzing the volatility connectedness and time-frequency interdependence between AI index and clean energy index. Specifically, we use the QVAR frequency connectedness, Wavelet Local Multiple Correlations (WLMC) and Granger causality quantile methods to check the risk spillovers and multivariate time and frequency relationships among the eight clean energy indexes and the AI index. This is over the period from December 18, 2017 to April 4, 2023. Our results show: (1) NASDAQ OMX Geothermal Index is the strongest net sender of short- and long-term shocks in the system during extreme upside market conditions. In downturn conditions, the S&P Global Clean Energy Index is the largest net shock sender. The AI Index exports shocks at all frequencies. In addition, market connectedness among markets is stronger under extreme market conditions. (2) We find that the AI Index predominantly exhibited positive co-movements with clean energy indices, primarily concentrated within the long-term frequency domain. However, they displayed robust cooperative dynamics across all frequency domains within the context of multivariate wavelet interconnections. (3) The quantile granger causality analysis revealed that below the extreme bullish threshold (0.95), the NASDAQ CTA Artificial Intelligence & Robotics index could predict changes in the risk associated with all clean energy indices. However, under extremely bullish quantile conditions, the NASDAQ CTA Artificial Intelligence & Robotics index statistically exhibited Granger causality only with respect to the NASDAQ OMX Renewable Energy Index, NASDAQ OMX Geothermal Index, and WilderHill Clean Energy Index.

Key word: Artificial intelligence; Clean energy; Tail risk; Quantile time-frequency; Wavelet; Quantile granger causality

JEL Classification: G11; G17; G32; Q43

1. Introduction

Global climate change is the most notable environmental concern facing humanity today and one of the most complex challenges to which humanity must respond. This is because climate change impacts international politics, economics, and trade. This trend will continue to increase in the context of both economic globalisation and environmental globalisation (Ioannou et al., 2023; Horoshko et al., 2023). It cannot be ignored that fossil fuels—coal, carbon, oil, and gas—are today the most significant cause of global climate transition. They account for over 75% of global climate change gas emissions and close to 90% of all secondary carbon dioxide emissions. Fossil fuels currently account for 80% of worldwide primary energy demand, and two-thirds of worldwide CO_2 emissions come from the energy system[1]. If greenhouse gas emissions continue to grow, the worldwide average temperature will rise by 4 degrees by the end of this century[2]. Such high emissions will catastrophically affect the global climate. Therefore, global climate change and sustainable energy have become a major concern. In this context, clean energy has been seen as an inevitable solution to achieve the purpose of the Paris Agreement (Tiwari et al., 2022) and is becoming a crucial tool for countries around the world to promote sustainable economic development and environmental protection. Currently, sustainable clean energy, which includes various forms of energy such as solar, wind, hydro, and bioenergy, offers a more pragmatic and balanced alternative to the prevalent fossil energy dependency for temperature solutions (Farghali et al., 2023). In summary, a clean energy index specifically constructed to estimate the financial performance of listed firms related to clean energy has a strong appeal to investors due to their concerns about climate risk and environmental issues, and existing research suggests that environmental assets such as clean energy have diversification potential and benefits for investors' portfolios (e.g., Kuang, 2021; Saeed et al., 2020), especially during the period of financial market stress following the period of COVID-19 and the Russian-Ukrainian war of 2022 (e.g., Zeng et al., 2023).

With the advent of the Fourth Industrial Revolution, human society has officially entered the era of artificial intelligence (Skilton and Hovsepian, 2018). Artificial intelligence (AI) is a rapidly evolving technology that has undergone many significant changes in the last two decades, as well as having a far-reaching impact. Venturini (2022) finds that AI technologies have a statistically and economically significant influence on total factor productivity. It is suggested that AI technologies may contribute to rapid productivity growth. Furthermore, Czarnitzki et al. (2023) found that AI application is connected with higher productivity of firms. They concluded that AI use and the intensity with which firms utilise its possible significantly increased sales and added value. With its efficiency and intelligence, AI technology has been widely used in many fields such as finance, intelligent manufacturing, robotics, autonomous driving, and healthcare (Zhang and Lu, 2021). As a result, AI has become a widely used tool that transforms all walks of life. It can rethink information integration, data analysis, and the use of insights generated to improve decision-making (Saggi and Jain, 2018). The digital overlay multiplier effect will be unleashed by AI technology. It will accelerate the development of strategic new industries and provide comprehensive competitive advantages.

Previous literature has examined the connection between Artificial Intelligence (AI) technologies and clean energy. Entezari et al. (2023) conducted a systematic review of the literature, emphasising the synergistic relationship between clean energy and AI.

[1] https://www.un.org/en/climatechange/science/causes-effects-climate-change
[2] https://scied.ucar.edu/learning-zone/climate-change-impacts/predictions-future-global-climate

They highlighted the significant role of AI in optimising clean energy production, environmental monitoring, and energy demand response. This integration is expected to propel the development of clean energy technologies and promote the sustainable development of the energy industry. Furthermore, Hu et al. (2022) investigated that AI algorithms have been widely applied in renewable energy systems, particularly in optimisation and control and fault detection applications. However, they also emphasised existing challenges, such as the interpretability of AI algorithms, and suggested that future work could accelerate the application of these methods in practical renewable energy systems. At the firm level, Liu et al. (2022) examined the influence and mechanisms of AI on the energy efficiency of manufacturing companies, employing both theoretical and empirical approaches. The findings demonstrated a substantial enhancement in the energy efficiency of these firms due to the integration of AI. Furthermore, the positive impact of AI on energy efficiency was predominantly achieved through expediting knowledge acquisition and creation, augmenting investment in research and development and talent, and fostering technological advancement within the manufacturing sector. Last but not least, Sharifi et al. (2021) discussed other technologies related to renewable energy and AI, such as health-oriented applications, disease tracking, and energy consumption management applications, which have grown with the outbreak of the pandemic. They also pointed out that only by focusing on new technologies, renewable energy, and AI can we address the various challenges brought about by COVID-19. The authors called for future research in the post-COVID-19 era to focus on new prospects for AI, energy efficiency and conservation, and the reduction and elimination of the environmental burden caused by electricity production, transmission, and distribution.

We summarized the conclusions of previous works. Specifically, the theoretical connections between clean energy and artificial intelligence encompass several aspects. These applications were predominantly focused on enterprise-level clients in clean energy production and supply chains. However, they also held potential implications for investors, as they may incorporate the stocks of these companies into their investment portfolios, i.e., (1) Optimisation of clean energy production: AI can play a significant role in the process of clean energy production. For example, machine learning algorithms can be used to optimise the power generation efficiency of solar and wind energy, as well as intelligently manage energy storage systems, thereby improving the efficiency and reliability of energy production. (2) Environmental monitoring and control: AI can be utilised for environmental monitoring and control in clean energy systems. Through sensors and data analysis, indicators such as pollutant emissions and energy consumption can be monitored in real-time, ensuring the environmental friendliness of clean energy systems. (3) Clean energy forecasting and demand response: AI can leverage big data analysis for energy demand forecasting, thereby optimising energy distribution and utilisation. Additionally, real-time energy demand response can be achieved through intelligent systems, enhancing energy utilisation efficiency. (4) Intelligent management of clean energy systems: AI can facilitate intelligent management of the entire clean energy system, including aspects such as energy production, storage, distribution, and usage. This intelligent management can improve the overall efficiency and reliability of the energy system. (5) Promoting the development of emerging clean energy-related technologies: The combination of clean energy and AI has also given rise to many emerging technologies and innovations, such as data-driven energy production models and intelligent energy storage technologies.

It is imperative to note that depending on the country, there may be legal and regulatory limitations that pose challenges to the meaningful collection or utilization of data for artificial intelligence applications in the clean energy sector. However, we contend that such concerns are relatively diminished for firm-level clients, underscoring the practical value of this article.

The theoretical framework driving risk transmission among AI and clean energy markets raises key issues that need further elucidation. Given that the market under consideration is a sub-sector of the financial system, risk spillovers can be inferred from asset substitution (Broner et al., 2006), market expectations (Philippas et al., 2021; Zeng et al., 2023), hedge demand (Tanin et al., 2022), risk appetite (Cui et al., 2023; Zeng and Ahmed, 2023), financial contagion (Cheikh et al., 2022), herding effects (Gaies et al., 2022), news decomposition (Tiwari et al., 2022), etc. Our hypothesis is therefore based on the existence of risk spillovers among AI and clean energy indices. Further, we assume that the level of spillovers among market segments is asymmetric. In addition, we assume that the level of spillovers existing among all market conditions and among different investment horizons is heterogeneous.

