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# Dynamic spillover effect among carbon finance, bitcoin, and green energy markets: a novel decomposed connectedness and portfolio analysis

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## Abstract

This study employs novel decomposed connectedness and portfolio analysis to assess the dynamic spillover effects among carbon finance, artificial intelligence, green energy markets, and bitcoin. The findings indicate that the average total connectedness index is 62%, especially during extreme market conditions. The decomposition of this measure into contemporaneous and lagged connectedness reveals that 56% of the metric can be attributed to contemporaneous dynamics. The portfolio exhibits high Hedging Effectiveness, particularly in extreme market conditions, suggesting that green assets can mitigate risks during periods of financial and geopolitical turmoil. The outcome shows that investments in Bitcoin and technology-related assets often yield the highest returns from 2018 to 2023. Based on the findings, relevant investment policies have been suggested for investors and policy decision-makers.

**Keywords:** Artificial intelligence, Carbon finance, Technology markets, Innovative connectedness

## Introduction

For many decades, portfolio diversification and the need for safe-haven tools have been considered important features of investment strategies (Huynh et al. 2020). In this context, gold is regarded as a hedge in the market during normal conditions and a safe-haven asset in periods of turmoil (Selmi et al. 2018). Nonetheless, the rising investment in gold, due to its hedging properties, may have altered its safe-haven characteristic (Arfaoui et al. 2023). In recent decades, investors have utilized new investment opportunities and various alternative investment prospects to mitigate risk. In increasingly volatile markets, investors are turning to alternative assets that may provide diversification and resilience beyond traditional safe havens (Baur and Lucey 2010). Four markets stand out at the intersection of technological change, climate policy, and digital finance: artificial intelligence (AI) and robotics equities, carbon finance, green energy, and cryptocurrencies. Prior work highlights their growing role in portfolio construction and risk transfer while also raising unsettled questions about their hedge/safe-haven properties. More precisely, investors have recently paid much attention to cryptocurrencies owing to their diversification characteristics and overall performance (Yousaf et al. 2025; Magdalena et al. 2025a, b; Naeem et al. 2022; Charfeddine et al. 2020). As of January 2022, the capitalization in the cryptocurrency market was $ 2.06 trillion. The highest-traded cryptocurrencies are Bitcoin and Ethereum. They account for 62 percent of the total market capitalization. Although cryptocurrencies were initially introduced as currencies similar to the US dollar, the Euro, or the yen, they are now used as assets similar to gold (Tu and Xue 2019; Gronwald 2019). Nonetheless, the function of digital currencies in financial markets remains uncertain. There are growing concerns for a clean environment, and investments in cryptocurrencies are considered investments in 'dirty assets'. In particular, transactions in cryptocurrency are processed through an algorithm that consumes a significant amount of energy (Mohsin 2021; Schinckus et al. 2020). According to (Huynh et al. 2022; Karim, et al. 2022), cryptocurrency transactions have unfavorable environmental impacts.

The second market consists of AI, which is a pivotal and strategic technology in the contemporary industrial revolution. Investments in AI have rapidly increased (Bughin et al. 2017; Magdalena et al. 2025a, b). In 2022, global private investment in AI amounted to $91.9 billion, representing a decline of 26.7% compared to the previous year (Standford University 2023). Various reasons enable companies to use AI. The application of AI reduces costs and enhances production quality. It improves the management of supply chain procedures (Webster and Ivanov 2020). While it is true that AI and robotics can improve efficiency and foster economic growth, the impact on employment prospects remains uncertain (Czarnitzki et al. 2023; Nasir et al. 2023). AI is utilized in various sectors, including manufacturing and alternative economic activities (Webster and Ivanov 2020). Such illustrations demonstrate that AI technology companies and robotics are becoming dominant areas in economic activities. Intuitively speaking, they thus represent interesting investment avenues for portfolio diversification.

Furthermore, scientists worldwide are scrutinizing climate change in all possible areas of the climate system, as per the Intergovernmental Panel on Climate Change (Khalfaoui et al. 2022). The progressive rise in average temperatures across various regions characterizes climate change. These processes have led to increased sea levels and a higher incidence of severe weather conditions, including recurring floods, prolonged droughts, and intensified storms. The impacts of climate risk extend to various facets of so-ciety and economy (Porter and Reinhardt 2007). Growing climate-connected risks pose threats to the business environment. Such threats are magnified by financial risks (Rudebusch 2021). The Federal Reserve has warned that climate-related risks will disrupt economic activities. Consequently, carbon pricing, when implemented as carbon taxes or emission trading processes, is one of the most effective remedies for easing the transition to a lower-carbon economy through economic incentives. Emission trading schemes involve allocating a predetermined quantity of carbon permits by the central authority of a given country. According to this system, it is incumbent upon countries that are responsible for carbon emissions to take responsibility for mitigating their emissions. Polluting firms can manage their carbon emission permits by trading carbon allowances within a market-driven framework.

Finally, green energy markets are also potential sources for diversification in the portfolio (Cifuentes-Faura et al. 2024). In recent years, they have emerged as the most prevalent financial instruments (Cortez et al. 2022). Green energy markets can address the need for financial stability and environmental concerns (Khurshid et al. 2024). Investments in green energy markets can enhance companies' financial performance. Furthermore, they also enhance green innovations. Green energy markets foster government policies. The policy instruments of governments include efforts to raise green innovation and expand clean energy technologies. Such steps enhance the welfare of the environment (Dutta et al. 2023).

Understanding the dynamic linkages among these assets is essential because shocks originate from heterogeneous sources, such as technology adoption, climate regulation, and geopolitical stress, and can propagate across markets at different horizons. Contextualizing the discussion above, this study examines the time-varying connectedness among these emerging markets, particularly cryptocurrency, AI, carbon finance, and green energy markets. The research endeavor is committed to delivering empirically supported insights into interrelated dynamics, a critical component for thoroughly comprehending global market trends. The research can make a substantial contribution to risk management strategies and portfolio diversification. It can provide valuable insights and information to effectively manage investments in these rapidly expanding sectors. To theoretically ground the analysis, we draw on portfolio diversification theory and the spillover transmission framework (Diebold and Yilmaz 2014). These theories suggest that assets connected through innovation, climate policy, and digitalization may transmit shocks via both financial and technological channels. Carbon finance reflects regulatory and environmental policy risk, green energy captures technological transformation risk, and Bitcoin embodies digital assets and speculative risk. Investigating their joint dynamics enables us to examine how sustainability-related and digital innovation markets interact within an integrated financial ecosystem. Additionally, the paper examines the potential of green assets to serve as a hedge in such turbulent environments, showing that these assets offer enhanced portfolio resilience while aligning with broader sustainable investing goals.

This study makes a significant contribution to the literature in four key ways. First, our study is the first to explore the fourfold association across AI technology, climate concerns, green technology, and cryptocurrency. Although the literature has studied each of these markets in a standalone configuration regarding traditional assets, such as oil, gold, and stock indices, the joint spillover dynamics of these new investment domains themselves are yet to be explored. Second, we fill a significant gap by investigating how the systemic dependencies between AI, green assets, and digital finance markets, which codetermine climate and technology-induced transitions, can provide novel insights into how these instruments comove with and impact each other. Second, this study is among the few literature deliberations that apply contemporaneous and lagged interdependence across the concerned markets. To this end, the present study adopts the $R^2$ decomposed connectedness ($R^2$DC) method to obtain intricate insights into the transmission process. This novel method addresses the earlier shortcomings in the literature, which have focused solely on contemporary spillover implications (Hanif et al. 2023). More specifically, the proposed $R^2$DC method relies on the theoretical application by Gabauer et al.

(2023), which encompasses the GFEVD and the goodness of fit (Genizi 1993). Thus, the proposed study framework is a generalization of the contemporaneous $R^2$DC method by Abubakr et al. (2024). Unlike prior studies limited to bilateral market linkages (Shahzad et al 2025), our framework introduces a multimarket $R^2$-decomposed connectedness approach that distinguishes between contemporaneous and lagged spillovers. This contributes theoretically by linking climate-finance integration and digital-asset contagion within a unified system. Empirically, it provides time-varying evidence on systemic comovements relevant for sustainable portfolio construction and policy coordination. Third, by studying the return transmission, the study can identify the potential sources of risk and assess market vulnerabilities. Such processes may help investors identify contemporaneous and lagged spillovers. Investors can optimize their portfolios and manage their risks. Fourth, this study utilizes daily data sets from December 19, 2017 to November 01, 2023. The time frame of this study is crucially important because it includes the implications of the COVID-19 (CV19) pandemic, Brexit, and the Ukraine-Russian war (RUW). The time-varying interrelatedness nature studied in this exercise will assist policymakers and investors in building their understanding of the association across the chosen markets and how the business is affected.

Our empirical outcomes indicate that dynamic total connectedness exhibits heterogeneity over time. Again, the total connectedness of the series is higher during CV19 and the RUW. Furthermore, the empirical discussion shows that contemporary spillovers are considerably higher than those that lag behind. In addition, Bitcoin has the maximum lagged value, followed by artificial intelligence. The carbon market played a significant role as a shock transmitter.

The subsequent portions of the paper are arranged as follows. Section "Review of Literature" analyzes the significant findings from the existing body of literature. Section "Model and Methodology" provides a comprehensive explanation of the data sets used and the methodology employed in this study. The discussion in Sect. "Main Findings and Discussion" pertains to the empirical findings. Finally, Sect. "Conclusions and policy implications" presents the main conclusions.

## Review of literature

From an investor's perspective, there are various approaches to determining whether a class is suitable for investment. From the perspective of risk reduction, including an asset in a portfolio can contribute to its diversification if it displays a negative correlation with another asset in the portfolio. Such actions will reduce risks (Bouri et al. 2017). Significant distinctions can be observed between a hedge, a diversifier, and a safe haven, as discussed by (Baur and Lucey 2010; Ratner and Chiu 2013). Diversification benefits can be attributed to an asset exhibiting an average positive (weak) correlation with another asset. Hedging benefits are attributed to an asset when it demonstrates a lack of correlation or is negatively correlated with other assets, on average. Safe-haven assets exhibit similar characteristics, albeit exclusively in times of market turmoil. Therefore, using a diversifier or hedger can effectively augment the advantages of diversification. Conversely, implementing safe-haven instruments mitigates risks in situations that require such measures (Baur and Lucey 2010).

Against the backdrop of portfolio adjustments, the current study has two facets. It can thus be related to two aspects of the literature: AI stocks, carbon finance, and green energy indices. Urom et al. (2022) explored the dependence on AI and energy markets, including renewable energy. Using both linear and nonlinear techniques, such as quantile regression and quantile spectral coherency models, the study found that the operation of the energy sector, particularly renewables, is strongly dependent on the functioning of the AI sector. The study suggested important implications for portfolio managers interested in investing in AI and clean energy stocks. Huynh et al. (2020) explored the interconnectedness of AI stocks, robotic stocks, and green bonds for portfolio diversification. Empirical observations derived from copulas and the generalized forecast error variance decomposition (GFEVD) reveal significant short-term volatility transmission. However, as time progresses, the extent of volatility transmission declines. The study concludes that the AI and general equity indices are not proper instruments for hedging.

Tiwari et al. (2021) documented the reliance on AI stocks and carbon prices. The empirical findings demonstrate a negative correlation between the return series of AI stocks and carbon prices. The research findings suggest that AI holds promise as a strategy for mitigating the impact of carbon pricing. The research results underscore the advantages of incorporating AI stocks into a diversified investment portfolio. Zhang and Umair (2023) explored the interrelationship between green finance and carbon markets. The findings derived from vector autoregressive and time-varying parameter models revealed substantial spillover influences among green bonds, renewable stocks, and carbon markets. The results offer valuable insights into the interconnectedness between green financial instruments and carbon markets. A substantial corpus of scholarly literature has previously investigated the correlation between stocks related to AI and a diverse range of other stocks and assets. Some studies have investigated the comovements of AI stocks with composite stock indices, commodities, green funds, and corporate bonds (Demiralay et al. 2021; Sharma, Aggarwal, Dixit, and Yadav 2023; Shahzad et al. 2023). Adekoya et al. (2022) explored dynamic connectivity among investor attention, Fin Tech, robotics, and AI. The results demonstrate that investor attention is the net recipient of spillovers.

Second, an interconnected thread within the scholarly discourse has directed its attention toward the domains of artificial intelligence, cryptocurrency, and green energy stocks. Arfaoui et al. (2023) explored dependency across clean energy, green markets, and cryptocurrencies. The results based on a network approach indicate that green bonds are not amalgamated with other markets. The results thus highlight the diversification benefits of green bonds in comparison to other financial markets. Mnif et al. (2024) explored the complex interconnections among digital currency, climate change, and sustainable investments using quantile time–frequency connectedness modeling. Their findings highlighted how coal's dominant market position and Ethereum's energy-intensive mining procedures generate volatility across various time scales, shaping both immediate and long-term macroeconomic conditions. By embracing the potential of digital currencies to augment green initiatives, fluctuations may be mitigated, and resources will be better managed. Furthermore, bitcoins are found to be an ineffective hedging instrument. Abakah et al. (2023) argued that there is bidirectional causality in variance across Fintech, Bitcoin, and AI stocks. Furthermore, robust price interlinkages exist for highly positive and negative alterations. Yousaf et al. (2025) scrutinized the relationships between renewable cryptoassets and energy stocks with a multivariate quantile-on-quantile analysis. It convincingly demonstrated that cryptocurrency price swings have a significant impact on energy costs, particularly in circumstances of acute geopolitical risk and uncertainty.

The study provided compelling evidence that sustainable cryptos may help dampen energy rate unpredictability and buffer volatile political forces. Rao et al. (2022) examined the interconnectedness among green bonds, the crude oil index, the emerging market index, and bitcoin from August 2011 to July 2021. The results document that the green bond index is strongly correlated with gold. Jabeur et al. (2024) investigated the interdependence between Bitcoin and stocks related to quantum computing, such as IBM and NVIDIA. Using the wavelet local multiple correlation (WLMC) and multivariate dynamic conditional correlation (DCC-GARCH) models, they revealed a growing interdependence between these financial assets after 2020. Overall, the study examines different portfolio strategies, and although the MVP exhibits lower returns, portfolios such as the MCP and MCoP mostly consist of Bitcoin and top quantum computing nodes, resulting in high performance. This knowledge is essential for both investors and policymakers to understand the relationship between advanced technology stocks and digital currencies, as well as how they can be utilized to inform investment decisions.