There is growing research into the relationship among traditional asset markets and technology-related markets (e.g., Le et al., 2021), but little is acknowledged about the risks of how artificial intelligence affects clean energy risks. Our paper is therefore motivated to provide insights into market behaviour and trends. This paper also provides market participants with accurate information and contributes to the dissemination of the technological revolution. It also contributes to the achievement of the Sustainable Development Goals. Specifically, the motivation for this paper is as follows: (a) As the development of clean energy markets is one of the key factors in combating climate change and reducing carbon emissions, AI has great potential in the energy sector to accelerate and support the global energy transition, thus helping to achieve more economic and sustainable energy systems. The development of clean energies and the achievement of sustainable development goals can be strongly supported by an in-depth study of the frequency and connectedness among these two markets. (b) Both the artificial intelligence (AI) index and the clean energy index are growing and emerging investment sectors are emerging. The rapid development of these two sectors has also attracted large amounts of investment capital. More and more investors are looking at investment opportunities in artificial intelligence (AI) technology and clean energy. In this paper, by examining frequency connectedness under different market conditions, we can better understand how market risk is transmitted among the AI and clean energy markets. This connectedness analysis can reveal the interactions and contagion effects among markets under various risk conditions, and our results provide insights into market behaviour and trends that can help market participants predict market volatility as well as potential risk factors, thus helping them to better understand the overall mechanics of market functioning. On the one side, investors may use the results of this research to improve their decision-making and risk measurement under both extremely negative and positive market conditions. Alternatively, policymakers can use this study to implement various policy mixes under heterogeneous market conditions. This study addresses the following research questions: (a). In different market conditions, what are the characteristics of AI index risk spillover patterns and clean energy indices? (b). What is the performance of risk spillover among the AI Index and multiple clean energy indexes at various frequencies (investment horizons)? (c). Is there asymmetry and heterogeneity in static and time-varying connectedness? (d) What was the influence of AI on specific clean energy indices within the context of the time-frequency domain multiscalar relationship, and how did their interconnected structures evolve over time? (e) Amidst the circumstances of multivariate temporal and frequency domain relationships, which variables emerged as dominant factors?

To answer the questions from above, this work uses a new quantile frequency connectedness method to investigate the risk transmission mechanisms among the Clean Energy Index and the AI Index under heterogeneous market conditions and investment horizons (short- and long-term frequencies). This approach analyses the connectedness among quartiles at specific quartiles of market conditions and at specific frequencies, not only due to the use of frequency connectedness methods that make them sensitive to outliers (Barunk and Kehlk, 2018) but also considering the impact of quartile changes. Our frequency-based approach is based on the idea that different market participants and economic agents may be interested in heterogeneous market states (bearish, normal, and bullish market conditions) and information that occurs on a variety of frequencies (Naeem et al., 2021; Chatziantoniou et al., 2022).). To be more specific, this study uses the QVAR connectedness model and examines both frequency and time. An analysis of the relationship between the NASDAQ CTA AI & Robotics Index and eight clean energy indices is presented. In this case, December 18, 2017 through April 4, 2023. S&P Global Clean Energy Index, WilderHill Clean Energy Index, NASDAQ OMX Bio/Clean Fuels, OMX Renewable Energy, OMX Geothermal, OMX Fuel Cell, OMX Solar, and OMX Wind Energy Indices transmission relationships and spillover structures, will assist investors in portfolio risk analysis during periods of market calm and volatility and will increase awareness of asymmetric tail-dependence structures when dividing portfolios into assets for investors of different investment horizons.

In addition, we extended our analysis with the innovative Wavelet Local Multiple Correlation (WLMC) method, yielding novel empirical outcomes. In contrast to conventional wavelet methods employed in prior research, such as Partial Wavelet

Coherence, Continuous Wavelet Transform, Continuous Wavelet Coherence, and Multiscale Wavelet Coherence, their primary limitation lay in their incapacity to concurrently capture correlations among arbitrarily chosen multiple indicators. Addressing this shortcoming, Polanco-Martínez et al. (2020) devised a multivariate form of wavelet correlation. One notable advantage of WLMC resides in its capacity to accommodate multiple variables, enabling us to visualize dominant variables and maximize multiple correlations over time domain (Aysan, 2023; Zhou et al., 2023). Moreover, WLMC allows us to depict single-scale-time correlations within an array of multiscale interactions. Consequently, it furnishes exceptional clarity regarding statistical dynamics within multivariate time series, a pivotal consideration, rendering the dynamics comprehensible and manageable. Thus, through the application of the WLMC approach to assess the multifaceted interrelations between AI and clean energy indices, we enriched our understanding of the intricate relationships among research variables. Simultaneously, our study expanded the results concerning quantile-frequency connectedness.

Furthermore, the controversies in the existing literature regarding risk transmission mechanisms are likely associated with the techniques employed. For instance, connectedness methods could only mechanically report the role of each variable in the system, or the temporal variation of connectedness, without offering a more comprehensive and clear perspective on the risk transmission mechanisms between two paired markets. To overcome these limitations in methodology, we subsequently employed cross-quantile Granger causality, enabling us to accurately infer the mechanisms of asymmetric impacts and the presence of quantile heterogeneity.

Our research fills a gap in the previous literature and, as far as we know, this is one of the first works to comprehensively analyse the relationship among the clean energy index and AI index under different investment cycles. This paper reports that (a) the total connectedness index is heterogeneous in the quantile and time domains. In extreme market conditions, total connectedness is more significant than the median condition. Short- and long-term dynamics are asymmetric, highlighting different market crisis events and their short- and/or long-term impacts. (b) In bearish markets, the NASDAQ CTA Artificial Intelligence & Robotics index is a risk sender at all frequencies. In contrast, the NASDAQ CTA Artificial Intelligence & Robotics index is only a short-term risk transmitter in bullish markets. And the S&P Global Clean Energy Index functions as a net sender of volatility spillover across all market conditions and frequencies. Finally, the NASDAQ OMX Fuel Cell Index acts as a risk sender only in the median and market upside conditions, and the NASDAQ OMX Renewable Energy Index acts as a risk sender only in the median and market downside conditions; (c) while in the frequency domain perspective, in the bearish market conditions and in the median conditions, it is interesting to note that the total connectedness is mainly driven by the long frequency domain connectedness rather than short-term frequency domain connectedness. In contrast, the spillover in the short-term frequency domain is greater in bullish markets, and the time-varying connectedness is more oscillatory. (d) The findings from the paired wavelet correlation analysis revealed that the Nasdaq CTA Artificial Intelligence and Robotics Index exhibited predominantly positive linkages with clean energy indices, concentrating primarily in the long-term frequency domain. However, within the multivariate wavelet interconnections between Nasdaq CTA Artificial Intelligence and Robotics Index and clean energy indices, a robust cooperative motion was discerned across all frequency domains. (e) The variables NASDAQ OMX Renewable Energy Index and S&P Global Clean Energy Index emerged as pivotal factors (dominant variables) driving the dynamics of correlations. (f) The Granger causality quantile analysis found that, apart from the extreme bullish quantile (0.95), at other common quantile levels, the NASDAQ CTA Artificial Intelligence & Robotics index was capable of predicting changes in the risk associated with all clean energy indices. However, under extreme bullish quantile market conditions (0.95), the NASDAQ CTA Artificial Intelligence & Robotics index statistically exhibited Granger causality only with respect to the NASDAQ OMX Renewable Energy Index, NASDAQ OMX Geothermal Index, and WilderHill Clean Energy Index.

The rest of the article is organised as follows: Section 2 shows the literature review and constructed the testable hypothesis. Section 3 explains the methodology and presents the data. Section 4 provides the descriptive analysis and main estimation discussion. Section 5 summarizes the study's conclusions.

2. Literature Review

Understanding the dynamics of AI and clean energy assets is critical for portfolio managers and policymakers alike. It can help increase clean energy investment and AI investment targets. As a result, the existing literature was compared to the main streams of research on the subject. The literature review aimed to i) explore the dynamic relationships between clean energy assets and other markets, and ii) investigate potential connections between green assets and artificial intelligence assets.