Many commodity and green markets are directly affected by stock returns rather than volatility. Such behavior demonstrates the reliance of green markets on the behavior of stock markets. Again, there have been instances of formidable volatility in the blockchain markets. Investors have attempted to diversify the benefits of cryptocurrencies (Karim and Naeem 2022).

Nonetheless, some studies have documented the hedging and safe-haven features of clean energy in relation to cryptocurrencies (Ren and Lucey 2022). Ren and Lucey's (2022) study examined two distinct categories of cryptocurrencies: dirty and clean. The findings indicate that there is no connection between clean energy stocks and cryptocurrencies in terms of hedging. Clean energy stocks can be considered a relatively less robust refuge for clean and dirty cryptocurrencies during periods of market decline. Li and Meng (2022) examined the interconnectedness between cryptocurrencies and renewable energy stocks in terms of time–frequency. The empirical evidence demonstrates that equities in the renewable energy sector serve as net transmitters of shocks in volatility. Hassan et al. (2022) conducted a study that examines the dynamic interconnectedness between cryptocurrency, the environmental attention index, clean energy, and green bonds. Researchers have employed advanced estimation methods to analyze these relationships. The results additionally indicate a significant level of interconnection among quintiles.

In summary, prior studies have not examined the association between AI stocks and their interaction with green energy stocks, carbon finance, and cryptocurrencies in the context of portfolio diversification. It is anticipated that the performance of AI stocks will exhibit similarities to that of other technology-intensive firms. The returns and spillover effects of AI stocks will likely surpass those of other stocks. Given the current immaturity of the AI stock market, it is probable that these stocks will exhibit significant responsiveness to fluctuations in other asset markets. Various perspectives exist regarding the hedging and safe-haven attributes of alternative assets and stocks for companies operating in the artificial intelligence sector. Previous research has established that green energy markets exhibit diminished returns and substantial spillover effects on adjacent markets. The burgeoning body of cryptocurrency research reveals significantly high returns and spillover effects (Wu et al. 2024). However, evidence regarding the relationship between cryptocurrency and other assets is available. Based on empirical evidence, it is suggested that cryptocurrencies have the potential to act as hedging channels or safe havens. Two recent contributions (Rehman et al. 2024; Rehman and Pata 2025) have investigated the interactions among sustainability, carbon, and digital asset markets using wavelet-based techniques. The former employs wavelet transform coherence (WTC), partial wavelet coherence (PWC), and multiple wavelet coherence (MWC) to uncover comovement across frequencies, focusing mainly on pairwise links (e.g., sustainability vs. $CO_2$ or Bitcoin vs. $CO_2$). In contrast, our study brings two methodological advances. First, we adopt an $R^2$-decomposed connectedness framework (also known as the extended spectral spillover approach) that simultaneously captures both contemporaneous and lagged spillovers in a multivariate system. This enables us to quantify directional transmission among three markets within a unified network, rather than relying on pairwise links. Second, we conduct event-sensitivity and stress-period decompositions (e.g., crisis versus normal regimes) to demonstrate how connectedness evolves under shocks, which is not fully addressed in prior studies. These methodological enhancements enable deeper insight into systemic joint dynamics, not just comovement at various frequencies.

The literature employs various methods to investigate the dynamic relationship between cryptocurrencies and other related markets. These studies show evidence of the hedging role of cryptocurrencies. Nonetheless, we have noticed that the research on AI stocks, carbon finance, green energy stocks, and cryptocurrencies is scant. This paper aims to fill this gap by documenting the portfolio specifications of AI stocks, carbon finance, green energy stocks, and cryptocurrencies. In addition, we apply some new dynamic connectedness models that will explore connectedness across lagged and contemporaneous spillovers. In summary, the literature provides fragmented evidence on the pairwise links between AI and energy, green finance and carbon, or cryptocurrencies and clean energy, but no unified framework connecting carbon finance, digital assets, and renewable markets within the same econometric setting. Our study addresses this gap by proposing a holistic perspective that captures both technological and environmental transmission mechanisms, offering a theoretical bridge between sustainable finance and digital innovation literatures.

## Model and methodology

### Data

As mentioned above, we examine the interrelation between clean cryptocurrency markets and the resistance level of carbon trading systems, AI-based indices, and environmentally friendly assets in the USA. Since several exogenous shocks affect the equity market, the choice of data leads to consistency with the purpose of the analysis. Daily data from December 19, 2017 to November 1, 2023 are used. This data set begins where the AI index was introduced (December 18, 2017). This period also included major disturbances on a planetary scale, such as CV19, the negotiations surrounding Brexit, and the RUW. We adopted the NASDAQ CTA and Robotics Index (AI) to assess the influence of AI in various economic sectors. This index covers firms developing and implementing AI and robotics in technological, industrial, medical, and other domains (Abakah et al. 2023). Companies in the index are categorized as facilitators, engagers, or enhancers in AI and robotics.

Bitcoin is selected as the representative cryptocurrency. The currency has become the third-largest market capitalization within the international monetary systems, ranking below only the United States Dollar (USD) and the Euro (EUR). According to statistical data, the price of Bitcoin experienced a fourfold increase between April 17, 2018 and May 17, 2022 rising from $7800 to $30,000 by November 2023. The market capitalization of Bitcoin increased from $190 billion to over $700 billion within the same time frame. Moreover, this study selects the carbon market ICI. This index, the first of its kind, was launched on July 31, 2014, and is the world's first liquid and investable benchmark for the global carbon market. Recently, academic studies have begun to scrutinize the potential of carbon credits as a new asset class, with a particular focus on their role in diversification and hedging purposes within the context of traditional and alternative asset classes (Demiralay et al. 2022; Di Febo et al. 2021). We consider the SP Clean Energy Index (SPCE), which serves as a metric for the green energy market and encompasses enterprises involved in clean energy initiatives. We use the Wilder Hill Clean Energy Innovation (NEX) to represent clean energy. This indicator shows that the mixed energy output (solar power companies, wind, biofuels, hydropower, and biomass) and climate solutions further green innovation. SPCE, AI, NEX, and ICI are acquired from Datastream, while the source of Bitcoin prices is extracted from the popular MarketCap (https://coinmarketcap.com/). The second data set of renewable energy indices includes global indices. Figure 1 illustrates the return for each variable. The return of the prices is discernible from the spikes. We hinge on the following equation to estimate the return:

$$V_{i,t} = \ln\left({}^{K_{i,t}}/_{K_{i,t-1}}\right) \times 100 \quad (1)$$

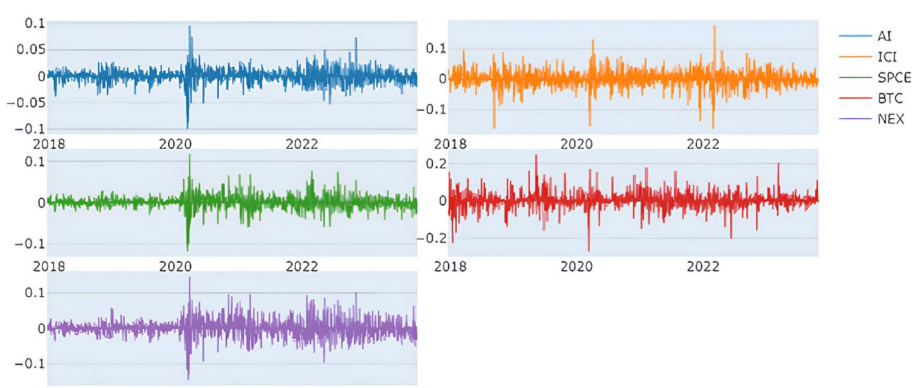

**Fig. 1** Data trend

where:

$V_{it}$: The market at time t.