Clean energy markets present new investment opportunities and challenges. Several previous studies have analysed the linkages among clean energy markets and related assets. Ren and Lucey (2022) examine the hedging and safe-haven assets of various clean energy indexes against two different types of cryptocurrencies. The empirical results show a weak link between clean energy and cryptocurrency. Sharma et al. (2022) discovered that both the Sustainability Index and the Green Index exhibit a bidirectional causal relationship, with both sets of indices influencing one another over time. In addition, after the COVID-19 outbreak, the linkage among the two sets of indices increased significantly. Ghosh et al. (2023) examine the connection among energy metals, clean and dirty energies during the COVID-19 period. The study shows that dirty and clean energy, and energy metals are most closely linked and most contagious under extreme market conditions. Naeem et al. (2023) evaluate the centrality of alternative energy markets and cryptocurrencies using the Minimum

Spanning Tree (MST) in a rolling window estimation to show time variation in dependent and central networks. They find that the Wilderhill Clean Energy Index, S&P Global Clean Energy Index, Kensho Electric Vehicle Index, and ETH are other market and system-wide net risk transmitters.

Countries demonstrated their commitment to comprehensive economic growth through technological advancements. In order to address climate disasters and a new wave of technological and industrial revolution, there was an urgent need to achieve sustainability and drive technological innovation. To attain these objectives, with the rapid development of artificial intelligence technology, utilizing it to aid in the advancement and proliferation of renewable energy technologies emerged as a crucial option. As a result, some previous studies have investigated the relationship between green assets and artificial intelligence assets. Huynh et al. (2020) investigated the role of AI, robot stocks, and clean bonds in portfolio management. In times of economic turmoil, portfolios consisting of these assets are likely to experience substantial losses due to their high levels of dependence. A large amount of volatility is also transmitted across all financial assets. As a result, portfolios are inherently risky, and diversification is essential. Hedge funds and general equities are not appropriate hedges. As a measure of artificial intelligence, Tiwari et al. (2021) explored the dependency framework among AI and carbon markets during the 4th Industrial Revolution. AI and carbon exhibit a negative dependency relationship in the return sequence. This suggests AI asset diversification advantages. Abakah et al. (2023) examined the distribution predictability among fintech, bitcoin, and AI assets. Results indicate that KFTX's predictive power for AI and Bitcoin volatility is largely dependent on normal market conditions. However, its strength weakens when the market moves towards extreme conditions. They also found a strong return correlation among highly extreme changes. As a result of these findings, portfolio investors can diversify their portfolios and avoid risk with technology-related assets. The fourth technological revolution and sustainable environmental management attract artificial intelligence and clean energy assets. Additionally, an investor's portfolio may include a wide variety of assets depending on their expected returns and the interconnection of the assets. It helps investors develop appropriate hedge plans. Currently, there is no specialized research focusing on the intricate dynamic connections between AI and clean energy assets. Therefore, the outcomes of this study broaden the potential for further investigations into the risks of the clean energy market within the context of artificial intelligence development. This aims to refine investor decision-making and guide policymakers in establishing policy priorities for investments in emerging technologies and green energy. Building upon the aforementioned review, particularly in light of prior findings that suggest specific connections between AI indices and green assets and energy assets, the study contributes to a more comprehensive understanding of the interplay between these domains, we have constructed the first testable hypothesis of this paper as below:

H1: There is a dynamic connection between artificial intelligence and clean energy assets.

Although limited consideration has been given to the current linkages among the clean energy and AI index and other asset classes, there are still shortcomings. This paper extends the literature on clean energy and AI indexes, as our paper is the first to report empirical finding on the dynamic link among clean energy and NASDAQ CTA Artificial Intelligence & Robotics index under different market conditions and frequencies.

3. Data and Methodology

3.1. Data

This paper collected daily closing prices from Datastream for 18 December 2017 to 4 April 2023. We performed first-order log-differencing, transformed the log data into volatility data to examine cross-quartile and frequency risk volatilie among the clean energy and artificial intelligence (AI) indices. Referring to Huynh et al. (2020) and Abakah et al. (2023), we select the NASDAQ CTA Artificial Intelligence & Robotics index as our AI index benchmark. NASDAQ has partnered with CTA to develop the NASDAQ CTA Artificial Intelligence & Robotics Index, a adjusted equal-weighted index. The NASDAQ CTA Artificial Intelligence and Robotics Index will track relevant firms engaged in the development and application of artificial intelligence and robotics technologies, including semiconductor chip design, databases, algorithm development, software and robotics production, smart healthcare, and the use of AI to enhance core competencies. The Clean Energy Index was launched on December 18, 2017, with a base value of US$1,000.00. To represent the clean energy market, eight clean energy indices were developed based on recent studies (Ren and Lucey, 2022; Zeng et al., 2023). This paper uses clean energy indices that consider fuel cells, solar, biofuels, wind, and geothermal companies. In addition to covering different renewable energy markets, the indices need to be composed so that they cover as many markets as possible. Table 1 shows used clean energy indices.

TABLE 1 IS IN HERE

3.2. Volatility Estimation

Owing to the absence of abundant high-frequency data, this study employs the conditional variance derived from the GARCH (1,1) model for our empirical investigation. This methodology for variance construction also adeptly addresses the issue of heteroskedasticity in returns. Within this paper, let's consider the close price of index *i* at time *t* as $S_{i,t}$. Subsequently, we formulate the one-step ahead conditional variance utilizing the GARCH (1,1) model as follows:

$$\frac{ln\ (S_{i,t})}{ln\ (S_{i,t-1})} = \mu_i + \epsilon_{i,t}$$

$$\epsilon_{i,t} \sim N\left(0, \sigma_{i,t}^2\right) \tag{1}$$

$$\sigma_{i,t}^2 = \alpha_0 + \alpha_1 \epsilon_{i,t-1}^2 + \beta_1 \sigma_{i,t-1}^2$$

Where $\mu_i$is the mean, $\sigma_{i,t}^2$ indicates the index *i*'s conditional volatility at time *t*, $\epsilon_{i,t}$ points the i.i.d error term of the index *i* at time *t*. It is assumed that they adhere to a normal distribution characterized by a mean of zero and a variance pointed as $\sigma_{i,t}^2$.

Next parts will describe methods for constructing frequency quantile tail connectedness. In order to examine the connectedness between AI and clean energy indices under distinct market conditions, alterations in quantiles signify varying market states. Lower quantiles could potentially signify heightened market risk, as they are associated with bearish market tendencies. For the above motivation, then we show the quantile-based VAR connectedness (QVAR) method introduced by Ando et al. (2022).

3.3. The QVAR method

According to Koenker and Bassett (1978), quantile method evaluates the connection among a group of variables and the outcome variable is a particular quantile τ (τ ∈ (0,1)), and the *p*-order quantile VAR (QVAR) for *N* variables will be showed as：

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + \varepsilon_t(\tau), \mathrm{t} = 1, \ldots, \tag{2}$$

where y_t is the *N* vector of the dependent variable at time t, $B_i(\tau)$ is the matrix of coefficients at lag i with quantile level τ, and $i = 1, .. p$, $c(\tau)$and $\varepsilon_t(\tau)$ denote the N vectors of the intercept and residuals at quantile τ, respectively.

The quantile connectedness measure for specify quantile τ will be computed by a generalized forecasts error variance decomposition (GFEVD). Clearly, the QVAR (p) in $y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + \varepsilon_t(\tau), \mathrm{t} = 1, \ldots, \mathrm{T}$ can be expressed by converting to its QVMA (∞) applying Wold's theorem as follows:

$$y_t = \mu(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) \varepsilon_{t-i}(\tau), \ \mathrm{t} = 1, \ldots, \mathrm{N}$$

With,

$$\mu(\tau) = \left(I_N - B_1(\tau) - \cdots - B_p(\tau)\right)^{-1} c(\tau) \tag{3}$$

$$\Psi_i(\tau) = \begin{cases} 0, i < 0 \\ I_n, i = 0 \\ B_1(\tau)\Psi_{i-1}(\tau) + \cdots + B_p(\tau)\Psi_{i-p}(\tau), i > 0 \end{cases}$$

where I_N denotes the *N* dimensional identity matrix.