$k_{t-1}$: The market at time $t-1$.

$k_{it}$: The market at time t.

Ln: Logarithm.

### Model estimation

(Engle 2002) proposed incorporating dynamic conditional correlation measures into a multivariate GARCH framework to monitor market return cross-sections effectively. Similarly, Kenett et al. (2010) proposed using partial or residual correlation coefficients to accurately assess the direct correlation between two series, taking into account the presence of one or more common components. A substantial corpus of scholarly work examines systemic risk within financial markets, focusing specifically on the interconnectedness and comovement of financial assets. Primary methodologies employed in the evaluation of systemic risk encompass the CoVaR approach developed by (Adrian and Working 2016), the Granger causality-based network proposed by (Billio et al. 2012), and the dynamic connectedness method devised by Diebold and Yilmaz (2012, 2014).

(Adrian and Workin 2016; Billio et al. 2012) designed to investigate the mutual interrelation of variables. On the other hand, Diebold and Yilmaz (2012, 2014) developed a more general framework capturing several time series dynamics. Their proposed GCM was generalized from a [0, 1] scale and cannot describe an arbitrary structure of interlinks among factors, although its connectivity structure of variables was restricted. The TCI suggests that market risk is theoretically not limited and can exceed 100%. Gabauer et al. (2023) introduced model-free and unconditional measures of connection. One such study shows that when VAR coefficients are not statistically significant, the GFEVD value is almost equivalent to the $R^2$ values of the bivariate regression, suggesting that it is challenging to reconcile TCI values with the normalized benchmark. This result has supported the recent plea by Diebold and Yilmaz (2012, 2014) for a unified framework.

Motivated by the previous work of Abubakr et al. (2024), the $R^2$ decomposition method was initially presented by Genizi (1993) as part of the network of partial correlation frameworks developed by Kennett and colleagues (2010, 2015). This was followed by the model-free and $R^2$-based connectedness framework of Gabauer et al. (2023), which introduces $R^2$DC. The model provides detailed insights into the importance of each variable in contributing to the total explanatory power ($R^2$) of the system. We estimate connectedness on a rolling 200-day window. This length strikes a balance between statistical precision and regime sensitivity, allowing the measures to adapt to structural breaks without being dominated by distant historical events. The 200-day horizon is widely used in financial time series to precisely address this bias–variance trade-off. At each window, the VAR order is selected using the Bayesian Information Criterion (BIC) to avoid overparameterization and preserve out-of-sample interpretability. The BIC favors parsimonious dynamics, reducing spurious lagged links that can inflate connectedness. Our robustness section further demonstrates that linear correlation artifacts do not drive conclusions by recomputing with rank-based dependence (Spearman/Kendall).

Following the model-free and R$^2$-based connectedness framework of Gabauer et al. (2023) and Balli et al. (2023), the VAR-VMA framework up to lag can be written as follows:

$$y_t = \sum_{n}^{h} \psi_n y_{t-n} + c_t = \sum_{n=0}^{\infty} \Omega_n c_{t-n}, \Omega_n = N_k \tag{2}$$

In Eq. (2), $y_t$, $y_{t-n}$, and $k*1$ stand as the endogenous parameter vectors and vectors of the intercept, respectively. $\sum$ and$\psi$ are $k*$ k-dimensional variance–covariance. We draw from (Pesaran and Shin 1998) to establish the framework for GFEVD-$R^2$. The GFEVD-$R$2 and GFEVD frameworks can be formulated as follows:

$$\psi_{ij}(h) = \frac{\sum q_{jj}^{-1} \sum_{h=0}^{h-1} (k_i' \Omega_h(\tau) \sum (q) k_j)^2}{\sum_{h=0}^{h-1} (k_{i\Omega_h}' \Omega_h(\tau) \sum (q) k_i)} = \left( \frac{\sum_{nj}}{\sqrt{\sum_{nj} \sum_{ii}}} \right)^2 = R_{ij}^2 \tag{3}$$

$$\psi_{ij}(h) = \frac{R_{ij}^2}{\sum_{h=1}^{k} R_{ij}^2}, \sum_{h=1}^{k} \psi_{ij}(h) = 1, \sum_{n,h=1}^{k} \psi_{ij}(h) = K \tag{4}$$

Next, we use the NET, which is the difference between “TO” and “FROM” other series:

$$TO = \sum_{j=1}^{k} R_{j,i}^{2g} \tag{5}$$

$$FROM = \sum_{j=1}^{k} R_{i,j}^{2g} \tag{6}$$

In Eq. (6), we can write $TO$ as $\sum_{j=1}^{k} R_{j,i}^{2g}$, and in Eq. (6), we can write $FROM$ as $\sum_{j=1}^{k} R_{i,j}^{2g}$. Consequently, the net connectedness index at quantile $\tau$ can be written as follows:

$$NCI_i(\tau) = \sum_{j=1}^{k} R_{j,i}^{2g} - \sum_{j=1}^{k} R_{i,j}^{2g} \tag{7}$$

denoted as $R_j^2$ represent bounded between 0 and 1.

### Hedging analysis

After estimating the DCC-GARCH model, we conduct a crucial hedging analysis for market participants, such as investors and fund managers, as it helps them manage risk and make more informed investment decisions. By mitigating downside risk, investors can achieve more favorable risk-adjusted returns. Specifically, we compute the Hedge Ratios (HR) following (Kroner and Jahangir 1993) as follows:

$$\theta_{cg} = \frac{h_{asset\ a-assest\ b}}{h_{assest\ bs}} \tag{8}$$

**Table 1** Descriptive statistics

| | AI | BTC | ICI | NEX | SPCE |
|---|---|---|---|---|---|
| Mean | 0.000254 | 0.001384 | 0.001888 | 0.000312 | 0.000437 |
| Median | 0.000702 | 0.000404 | 0.001452 | 0.000000 | 0.000152 |
| Maximum | 0.095281 | 0.250035 | 0.175129 | 0.144568 | 0.116664 |
| Minimum | −0.099 | −0.272 | −0.163 | −0.145 | −0.117 |
| Std, Dev, | 0.014045 | 0.042741 | 0.027768 | 0.025716 | 0.016911 |
| Skewness | −0.335 | −0.068 | −0.295 | −0.045 | −0.186 |
| Kurtosis | 8.815473 | 7.687668 | 7.133163 | 6.177713 | 9.975875 |
| Jarque–Bera | 2181.716 | 1400.191 | 1109.792 | 643.4063 | 3107.035 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 1528 | 1528 | 1528 | 1528 | 1528 |

**Table 2** The correlation results

| | AI | BTC | ICI | NEX | SPCE |
|---|---|---|---|---|---|
| AI | 1 | | | | |
| BTC | 0.175 | 1 | | | |
| | 0.000 | – | | | |
| ICI | 0.082 | 0.022 | 1 | | |
| | 0.000 | 0.024 | – | | |
| NEX | 0.570 | 0.182 | 0.057 | 1 | |
| | 0.000 | 0.000 | 0.001 | – | |

where $h_{uncertainty-bond}$ represent the conditional. $h_{assest\ b}$ denotes the variance of the variable's market returns. To evaluate the hedge effectiveness (HE), we adopt the approach outlined by (Ederington 1979):

$$HE = 1 - \frac{Var\left(Hedged\right)}{Var\left(Unhedged\right)} \tag{9}$$

## Main findings and discussion

### Descriptive statistics

This section specifically reviews the first-round outputs from both the descriptive statistics (Table 1) and pairwise correlations (Table 2). In addition to the general summary statistics, we check for nonlinearity, nonnormality, skewness and kurtosis of the selected series. All series contain a total of 1528 observations. All data values are centered at very close to zero and have a positive mean. The median values are close to the mean values, with small deviations. The smallest extreme returns from all the considered time series are negative, indicating how much a shock changes data during different financial turbulence, such as CV-19 and RU19. The data points are in proximity to the respective mean values for all reports, as reflected by standard deviation (SD) values. The variables are not symmetric, as indicated by the nonzero negative skewness coefficients. The kurtosis of these series is also rejected for reference, with a number larger than three suggesting a departure from a normal distribution. The Jarque–Bera test is passed, and normality tests fail for all series, as seen from the probabilities, which are significant at the 99% level. Therefore, the periods of the series do not follow a normal distribution.

The results of the pairwise Kendall rank correlation between the two series are documented in Table 2. All paired correlations are statistically significant. Bitcoin demonstrates a robust positive correlation with the NEX index, as indicated by a coefficient of 0.182. The correlation between the two variables is 0.175, indicating a strong association. On the other hand, it is worth noting that Bitcoin exhibits a significant correlation with the use of green energy. In contrast, its correlation with carbon prices is minimal, as indicated by a coefficient of 0.002. The AI demonstrates a notable positive correlation with NEX and SPCE, with corresponding correlation coefficients of 0.57 and 0.49, respectively.

Conversely, its correlation with ICI is relatively weak, with a correlation value of 0.08. Likewise, a positive correlation exists across the carbon and sustainability markets, albeit with apparent limitations observed in the case of NEX and SPCE. The highest observed correlations, reaching approximately 0.61, were identified between the NEX and SPCE variables.

### *Findings of the $R^2$ decomposed*

Figure 2 and Table 3 represent the $R^2$DC for the selected series. It captures aggregate behavior rather than isolating the dynamics and interactions of the various variables in specific market regimes or temporal nonstationarity. The results reveal the degree to which shocks influence variations in each series of other variables in the system. A series is considered a net transmitter of shocks if it has a greater impact on the variability of others than it does on itself, and as a net receiver, the opposite applies. Furthermore, the values presented in the table illustrate the overall $R^2$ decomposed measures, denoted as O, which indicate the contemporaneous (C) and lagged (L) $R^2$ decomposed connectedness, respectively. We employ the rolling window (200 days) based on the literature, including Diebold and Yilmaz (2012, 2014), which provides some systematic framework to measure connectedness in financial markets, a cornerstone for the comprehension of the dynamic interrelations papered in time among the different asset classes. The

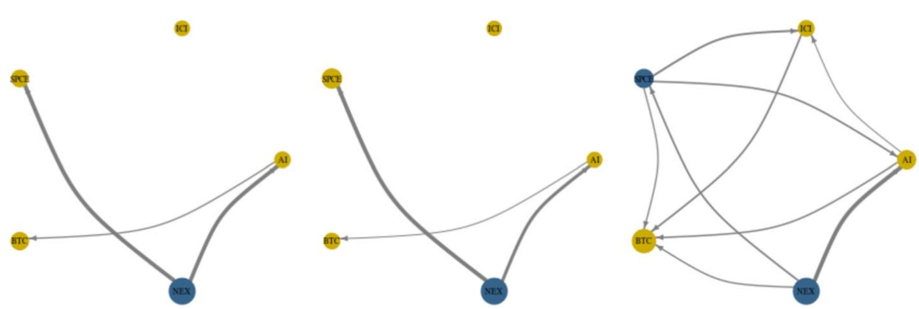


**Fig. 2** The connectedness diagram of *R2 decomposed measures*

**Table 3** decomposition connectedness

| | O,AI | O,ICI | O,SPCE | O,BTC | O,NEX | O,FROM | C,AI | C,ICI | C,SPCE | C,BTC | C,NEX | C,FROM | L,AI | L,ICI | L,SPCE | L,BTC | L,NEX | L,FROM |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AI | 0.79 | 2.32 | 22.80 | 5.55 | 34.89 | 65.56 | 0.00 | 2.04 | 22.04 | 5.22 | 33.88 | 63.18 | 0.79 | 0.28 | 0.77 | 0.32 | 1.01 | 2.37 |
| ICI | 2.75 | 1.10 | 2.46 | 1.01 | 2.51 | 8.73 | 2.30 | 0.00 | 1.88 | 0.50 | 2.01 | 6.69 | 0.45 | 1.10 | 0.58 | 0.51 | 0.50 | 2.04 |
| SPCE | 22.77 | 2.01 | 0.96 | 3.83 | 42.01 | 70.63 | 22.29 | 1.76 | 0.00 | 3.55 | 41.29 | 68.89 | 0.49 | 0.26 | 0.96 | 0.27 | 0.72 | 1.74 |
| BTC | 6.40 | 1.29 | 4.21 | 0.25 | 4.84 | 16.74 | 5.82 | 0.50 | 3.71 | 0.00 | 4.35 | 14.38 | 0.58 | 0.80 | 0.49 | 0.25 | 0.49 | 2.38 |
| NEX | 32.44 | 2.26 | 39.46 | 4.35 | 0.44 | 78.50 | 32.08 | 1.83 | 39.02 | 4.10 | 0.00 | 77.03 | 0.35 | 0.43 | 0.43 | 0.26 | 0.44 | 1.47 |
| TO | 64.36 | 7.88 | 68.92 | 14.73 | 84.25 | 240.16 | 62.49 | 6.12 | 66.65 | 13.37 | 81.52 | 230.16 | 1.87 | 1.76 | 2.27 | 1.36 | 2.73 | 10.00 |
| Inc.Own | 65.15 | 8.98 | 69.89 | 14.99 | 84.69 | TCI | 62.49 | 6.12 | 66.65 | 13.37 | 81.52 | TCI | 2.66 | 2.86 | 3.24 | 1.61 | 3.17 | TCI |
| NET | -1.20 | -0.85 | -1.70 | -2.01 | 5.75 | 60.04 | -0.69 | -0.57 | -2.24 | -1.00 | 4.49 | 57.54 | -0.51 | -0.28 | 0.53 | -1.00 | 1.26 | 2.50 |
| NPT | 2.00 | 1.00 | 3.00 | 0.00 | 4.00 | | 3.00 | 0.00 | 2.00 | 1.00 | 4.00 | | 2.00 | 1.00 | 3.00 | 0.00 | 4.00 | |

*Note* The $R^2$ DC measures utilized a 200-day rolling window and the Bayesian Information Criterion (BIC) lag. The overall variable, denoted as O, represents both contemporaneous (C) and lagged (L) components choice of a 200-day rolling window strikes a balance between having a sufficient sample size to estimate volatility and correlations reliably, while not being overly responsive to changes in market conditions over time. This window size is often used for financial time series because it delivers a fast yet fairly representative estimate of longer-term trends and cyclicality without sacrificing temporal accuracy. Our estimations utilize the least lag structure to identify potential precursors to price action. The Bayesian Information Criterion (BIC) was used to select the lag structure that captures the dynamics in the data without overfitting.