With the help of QVMA (∞), y_t is represented by the sum of the residuals at each quantile. That is also to say that the GFEVD method of Koop et al. (1996), which is invariant to the ranking of the markets, could be applied to decompose the variance. The GFEVD can be calculated to account for the effect of shocks on the k and j variables at quantile τ.

$$\theta_{j,k}^{H}(\tau) = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H-1}\left(e_j'\Psi_h(\tau)\Sigma e_k\right)^2}{\sum_{h=0}^{H-1}\left(e_j'\Psi_h(\tau)\Sigma\Psi_h'(\tau)e_j\right)} \tag{4}$$

where $\theta_{j,k}^{H}(\tau)$ is the variance contribution of the k variable at H steps ahead to the j variable, e_j denotes the selection vector, where the jth element is equal to 1 and 0 otherwise, $\sum$ indicates the covariance matrix of the error vector ε, and σ_{kk} indicates the standard deviation of the error term at k^{th} diagonal. Typically, each process of the covariance decomposition matrix can be normalised to：

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

where $\tilde{\theta}_{j,k}^{H}(\tau)$ denotes the k to the j (pairwise spillover) at quantile level τ. Then we may accumulate the spillover from $\tilde{\theta}_{j,k}^{H}(\tau)$ to get the connectedness measure at quantile level τ. And at quantile τ, the total spillover (QC) is,

$$QC(\tau) = \frac{\sum_{j,k=1,j\neq k}^{N}\tilde{\theta}_{j,k}^{H}(\tau)}{\sum_{j,k=1}^{N}\tilde{\theta}_{j,k}^{H}(\tau)} \times 100 \tag{6}$$

Secondly, the total directional connectedness (denoted as "to connectedness") from the j market to the other markets in quartile τ is：

$$\mathrm{QC}_{j\rightarrow\cdot}(\tau) = \frac{\sum_{k=1,k\neq j}^{N}\tilde{\theta}_{k,j}^{H}(\tau)}{\sum_{j,k=1}^{N}\tilde{\theta}_{k,j}^{H}(\tau)} \times 100 \tag{7}$$

Third, the total directional connectedness from all the other variables to j at the quantile τ is：

$$\mathrm{QC}_{j\leftarrow\cdot}(\tau) = \frac{\sum_{k=1,k\neq j}^{N}\tilde{\theta}_{j,k}^{H}(\tau)}{\sum_{j,k=1}^{N}\tilde{\theta}_{j,k}^{H}(\tau)} \times 100 \tag{8}$$

Clearly, directional connectedness may be accumulated to get connectedness.

3.4. Frequency base of QVAR connectedness

To characterise the different frequency profile of tail risk connectedness among variables, we use spectral analysis to decompose quantile-based connectedness into three frequency bands (high, medium and low frequencies). Similar to Section 3.1, we pay attention to the GFEVD, which is the core part of spillover. In contrast to the quantile variance decomposition estimated by the shock impulse response, the spectrum of the variance decomposition represents the shock-based frequency response. The frequency response framework $\Psi\left(e^{-i\omega};\tau\right)=\sum_h e^{-i\omega h}\Psi_h(\tau)$, which Ψ_h is estimated by the fourier transform,and $i=\sqrt{-1}$, and the generalised causal spectrum at a specific frequency τ on quantile $\omega\in(-\pi,\pi)$ is defined as：

$$(f(\omega;\tau))_{j,k}=\frac{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-i\omega};\tau\right)\Sigma\right)_{j,k}\right|^2}{\left(\Psi\left(e^{-i\omega};\tau\right)\Sigma\Psi'\left(e^{+i\omega};\tau\right)\right)_{j,j}} \tag{9}$$

where $(f(\omega;\tau))_{j,k}$ denotes the part of the spectrum of the k at any frequency ω when the j variable experiences a shock.

Because measuring spillover on a frequency band is more informative than measuring spillover on a certain individual band ω, we aggregated the generalized causal spectrum on band $\mathcal{D}=(a,b)\colon a,b\in(-\pi,\pi),a<b$. Thus, the GFEVD function on band $\mathcal{D}$ can be estimated as below:

$$\theta_{j,k}^{\mathcal{D}}(\tau)=\frac{1}{2\pi}\int_{\mathcal{D}}\Gamma_j(\omega;\tau)(f(\omega;\tau))_{j,k}d\omega \tag{10}$$

where $\Gamma_j(\omega;\tau)$ is a weighting function, defined as $\Gamma_j(\omega;\tau)=\frac{\left(\Psi\left(e^{-i\omega};\tau\right)\Sigma\Psi'\left(e^{+i\omega};\tau\right)\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Psi\left(e^{-ij};\tau\right)\Sigma\Psi'\left(e^{+i\bar{\iota};\tau}\right)\right)_{jj}d\lambda}$, indicating the power of the j at any frequency ω.

In the same way, the GFEVD function on the band $\mathcal{D}$ can be regularized to：

$$\tilde{\theta}_{j,k}^{\mathcal{D}}(\tau)=\frac{\theta_{j,k}^{\mathcal{D}}(\tau)}{\sum_{k=1}^{N}\theta_{j,k}^{\infty}(\tau)} \tag{11}$$

$\tilde{\theta}_{j,k}^{\mathcal{D}}(\tau)$ denotes the pairwise spillover from the k to j on a specify band $\mathcal{D}$ at τ^{th} quantile. Therefore, we can aggregate the information from $\tilde{\theta}_{j,k}^{\mathcal{D}}(\tau)$ to get some quantile spillover estimates on band $\mathcal{D}$. Then, the total connectedness index can be caculated on band $\mathcal{D}(\mathrm{QC}^{\mathcal{D}})$:

$$\mathrm{QC}^{\mathcal{D}}(\tau) = \frac{\sum_{j,k=1,j\neq k}^{N} \tilde{\theta}_{j,k}^{\mathcal{R}}(\tau)}{\sum_{j,k=1}^{N} \tilde{\theta}_{j,k}^{\infty}(\tau)} \times 100 \tag{12}$$

The NET connectedness on Band $\mathcal{D}$ are:

$$QC_{j\rightarrow\cdot}^{\mathcal{D}}(\tau) = \frac{\sum_{k=1,k\neq j}^{N} \tilde{\theta}_{k,j}^{Q}(\tau)}{\sum_{j,k=1}^{N} \tilde{\theta}_{k,j}^{\infty}(\tau)} \times 100 \tag{13}$$

and

$$QC_{j\leftarrow\cdot}^{\mathcal{D}}(\tau) = \frac{\sum_{k=1,k\neq j}^{N} \tilde{\theta}_{j,k}^{\mathcal{V}}(\tau)}{\sum_{j,k=1}^{N} \tilde{\theta}_{j,k}^{\infty}(\tau)} \times 100 \tag{14}$$

In summary, if we set band $\mathcal{D}$ as the relevant interval, then this paper will break down the quantile connectedness (QC) into upper, medium, and low frequency ($\mathrm{QC}^{\mathcal{D}}$) frequencies. In order to briefly, we will denote this as the frequency component of the tail risk spillover.

Drawing from prior research (for instance, Chen et al., 2022), we apply three quantile levels—0.01, 0.5, and 0.99—to illustrate instances of significant downturns, typical market states, and positive market conditions correspondingly. And consistent with the configuration of Chatziantoniou et al. (2022), we designate the "1-5 days" interval as the short-term frequency domain, while the "5-Inf days" interval is regarded as the long-term frequency domain.

3.5. Wavelet Local Multiple Correlations (WLMC)

Then we will use the WLMC method proposed by Polanco-Martínez et al. (2020). This approach aims to quantify the time and frequency domain correlation structures in multivariate indices. Additionally, it evaluates the causal impact within the multivariate context in the multi-scale domain. The WLMC framework is especially suitable for analyzing variable series that exhibit noise or non-stationarity. This is due to its non-reliance on assumptions regarding the series distribution, rendering it a robust approach for investigating non-stationary or noisy series.

Where $U_{it}, t = 1, \cdots, T, i = 1, \cdots$N be a n-variate series. According to Aysan et al. (2023), $U_{-i} = U \setminus \{u_i\} \cup \{\vec{1}\}$ for any $u_i \in U$. We get a linear

structure$g_s(U_{-i})$ that for a fixed $s \in [1, \cdots, T]$, minimizes a weighted number of squared errors showed as bellows:

$$S_s = \sum_t \delta(t-s)\left[g_s(U_{-i,t}) - u_{it}\right]^2 \tag{15}$$

Where the moving average weight function is denoted as $\delta(u)$. The definition of the local weighted least squares approximation is provided below:

$$g_s(U_{-i}) = Z_i\gamma_s, Z_i = U_{-i} - \bar{U}_{-i} \quad (16)$$

Where $\bar{U}_{-i}$ points to the vector of amounts of U_{-i} at fixed s, and an calculate of the coefficients γ_s is

$$\hat{\gamma}_s = [\sum_t \delta(t-s)Z_{it}Z'_{it}]^{-1}\sum_t \delta(t-s)Z_{it}u_{it} \quad (17)$$

$\hat{\gamma}_s$ possessed the subsequent variance-covariance matrix:

$$V(\hat{\gamma}_s) = \sigma_s^2[\sum_t \delta(t-s)Z_{it}Z'_{it}]^{-1} \quad (18)$$

Here, σ_s^2 signifies the error variance within an approximately stationary local neighborhood of *Us* as established by Fernández-Macho (2018). As *s* progresses over time, the local regression is represented by $\hat{g}_s(U_{-i}) = Z_i\hat{\gamma}_s$ and the corresponding sum of squares is weighted by the errors:

$$RaUU_s = \sum_t \delta(t-s)[Z'_{it}\hat{\gamma}_s - u_{it}]^2 \quad (19)$$

The aforementioned error terms (Eq.18) were subsequently utilized to calculate a sequence of local coefficients of determination (Eq.20).

The discrete wavelet transform coefficients for the Maximum Overlap Discrete Wavelet Transform of each variables $u_{it} \in U$ at scale $\lambda_j, j = 1, \cdots J$ (where J determines the maximum scale of wavelet decomposition) were denoted as $A_{jt} = (a_{1jt}, \cdots, a_{Njt})$. In accordance with the findings of Polanco-Martínez et al. (2020), the WLMC coefficients for each scale λ_j are expressed as follows:

$$\tilde{\rho}_{U,s}(\lambda_j) = \sqrt{R_{js}^2}, j = 1, \cdots, J, \text{ for fixed } s = 1, \cdots T \quad (20)$$

Where

$$R_s^2 = 1 - \frac{RaUU_s}{TaUU_s}, \text{ for fixed } s = 1, \cdots, T \quad (21)$$

Where *RaUUs* is pointed in Eq. (18) and $\mathrm{TaUU}_s = \sum_t \delta(t-s)(u_{is} - \bar{u}_i)^2$.

The values *RaUUs* and *TaUUs* represent the error and the total weighted sum of squares, respectively. Given that R^2 denotes the coefficient in the regression of *zi* (such as GMTV) on the remaining regressors within the system, the square correlation between the estimated values $\hat{z}_i$ derived from this regression is equivalent. In line with Fernández-Macho's approach (2018), the consistent sample estimate of the Wavelet Local Multiple Correlation (WLMC) is formulated as follows:

$$\tilde{\rho}_{U,s}(\lambda_j) = \mathrm{Corr}\left[\delta(t-s)^{1/2}a_{ij}, \delta(t-s)^{1/2}\hat{a}_{ij}\right], s = 1, \cdots, T \quad (22)$$

Here, a_{ij} was selected in a manner that its local regression on the set of regressors $\{a_{kj}, k \neq i\}$ maximized the associated coefficient of determination, and $\hat{a}_{ij}$ defined the corresponding vector of fitted values.

3.3. Quantile Granger causality test

This subsection elucidates the quantile method employed for examining causality between the carbon futures market and the green bond market. In essence, Granger causality posits that variable X_T does not Granger-cause Y_T if it cannot forecast Y_T. The parameter T is adjustable based on the research objectives. In this section, we introduce the method, using X_t and Y_t (during the same period t) as illustrative examples. Mathematically, $I_t \underline{\underline{def}} (I_t^Y, I_t^X)' \in R^d, d = s + q$ denotes an explanatory vector, while I_t^X represents the past information set of X_t, $I_t^X := (\overline{X_{t-1}}, \ldots, X_{t-q})' \in R^q$. The null hypothesis of Granger noncausality is formulated as follows:

$$H_0: F_Y(y \mid I_t^Y, I_t^X) = F_Y(y \mid I_t^Y). \forall y \in R \quad (23)$$

In this context, $F_Y(y \mid .)$ signifies the conditional distribution of (I_t^Y, I_t^X). X_t does not exhibit Granger causality with respect to Y_t in terms of the mean if:

$$E(Y_t \mid I_t^Y, I_t^X) = E(Y \mid I_t^Y) \quad (24)$$

Where $E(Y_t \mid I_t^Y, I_t^X)$ and $E(Y \mid I_t^Y)$ denote the mean values of (I_t^Y, I_t^X) and $(Y \mid I_t^Y)$, respectively. Nevertheless, the Granger test outcomes for the means fail to capture the influences on distinct quantiles and may be subject to diverse factors. Consequently, Jeong et al. (2012) introduced Granger causality within quantiles. If we define $Q_T^{Y,X}(. \mid I_t^Y, I_t^X)$ as the τ-quantile of $F_Y(. \mid I_t^Y, I_t^X)$, we derive the value of $Q_T^Y(. \mid I_t^Y)$.

We reformulate the null hypothesis as follows (where T pertains to the compact set and $T \in [0,1]$):

$$H_O: Q_\tau^{Y,X}(Y_t \mid I_t^Y, I_t^X) = Q_\tau^Y(Y_t \mid I_t^Y), \text{a.s.} \ \forall \tau \in \mathrm{T} \quad (25)$$

The conditional τ-quantile of Y_t adheres to the following constraints:

$$\begin{aligned} &\Pr\{Y_t \leq Q_T^Y(Y_t \mid I_t^Y) \mid I_t^Y\} := \tau, \text{ a.s. } \forall \tau \in \mathrm{T}, \\ &\Pr\{Y_t \leq Q_T^{Y,X}(Y_t \mid I_t^Y, I_t^X) \mid I_t^Y, I_t^X\} := \tau, \text{ a.s. } \forall \tau \in \mathrm{T}, \end{aligned} \quad (26)$$

Considering the independent variable I_t and the probability $\Pr\{Y_t \leq Q_T(Y_t \mid I_t) \mid I_t\} = E\{1[Y_t \leq Q_T(Y_t \mid I_t)] \mid I_t\}$. where an event is represented by an indicator function $1[Y_t \leq Y]$. The Granger non-causality null hypothesis can thus be reformulated as follows:

$$E\{1[Y_t \leq Q_T^{Y,X}(Y_t \mid I_t^Y, I_t^X)] \mid I_t^Y, I_t^X\} = E\{1[Y_t \leq Q_T^Y(Y_t \mid I_t^Y)] \mid I_t^Y\}, \text{ a.s. } \forall\tau \in \mathrm{T}.$$

(27)

If we assume that $Q_T(. \mid I_t)$ is appropriately specified through a parametric model referencing a family of functions defined by $M = \{m(. \mid \theta(\tau)) \mid \theta(.):.\tau \to \theta(\tau) \in \Theta \subset R^p$, then the dependence of Granger non-causality is as follows:

$$H_O: E\{1[Y_t \leq m(I_t^Y, \theta_0(\tau))] \mid I_t^Y, I_t^X\} = \tau, \text{ a.s. } \forall\tau \in \mathrm{T}. \qquad (28)$$

Where $m(I_t^Y, \theta_0(\tau))$ represents the actual conditional quantile for $Q_T^Y(. \mid I_t^Y)$. We have subsequently redefined the null hypothesis based on a sequence of unconditional moment restrictions, as illustrated below:

$$E\{1[Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0] - \tau\}\exp(i\omega' I_t)\} = 0. \qquad (29)$$

Utilizing the test statistic as introduced by Troster (2018), we obtain:

$$\begin{aligned} P_T &:= \int_\tau \int_Z |v_T(\omega,\tau)|^2 dF_\omega(\omega) dF_\tau(\tau), \\ v_T(\omega,\tau) &:= \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \{1[Y_t - m(I_t^Y, \theta_0(\tau)) \leq 0] - \tau\}\exp(i\omega' I_t). \end{aligned} \qquad (30)$$

Let $\phi_{\tau_j}(.)$ denote the function, and by applying the test statistic $\phi_{\tau_j}(\varepsilon) := 1(\varepsilon \leq 0) - \tau_j$, we derived the estimation for the test statistics.

$$P_T = \frac{1}{Tn} \sum_{j=1}^{n} \left|\vartheta_j' Z \vartheta_j\right| \qquad (31)$$

In the context of this paper, Z was defined as the TxT matrix, with ϑ_j representing the jth column of ϕ. Troster (2018) illustrated a subsampling procedure for estimating critical values of P_T. While the Granger causality test did not reveal a significant causal relationship, our initial step encompassed the conduction of the Granger causality test to assess any correlation between the two variables and to establish whether this relationship was unidirectional or bidirectional.