It has been observed that the average TCI is 60.04%. This indicates that, on average, 60.04% of the variance in the left-hand side (LHS) factor can be accounted for by the right-hand side (RHS) elements. Upon decomposing this measure into its contemporaneous and lagged components, it is evident that 57.54% of the metric can be attributed to contemporary dynamics, while a mere 2.5% is associated with lagged interdependencies. A system-wide TCI of approximately 60% implies that, on average, more than half of each market's variation is explained by other markets. For investors and portfolio managers, this means that naive diversification across AI, carbon, clean energy, and Bitcoin will not fully insulate portfolios, as cross-market shocks are material. For policymakers, a high TCI indicates that stress in one pillar of the transition (e.g., energy or digital assets) can rapidly transmit to others, justifying coordinated communication and macroprudential monitoring across these markets during volatile periods.

Notably, the contemporary measures of connectedness between the FROM and TO variables are significantly higher than their lagged measures. Specifically, the contemporary measures for NEX, SPCE, and AI are 78.5, 70.6, and 65.65, respectively. Additionally, it is observed that Bitcoin has a higher lagged measure of 2.38, followed by AI with a measure of 2.37. Dominant contemporaneous connectedness indicates common information shocks, such as policy headlines, macro prints, or global risk-on/off moves, which move these assets together within the day. Hedging that relies on same-day offsets (e.g., intraday overlays, index futures) is therefore more relevant than slow-moving reallocations. Smaller but nonzero lagged channels (e.g., BTC and AI) imply that some shocks propagate with a delay, opening the door for next-day rebalancing rules and signal-based overlays (e.g., reducing AI beta after BTC-led risk-on episodes).

The results also indicate that BTC experiences a significant self-driven influence of 0.25%. The remaining variation of approximately 16.74% in BTC can be attributed to the system network, which accounts for approximately 15% of the total variation. After disaggregating this metric into its contemporaneous and lagged constituents, it becomes apparent that 4.35% of the metric can be ascribed to contemporaneous dynamics. In contrast, a mere 2.38% is linked to lagged interdependencies. The study identifies induced spillover effects from the technology sector rather than the clean energy market. These spillover effects are found to be transmitted to the field of AI rather than SPCE. The analysis considers various measures, including contemporaneous and lagged variables, to capture the extent of these spillover effects.

The findings also demonstrate that NEX exhibits a statistically significant self-driven influence of 0.44%. Approximately 35% of the remaining variation in NEX can be attributed to the system, especially the top avenues of the AI and SPCE markets, accounting for approximately 42% and 34% of the transmission in these respective markets.

Upon disaggregating this metric into its contemporaneous and lagged constituents, it is observed that the same constitution dominates among the series presented in the overall, contemporaneous, and lagged measures. Similarly, dominant spillover effects in the clean energy market originate from and extend to the technology sector and AI. These effects can be observed through contemporaneous and lagged measures. The ICI was responsible for both receiving and transmitting 8.73% of the total shocks between system counterparts. This indicates that ICI played a significant role as a net shock transmitter in the respective market, accounting for 0.32% of the overall shocks. The spike in TCI around March 2020 reflects global liquidity shocks and forced derisking, which compress cross-asset correlations and weaken diversification. The renewed elevation after March 2022 aligns with the Russia–Ukraine war, raising energy-transition risk premia (input costs, supply bottlenecks) and synchronizing clean-tech and carbon pricing with broader risk assets. For portfolio construction, this means hedges that work in calm regimes (low TCI) decay during global shocks (high TCI); stress-regime overlays (e.g., volatility-targeting, tail-risk hedges) should be prepositioned rather than reactive.

This finding is logical, as it suggests that the United States is increasingly capable of adopting and integrating technology, renewable energy sources, and bitcoin over an extended period. This capacity is essential for achieving sustainable environmental growth and establishing an eco-friendly system. This discovery aligns with previous research conducted by other scholars, such as Urom et al. (2022). The close interconnection observed between these markets, coupled with their susceptibility to external disturbances, can elucidate the operational performance of the market. Based on the observations, it can be concluded that a significant relationship exists among the variables, despite the distinct characteristics in each pair. Nevertheless, it would be imprudent to depend on the system's interconnections to inform trading decisions, as the stability of these connections between pairs can vary significantly over time. Our findings are consistent with the findings of Huynh et al. (2020), who concluded the interconnectedness of AI stocks, robotic stocks, and green bonds, and Tiwari et al. (2021), who concluded the reliance on AI (AI) stocks and carbon prices. Cross-market leadership. The clean-tech equity complex (NEX/SPCE) exhibits the highest contemporaneous "TO" shares, marking it a net transmitter under shared shocks—consistent with news about subsidies, rates, or supply chains repricing growth-sensitive clean-tech first. Bitcoin shows comparatively higher lagged "FROM", positioning it as a net receiver over short lags; speculative/liquidity cycles tend to absorb rather than initiate broader spillovers. Carbon plays a smaller but nonnegligible role as a transmitter, consistent with policy-driven adjustments that ripple into clean-tech valuations and AI-exposed industries. For asset allocators, this leadership map suggests monitoring clean-tech as an early barometer and treating BTC primarily as a risk amplifier rather than a hedge.

Figure 2 presents the $R^2$DC, which quantifies the degree of association between the series. The black color represents the overall interconnectedness of various time-varying variables, while the brown and green colors represent contemporaneous and lagged relationships, respectively. The results indicate a significant level of overall connectivity exceeding 40%. In addition, the level of TCI among the examined series is found to be highest during extreme market conditions, particularly following the declaration of CV19 in March 2020, with a degree of approximately 80%. Additionally, a notable increase in interconnectedness was observed after March 2022, coinciding with significant events related to the Russia-Ukraine conflict, reaching above 60%. This level of interconnectedness was higher compared to the periods following C19 and the subsequent war. The obtained results exhibit homogeneity and comparability with previous investigations, aligning with the findings of (Demiralay et al. 2022; Lorente et al. 2022; Shahzad et al. 2023); they reported that the interconnectivity and interdependence among financial markets have increased throughout various time scale domains. Upon decomposing this metric into its contemporaneous and lagged components, it becomes apparent that the contemporary component of the metric exhibits consistent dynamics of overall connectedness. In contrast, the lagged interdependencies show only minimal changes.