4. Empirical results

Table 2 reports the descriptive characteristics of the return data. We observe the lowest mean value for BI (-0.003833) and the highest mean value for FUEL (0.089904). The skewness values indicate a negative skewness for all variables except WILDER, GEO, and FUEL. For all return series considered, the kurtosis test statistic indicates fat tails. We can infer that all return series show a spikey, thick-tailed pattern.

TABLE 2 IS IN HERE

FIGURE 1 IS IN HERE

At the same time, the Jarque-Bera test does not obey the null hypothesis of normality at the 1% statistic level. Consequently, models with non-constant variance (such as GARCH) are appropriate for non-normality and hefty tails in log-return series (Lobato et al., 2021). Finally, the ERS test indicates that the return series is stationary for all variables. Finally, the volatility data is determined by a GARCH(1,1) model. Figure 1 shows a time series plot of daily log returns, where all variables experienced common and significant extreme jumps in early 2020.

Quantile and frequency market risks are discussed in the following subsections. Accordingly, the lower and upper quartiles have high total connectedness (TCI). Therefore, when markets are in extremely positive or negative states, markets are more tightly connected. For example, at the 1st, 50th and 99th percentiles, total TCI reaches 64.77%, 58.27% and 87.98% respectively.

4.1 Spillover analysis during extreme lower quantile (q=0.01)

Under the bear market condition (q = 0.01) of Table 3, we find that the highest owning spillover occurs for the AI index, at 29.42%. Of this 29.42%, 27.41% is long-term own risk spillover, while 2.01% is short-term own risk spillover. This shows that all other factors reach 70.58% of the AI Index forecast error variance. In addition to RE (12.72%), we find that 11.92% of long-term spillovers are caused by RE, while 0.8% are short-term spillovers. Overall, we see that the AI index has a high level of spillover among 76.54% to the system sending and 70.58% to the receiving system. This indicates that the AI index is a net shocker (5.96%). At the same time, we see that the AI index is a net sender of shocks across the frequency domain. Figure 2 shows that the long-term net connectedness of the AI index on the system equals 3.97%, while the short-term net connectedness is 1.99%. It is not surprising that the AI index is a net sender of risk shocks across the system, as AI is shaping humanity's future in almost all industries. It is already a significant driver of new technologies like big data, robotics, and the Internet of Things, and it will continue to serve as a technology pioneer for the foreseeable future (Willcocks, 2020). We then focus on systemic risk shocks driven by the clean energy index. On the one hand, we note that the major net propagator of risk shocks in the system is SP (19.50%). Shocks are also propagated primarily in the frequency domain by this network (14.92%). Secondly, RE has also been shown to be a strong net propagator of shocks (19.38%), as well as of long-run market downside conditions (15.61%). On the other hand, the biggest net recipient of the strongest shocks across the frequency domain in the system is Wilder. This outcome is in line with Tan et al. (2021), who find that the WilderHill Clean Energy Index receives strong volatility spillovers from other markets during difficult economic conditions. Finally, by looking at the Total Connectedness Index (TCI) in Figure 3, the results reveal that the long-term spillover effect (59.67%) is more than eleven times bigger than the short-term spillover effect (5.10%), proving once again that long-term spillover volatility in the system is more significant than short-term spillover volatility in a market downturn. Overall, as Table 3 only measures static connectedness, which may mask the effects of time-specific and investment horizon (time-domain) changes (Lu and Zeng, 2023), we continue to focus on dynamic connectedness plots.

TABLE 3 IS IN HERE

This paper explains in detail the lower tail of dynamic sum frequency connectedness. Figure 2 shows the results. It is evident that the long-term spillover (green block) dominates the frequency domain propagation mechanism between 2019 and 2020, market spillover will be higher for total and long-term TCI, at around 60%. The total TCI and long-term TCI then rise abruptly in early 2020, showing the highest value of the entire survey period at around 80%. This indicates that the amount of risk connectedness increases with extreme events (the COVID-19 pandemic). A decline ensues until a 50% trough is reached in early 2022. Afterwards, we see an increase in market risk until a small peak (70%) in early 2022, possibly influenced by the Russian-Ukrainian war. It is worth reminding that the short-term TCI remains at a low volatility spillover level of less than 10% over the whole period, regardless of the volatility of the total TCI and long-term TCI. It is therefore critical to examine the trends in the short and long term, which should be considered separately. Analysing only the aggregate TCI would ignore investment horizon information. This is particularly pertinent when looking at crises covering the recent past (e.g., COVID-19 and the Russia-Ukraine war in 2022). A frequency analysis reveals that long-term dynamics drive total TCI increases during market downturns, not short-term dynamics. A significant change in the long-term TCI indicates a serious change in the overall market framework for fund managers and institutional investors. Long-term dynamics are more unstable than short-term dynamics, according to additional information on short- and long-term TCI dynamics.

FIGURE 2 IS IN HERE

4.2 Medium quantile spillover analysis (q=0.5)

Panel A of Table 4 reports the static total volatility connectedness measure among the AI Index and the Clean Energy Index. Panel B and Panel C represent the different frequency components for the short and long terms. First, the total volatility connectedness is 58.27%, which means that on average, approximately 41% of the forecast error variance in the systematic network can be attributed to risk transmission in the markets under study. The situation is different when an overall connectedness is decomposed into medium and long-term frequencies. We note that the inter-market volatility correlations are primarily driven by long-term volatility connectedness (51.77%) rather than short-term volatility transmission (6.50%). Wang et al. highlight the long-term volatility transmission pattern. (2023) and Huang et al. (2022), argue that many black swan events in recent years (e.g., COVID-19) may have led to significant changes in investor preferences and preferences, thereby increasing long-term systemic risk.

TABLE 4 IS IN HERE

We extend the findings on static connectedness by examining time-varying measures of volatile connectedness. Figure 3 clearly illustrates the overall trend of the total volatility connectedness index (corresponding to the black-shaded part) in a calm market state and shows the decomposition of short-term (i.e., the red-banded area) and long-term frequencies (i.e., the clean shaded part). There are several significant time-varying features of total volatility transmission dynamics in Figure 3. First, the TCI rises sharply after 2020, suggesting that the COVID-19 outbreak has led to a sharp increase in the global financial market's risk level. Second, there is a clear downward trend in total volatility contiguity following the announcement of the end of the COVID-19 epidemic in the US in mid-2021. Thirdly, the decomposition of aggregate frequency volatility spillover is documented. This suggests that the aggregate spillover in the sample period is mainly driven by long-run spillover, which indicates longer-term shock transmission. Finally, we note that since February 2022, dynamic volatility contagion has reversed the downward trend since mid-2021, which is inevitably closely related to the financial market turmoil and commodity shortages brought about by the Russia-Ukraine war in 2022. In sum, we note that long-term spillovers dominate short-term spillovers, and for value investors and fund managers, it is critical to know the increased risk associated with holding a portfolio in the underlying market for the long term (Barunk and Kehlk, 2018). Also, in periods of increased market uncertainty, uncertainty drives aggregate connectedness (Akyildirim et al., 2022).

FIGURE 3 IS IN HERE

4.3 Spillover analysis during extreme upper quantile (q=0.99)

As Table 5 reports, under bull market (q = 0.99), volatility transmission to other variables is significantly influenced by SP, GEO, and FUEL. Consistent with expectations, SP, GEO, and FUEL are also net propagators of shocks across frequencies. Of these, GEO is the biggest net cross-frequency sender in the system (11.35%), dominating all other markets in the network. Conversely, WIND is the most vulnerable to shocks and the largest recipient in the system (-6.13%). We further explore the notion that each variable has different roles over different periods by dividing total connectedness into short-term and long-term. Notably, Wilder is the most significant short-term net shock receiver, but its impact diminishes as the investment horizon progresses, and then we observe a transition from a short-term net shock recipient to a long-term net sender of risk shocks. Finally, it is imperative to mention that GEO and WIND are also net propagators of shocks across frequencies throughout the period. In the case of the AI index, which is our main target, the short-term connectedness results confirm that the AI index is an active sender of shocks (0.64%), but only temporarily, and that the AI index is subject to volatility spillovers from the system in the long-run frequencies, making it primarily a receiver of risk shocks (-2.43%). This situation can be explained by externalities affecting the AI index, which can be of various types, such as assets invested in AI moving to green financial markets for more lucrative short-term returns when markets are optimistic (Sharma et al., 2022).

TABLE 5 IS IN HERE

As shown in Figure 4, in marked contrast to median and downside market conditions, bullish market conditions are primarily responsible for the total TCI's rise (q = 0.99). This suggests that speculators' short-term investment behaviour dominates the market under boom market conditions (q = 0.99). This also confirms Mensi et al.’s findings. (2021). However, the time-domain variation shows a clear oscillation in the time-varying spillover effect of the TCI, with long-term connectedness overwhelming short-term connectedness from time to time. The increase in long-term frequency connectedness seems to be associated with a vision of long-term growth, which seems to be concentrated in periods of market booms, especially during periods when many technological changes occur (Chatziantoniou et al., 2022). Finally, we observe that the magnitude of the volatility spillover of the total TCI remains largely unchanged over the sample period, at around 85%.

FIGURE 4 IS IN HERE

Overall, the above results suggest that extreme risk spillovers need to be considered when designing portfolio diversification strategies and developing appropriate policy responses. In order to maintain financial stability, global events must be mitigated. The findings of the frequency study also provide investors with different investment horizons (such as speculators and fund managers) with critical perspectives into the structures of financial markets (Lu et al., 2023), allowing the identification of risky or undervalued assets associated with investment horizons and creating investment opportunities for investors.

4.4 Network plot analysis

Table 6 extracts the connectedness networks at different quantile levels in the distribution. This allows us to observe how connectedness varies across the quantile fluctuations network. For example, the connectedness at the lower quartile reveals how a significant volatility shock is transmitted through the network. This is when the market is downward. Also, this visual comparison illustrates the main differences in network connectedness across the system at different investment horizons (short or long-term), which is key information of interest to market participants. Variables in the system are represented by their colours (yellow for receivers and blue for senders), while their sizes indicate their net sender or receiver roles. Moreover, the arrow denotes the direction of net connectedness among the pair variables on the line.

TABLE 6 IS IN HERE

We first observe network pairing frequency band at the 0.01 quantile level (extreme bear) at the top of Table 6. First, we find that consistent with the results for static connectedness, only the RE, SP, and AI index play the role of net spillover senders. This occurs in a system that is completely interconnected. Wilder receives net spillovers from all other markets in the time domain, while the AI index sends net volatility spillovers to all other markets. It is mainly GEO in the short-term, while FUEL and BI act as risk takers in the long-term for the risks sent by the AI index. Interestingly, SOLAR, FUEL, and WIND translate into net spillover senders in the short-term, while they maintain their net receiver roles in the long-term and in terms of total connectedness. Our findings agree with Naeem et al. (2020), who observe that clean energy is more active as a network spillover in the short-term.

Next, the connectedness networks in the median of Figure 3 In the time domain, mainly SP, FUEL, and RE are the sources of net spillover across the frequency domain. The largest recipient of net spillover in the system is Wilder. Also, consistent with the short-term frequency network spillover pattern at bearish moments, SOLAR, fuel, and WIND only play the role of senders of net spillover in the short-term.

Notably, the AI index is the major net receiver of net pairing spillovers from clean energy in the long-term frequency (5-Inf Days), receiving mainly pairing volatility shocks from RE while assuming a net sender role in the long-term frequency and on the total connectedness network. In a previous study, Abakah et al. (2023) noted that AI index returns are predictable under normal market conditions. However, their study failed to address the differences in risk spillover across all different time-frequency domains, whereas our study highlights the heterogeneity of cross-frequency domain risk spillover for the AI index.

Finally, in the bullish state (q = 0.99), the net pairwise directional time-frequency correlation network emerges as the net pairwise volatility spillover senders across the frequency domain in the system. However, WIND appears to be the largest risk receiver, which seems to change at bearish and normal quantile levels. For the AI index, we are surprised to find that the AI index is a risk taker for clean energy in the long-term frequency domain (5-Inf Days), receiving mainly paired volatility shocks from GEO. In sum, under heterogeneous market conditions (all tails of distribution), the AI index maintains a shock to the clean energy market in the short-run frequency domain. Another result of interest is that by analysing Table 6, we observe the SP as a sender of risk at all frequencies at each quartile level. This is in line with previous papers (Tiwari et al., 2022; Chatziantoniou et al., 2022).

4.4 The result of Wavelet Local Multiple Correlations (WLMC)

Due to the prior outcomes in frequency connectedness merely providing a succinct summary of the frequency connectedness status of variables, without delving into the intricate time-frequency dependencies observed among AI and various clean energy indices, there existed a demand for more detailed and diversified time-frequency dependency outcomes. This arose from the fact that investors, based on their investment horizons, favored trading within distinct investment time frames. For instance, fund managers exhibited interest in medium-term investments (Baruník and Křehlík, 2018), while institutional investors and policy makers focused on the long-term due to their enduring investment strategies. To address this research query, the latest Wavelet Local Multiple Correlation (WLMC) approach will be employed. WLMC concurrently captures frequency-domain relationships among two or more variables, thereby furnishing a more intricate exploration of variables and their time-frequency relationships, while simultaneously extending the findings of the earlier QVAR frequency connectedness results.

Figures 5 and 6 illustrate WLMC in the bivariate and multivariate contexts, incorporating the interplay between AI indices and clean energy indices. Firstly, it is imperative to elucidate that the bivariate analysis presents a general overview of the interlinkages across various time scales, encompassing long, medium, and short terms. The vertical axes in each figure denote time frequency, while the horizontal axes indicate periods. WLMC shows regions where the two series interact across distinct time frequencies. The black lines indicate the correlations among the two sequences, while blank areas indicate insignificant correlations across different time frequencies and domains. In the time-frequency domain, warmer and cooler tones respectively signify the strongest and weakest linkages.

FIGURE 5 IS IN HERE

Figures 5(a)-(h) exhibit the WLMC between AI and various clean energy indices. It is evident that, when considering the short to medium-term time frequencies (2-32) for all combinations of AI and clean energy, significant correlations do not appear to exist, and evidence of negative correlations even emerges. This implies that within the medium-term time frequencies, AI does not significantly impact most periods of the clean energy indices, or in some cases, exerts a negative influence. However, at higher frequencies, particularly before the 400-day mark (2019-07-23) and after the 800-day mark (2021-02-23) in the sample period, correlations become significantly positive. This is evident in the concentration of positive linkages (warm colors) primarily within the frequency range of 64-128 and beyond. In other words, the positive correlation between AI and clean energy indices' volatility strengthens as the frequency increases. In summary, the interactions between AI and various clean energy indices are predominantly concentrated in the long-term frequency domain, aligning closely with the findings of previous frequency connectedness analyses.

Based on the aforementioned outcomes, we present the following investment recommendations. The notable evidence of a substantial correlation in the long-term frequency domain between AI and clean energy implies that investors inclined toward long-term investment strategies for AI indices and clean energy should be mindful of devising appropriate risk mitigation strategies to hedge against potential risks.

FIGURE 6 IS IN HERE

Figure 6(a) presents the scenario involving nine variables in wavelet correlation. Combining these nine variables in a single model enables the detection of dominant variables and facilitates an understanding of each variable's contribution to multivariate correlations across frequencies (Shah et al., 2022). As depicted in Figure 6, all nine variables exhibit positive correlations. At lower frequencies (2-16), the correlation exceeds 65%. At higher frequencies (64-128 and beyond), it even reaches 80%-90%. In the temporal domain, particularly post the outbreak of the COVID-19 crisis (early 2020), correlations among variables substantially escalate across all frequencies. This outcome can be explained by the rapid growth in remote working and other AI-related applications during COVID-19, positioning the AI industry as a superior technological solution, receiving substantial financial support and governmental policies (He et al., 2021). Furthermore, from a macroeconomic standpoint, the AI domain was considered a primary battleground for technological competition within major global geopolitical conflicts such as the U.S.-China tensions. In some countries, the AI sector was intertwined with national security, enhancing the industry's market standing and attention (Khan et al., 2022). From the perspective of clean energy, it gained prominence alongside AI as an investment target sought by investors due to increasing global concern about climate change and environmental issues.