The net connectivity of each series can be observed in Fig. 3. The black symbolizes the comprehensive interconnections among various time-varying elements. On the other hand, the colors brown and green represent contemporaneous and lagged relationships, respectively. Green (lagged) net connectivity variation-induced spillover is primarily observed within the carbon credit market and Bitcoin, with a lesser impact on the AI market. In contrast, the green energy and technology markets are predominantly influenced by contemporaneous (brawn) net connectivity. Furthermore, it is worth noting that the connectivity decomposition for Bitcoin has been observed to be influenced by the CV19 pandemic, as well as the markets connected to AI and technology. The strong and event-driven interconnectedness observed among transition-related markets highlights the importance of integrated financial supervision. Sudden policy shifts, such as new carbon pricing mechanisms, emissions trading adjustments, or cryptocurrency regulations, can quickly transmit shocks across technology, energy, and digital asset markets. This synchronicity reflects the role of climate policy and technological innovation cycles as intertwined channels of transmission. To mitigate these systemic effects, regulators should coordinate policy communication, closely monitor cross-market liquidity, and adopt countercyclical tools that stabilize clean-tech and digital-asset funds during episodes of heightened volatility.

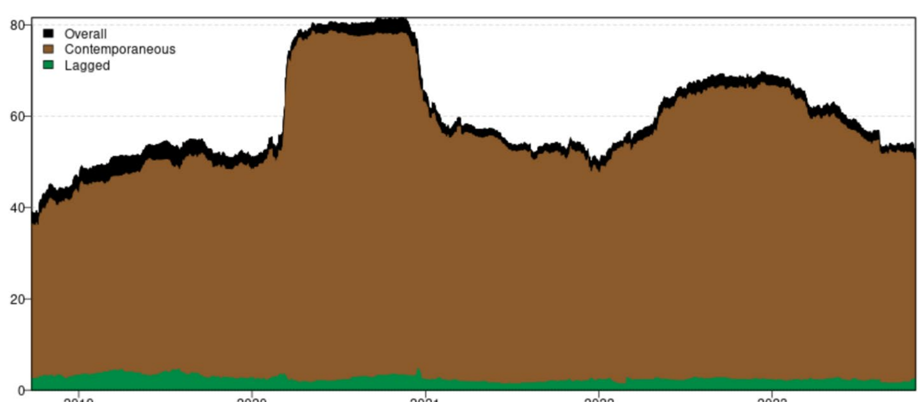


**Fig. 3** $R^2$DC measures are calculated on a 200-day rolling window (VAR) approach

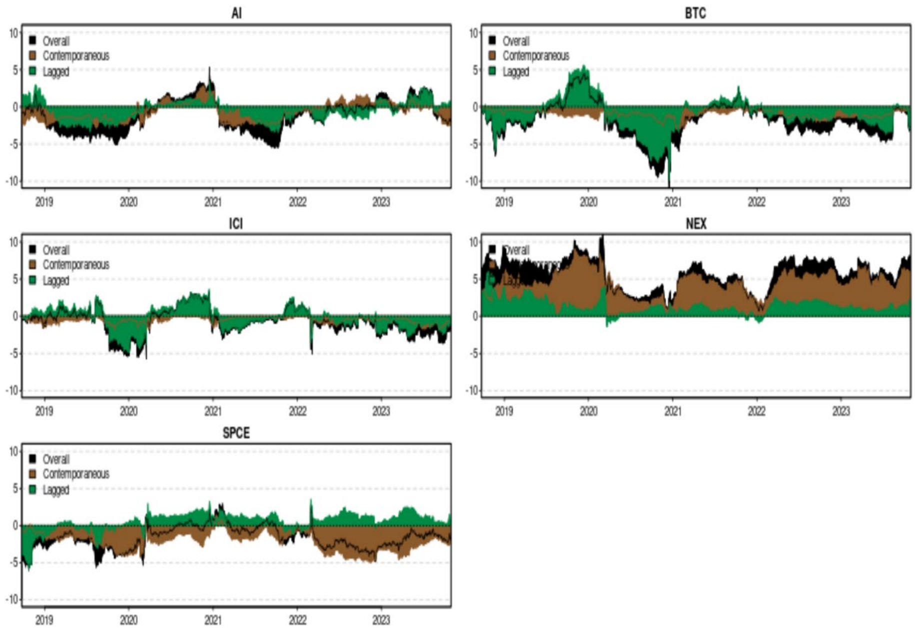


**Fig. 4** $R^2$DC based on a 200-day rolling window (VAR) approach

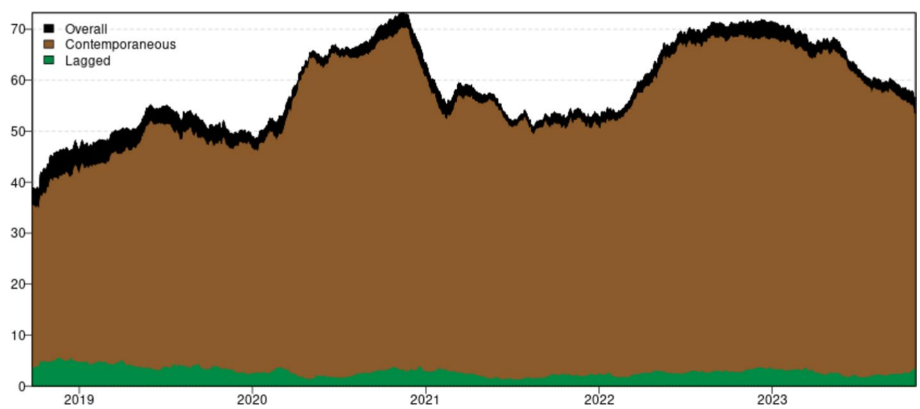


**Fig. 5** $R^2$DC based on a 200-day rolling window (VAR) approach and Spearman coefficient

## Robustness check

Figures 4 and 5 show a comprehensive analysis of the robustness of the findings, employing dynamic total connectedness as the basis for these checks. The Pearson correlation coefficients are replaced by the Spearman and Kendall rank correlation coefficients to address the impact of outliers. These alternative coefficients demonstrate decreased susceptibility to the influence of outliers. Based on the observed quantitative similarities in the results, it can be deduced that the empirical findings demonstrate a high degree of robustness. The analysis demonstrates that the examined series displays the highest level of TCI during periods of extreme market conditions, specifically in the aftermath of significant events such as the declaration of tCV19 and the RUW. The TCI level surpasses 70% and 60% for Spearman and Kendall, respectively (Fig. 6).