Figure 6(b) redefines SP and RE as dominant factors. Specifically, in low and approximately half of the medium-frequency instances, the volatility of SP played a significant role across all markets for the majority of the sample period. In approximately half of the medium and high-frequency cases, RE exhibited a dominant impact on the volatility of other markets. Therefore, it can be deduced that the volatility of SP and RE played crucial roles in defining other markets. Finally, as observed, AI only contributed positively to the volatility correlations within the clean energy market in the high-frequency domain towards the end of the sample period. Hence, based on this, AI cannot be regarded as a dominant force driving volatility impacts within the clean energy market. This finding resonates with the previous quantile connectedness results, which suggest that AI is not the dominant transmitter of volatility spillovers. Conversely, SP and RE consistently assume the role of net senders of spillovers in all cases.

To further validate the correlation between AI and clean energy indices, we employed the Wavelet Local Multiple Correlation (WLMC) approach, using AI as the dependent variable. In this context, we aimed to investigate multiple correlations to discern where positive correlations between AI and clean energy indices predominantly occurred in terms of time domains and frequencies. Figure 7 presents the heatmap results of the WLMC multiple correlations among AI and clean energy indices.

FIGURE 7 IS IN HERE

Figure 7 illustrates that the correlation between AI and clean energy indices is most pronounced at medium and long-term time frequencies (32-64 and beyond). However, the graph also presents intriguing results that mutually support prior findings and highlight a structurally impactful outcome resulting from the COVID-19 pandemic. It is discernible that prior to the 400-day mark in the sample period (before 2019-07-23), AI and clean energy indices exhibited merely modest levels of positive correlation in the low frequency range (2-8) and the medium frequency range (8-64). Subsequent results, post the 400-day mark, demonstrate an incremental escalation in correlations, further accentuated by the onset of the COVID-19. It is our understanding that individually, AI had a comparable influence on clean energy indices (bivariate analysis). However, within the framework of a multivariate correlation model, they imply distinct correlation dynamics (Shah et al., 2022), evident in AI's interlinkage behavior observed across all frequency domains with clean energy indices.

TABLE 7 IS IN HERE

Furthermore, we utilized quantile Granger causality tests to investigate the spillover mechanisms of AI on the segmented Clean Energy Index under varying market conditions. As connectedness methods can only descriptively report which nodes acted as net senders, and net receivers, or whether connectedness increased or decreased during a specific period within the system, they do not authenticate the existence and specific manifestations of relationships between these two markets. According to Table 7, through Granger causal quantile analysis, we determined that in extremely bullish market conditions, AI statistically exhibited no Granger causality with respect to clean energy indices other than RE, GEO, and Wilder. However, in scenarios outside of extreme bullish quantiles, AI demonstrated an inevitable risk-dependence relationship with all clean energy indices.

4.5 Robustness Test

In this part, for robustness aims, we use the mean based QVAR connectedness method (Ando et al., 2022) for robustness checks. We update the rolling days to 150 days and otherwise set the same settings as the main results for robustness testing. Looking at the time-varying total connectedness at different quartiles in Figure 8, we find that the robustness test results are almost identical to the primary empirical findings. It is easy to see similar trends to the main empirical findings for the tail and median conditions under market extremes. We can therefore conclude that our robustness tests confirm that our primary empirical findings are reliable.

FIGURE 8 IS IN HERE

4.6 Impact mechanisms and discussion of results

The purpose of this study was to investigate the interdependence of risk between AI and clean energy indices. Our results underscored the importance for investors and policymakers to monitor the cross-quantile connections and time-frequency linkages of risk between AI and clean energy indices.

Regarding the practical significance of the empirical results, we found robust evidence indicating that the risk dependence between AI and clean energy indices was asymmetric at different quantile levels. At the frequency level, the risk between AI and clean energy indices exhibited long-term domain cooperation. In this scenario, empirical research results did not support the notion of artificial intelligence serving as a safe haven in the long-term frequency domain of the clean energy market. Possible factors include the influence of multiple uncontrollable elements on the energy market, many of which are beyond the control of any artificial intelligence system. While AI may contribute to understanding certain patterns or correlations, it is less likely to predict or manage all aspects of these complex systems. Especially for short-term forecasts, there are often high demands on the accompanying facilities of AI such as algorithms, computing power, servers, and chips.

Furthermore, due to risks such as potential unexpected developments in AI technology, chip supply shortages, concerns about privacy, and legal risks associated with the disabling of large-scale models, investors, though optimistic about the long-term broad market prospects of AI as an emerging technology, tend to prefer long-term holdings to mitigate short-term market and economic uncertainties. In this scenario, long-term linkage may be the dominant mechanism. Additionally, empirical results confirm our viewpoint on the importance of information about the tail distribution of AI and green energy assets (Abakah et al., 2023). The risk formation of these new assets is influenced by economic outlooks and market expectations. For example, during a bull market, topics promoting economic growth through innovation tend to receive more attention (Huynh et al., 2020).

Moreover, the significant role played by emerging tech assets in an eco-friendly financial context is of paramount importance. The findings of this study will contribute to achieving the dual goals of social technological development and environmental sustainability. For instance, the use of artificial intelligence often raises concerns about privacy, especially when it involves the collection and analysis of sensitive information. If an investigation could potentially infringe on privacy, it may not be worth the potential backlash or legal consequences. The incorporation of legislative mechanisms to promote the use of artificial intelligence will enhance its integration with clean energy technology and its broader application - not only at an industrial level but also in everyday social life. These measures will contribute to achieving SDG-13 on climate action and SDG-8 on technological innovation in the context of the Fourth Industrial Revolution. Thus, governments should actively strengthen relevant legislative practices and enhance environmental standards while guiding investors in their investments in emerging tech assets. This will align the vision of innovation driving social development with the realization of sustainable development goals.

4 Conclusions and Policy Implications

This paper investigates the risk correlation mechanisms between eight clean energy indexes (S&P Global Clean Energy Index, WilderHill Clean Energy Index, NASDAQ OMX Bio/Clean Fuels, OMX Renewable Energy, OMX Geothermal, OMX Fuel Cell, OMX Solar, and OMX Wind Indices) and the NASDAQ CTA Artificial Intelligence & Robotics index for the period from December 2017 to April 2023 using both inter-temporal and quantile connectedness methods. As opposed to Ando et al. According to the standard quantile connectedness method, the cross-time and quantile connectedness approach examines heterogeneous risk spillover effects across frequencies by decomposing the time-domain connectedness metric into different temporal frequencies. And utilizing the estimation outcomes based on Wavelet Local Multiple Correlation (WLMC) and Granger causal quantile analysis, novel evidence is furnished regarding the intricate time-frequency dynamic correlations and quantile risk dependence between AI and clean energy indices. Our results of frequency connectedness are also robust compared to those of quantile frequency connectedness.

For policymakers, competition in the semiconductor sector, on which artificial intelligence devices depend, is becoming an important aspect of the game in the high-tech sector among major powers in the context of the 4th industrial revolution and increased global geopolitical competition. For example, the Science Act in the US supports cutting-edge technologies such as artificial intelligence. Relevant policymakers must pay more attention to the dynamics of spillover effects between the indices investigated in this research. This is to make predictable long-term policies in the current situation of increased geo-environmental competition. Furthermore, at the market level, policymakers must understand risk spillover patterns, particularly under extreme market conditions. In response to extremely positive or negative market conditions, policymakers need to intervene by implementing policies and strategies.

For investors, our findings will enhance their insights into the asymmetric tail dependence structure when segmenting their portfolios into different assets. They need to understand the risk patterns of market segments with different investment horizons while ensuring that they should pay more attention to the trends of net directional spillovers among the indices under study. The spillover dynamics of normal market periods and bear markets, for example, should be of more interest to long-term investors while short-term investors should have opportunities during bull markets. As investors consider portfolio diversification strategies and risk management in the future, they should consider these findings.

Overall, our research results deepened policymakers' clear understanding of the risk transmission mechanisms between the artificial intelligence market and the clean energy market from various perspectives. For instance, we found that risk spillover activities in extreme market conditions were more pronounced compared to normal conditions. To validate our findings and provide additional reference dimensions for the risk transmission mechanisms, we employed different methods to estimate the risk transmission patterns between the artificial intelligence market and the clean energy market, enhancing the reliability of our empirical findings.

Given the limitations of this study, there are several additional topics to investigate in future research. Firstly, another potential area for future study may be the uncertainty index for system variables, such as social network uncertainty or other measures of uncertainty. In addition, future research can apply different approaches to observe relationships between system assets.

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