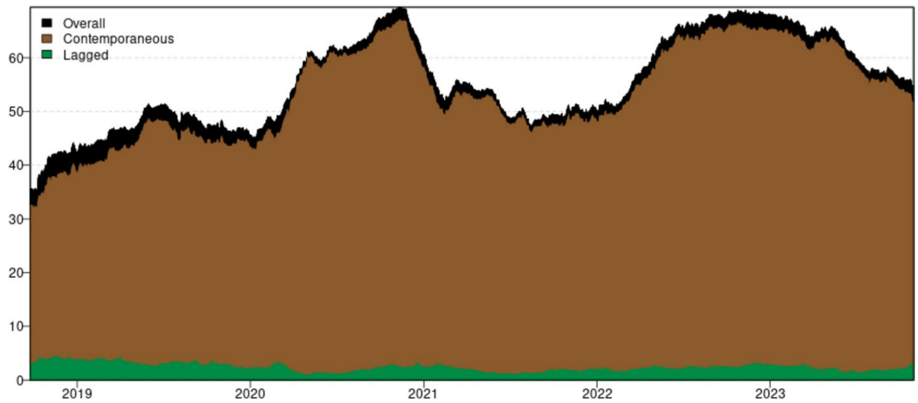

**Fig. 6** $R^2$DC based on a 200-day rolling window (VAR) approach and Kendall coefficient

**Table 4** Portfolio analysis

| | Mean | Std.Dev | 5% | 95% | HE | *p* value |
|---|---|---|---|---|---|---|
| AI/ICI | 0.86 | 0.05 | 0.77 | 0.93 | 0.12 | 0.00 |
| AI/SPCE | 0.69 | 0.27 | 0.26 | 1.00 | 0.09 | 0.00 |
| AI/BTC | 0.98 | 0.02 | 0.94 | 1.00 | 0.02 | 0.00 |
| AI/NEX | 1.00 | 0.01 | 1.00 | 1.00 | 0.00 | 0.00 |
| ICI/AI | 0.14 | 0.05 | 0.07 | 0.23 | 0.78 | 0.01 |
| ICI/SPCE | 0.22 | 0.10 | 0.07 | 0.40 | 0.71 | 0.00 |
| ICI/BTC | 0.71 | 0.09 | 0.57 | 0.83 | 0.31 | 0.00 |
| ICI/NEX | 0.43 | 0.16 | 0.19 | 0.64 | 0.51 | 0.00 |
| SPCE/AI | 0.31 | 0.27 | 0.00 | 0.74 | 0.37 | 0.06 |
| SPCE/ICI | 0.78 | 0.10 | 0.60 | 0.93 | 0.22 | 0.00 |
| SPCE/BTC | 0.95 | 0.04 | 0.87 | 1.00 | 0.04 | 0.00 |
| SPCE/NEX | 1.00 | 0.00 | 1.00 | 1.00 | 0.00 | 0.00 |
| BTC/AI | 0.02 | 0.02 | 0.00 | 0.06 | 0.89 | 0.73 |
| BTC/ICI | 0.29 | 0.09 | 0.17 | 0.43 | 0.71 | 0.00 |
| BTC/SPCE | 0.05 | 0.04 | 0.00 | 0.13 | 0.85 | 0.48 |
| BTC/NEX | 0.19 | 0.10 | 0.06 | 0.34 | 0.69 | 0.00 |
| NEX/AI | 0.00 | 0.01 | 0.00 | 0.00 | 0.70 | 0.99 |
| NEX/ICI | 0.57 | 0.16 | 0.36 | 0.81 | 0.43 | 0.00 |
| NEX/SPCE | 0.00 | 0.00 | 0.00 | 0.00 | 0.57 | 1.00 |
| NEX/BTC | 0.81 | 0.10 | 0.66 | 0.94 | 0.14 | 0.00 |

*Note* The portfolios are estimated using the AR(1) GARCH(1,1) DCC-t-copula estimation method, which incorporates Kendall's measure. The term "Q(5%)" refers to the 5th percentile, while "Q(95%)" refers to the 95th percentile. Hedge effectiveness refers to the degree to which a hedge successfully mitigates or offsets potential losses in an investment or portfolio. The *p* values are derived from the statistical methodology proposed by Fligner and Killeen in their seminal 1976 work

## Portfolio analysis

The DCCt-Copula scheme created 20 bivariate portfolios to examine the net pairwise spillovers. Our analysis has focused on the hedging role of green assets, AI technologies, Bitcoin, and the carbon market against infrequent, nonfundamental global shocks. We selected these assets based on the types of portfolios relevant to the emerging world of sustainable investing and innovation. The absence of gold in our study was intentional, as we explored the behavior of nontraditional assets that have become increasingly consequential in shaping investment strategies in the twenty-first century. The role of gold as the bedrock in portfolio risk hedging is undisputed and well documented, as its provenance goes back thousands of years with an exceptional physical display and an exceptional monetary role; our paper proposes an investigation into the potential of alternative assets that can serve as complementary assets that empower more traditional assets (such as gold) in modern portfolios. Table 4 presents the outcomes of the optimization process, wherein the mean column represents the average proportion of the asset within the portfolio. For example, the mean value of the AI/SPCE portfolio was determined to be 0.7, indicating that the average weight of the AI market within the portfolio was 70%. Additionally, the HE was calculated to be 0.09. In addition, the variable Q at a 5% level signifies a state of market turmoil, whereas Q at a 95% level indicates a bullish market condition. The AI/SPCE portfolio exhibited Q values of 0.26 and 1 for the 5% and 95% quantiles, respectively. The final column of the analysis represents the p value, indicating the significance of the bivariate portfolios for each couple. The portfolio exhibits a high level of HE, with values of 0.78%, 0.71%, and 1% observed for the carbon market concerning clean energy, AI, and technology, respectively. The portfolio exhibits high HE, especially during extreme market conditions and the mean. The weight is significantly low. BTC is timing-sensitive. BTC pairs show mixed HE and higher lagged dynamics. In risk-off spirals, BTC tends to correlate positively with growth assets (a weak hedge); in liquidity recoveries, it can deliver idiosyncratic upside that improves risk-adjusted returns ex post. This asymmetry cautions against treating BTC as a hedge against structural risk. If used, it should be tactically sized with drawdown limits and volatility caps rather than as a core defensive allocation. This implies that hedging mechanisms that rely on eco-friendly assets can effectively mitigate risks, particularly in the face of financial and geopolitical instability. Our results relate to previous studies (Abuzayed and Al-Fayoumi 2023; Broadstock et al. 2022; Dawar et al. 2021), highlighting how eco-friendly assets are effective hedging instruments relative to other investment assets, highlighting the strong hedging capability in new asset classes in times of noneconomic global shocks characterized by market volatility, which can be complementary hedging vehicles with traditional hedging instruments. The extensive support, spanning the government and potential interest groups, such as preferential loans, grants, and fiscal incentives, may explain the perception of stability and attractiveness of these assets, as well as how external support enhances eco-friendly assets and their performance.

Finally, we conclude that high HE for ICI vs AI/SPCE pairs indicates that carbon exposure hedges a portion of the technology/clean-tech beta because carbon prices embed policy risk and compliance demand that is partially orthogonal to growth/innovation shocks. Conversely, AI/SPCE pairs show low HE, reflecting shared exposures (long-duration cash flows, supply-chain/interest-rate sensitivity). In other words, pairing assets that are rally and correct in response to the same news (such as policy support, rates, or input costs) yields weak protection; pairing with a policy-anchored asset (such as carbon) delivers better diversification. Allocator playbook. When TCI is low, cross-market diversification becomes meaningful, and AI/clean-tech pairings can effectively reduce idiosyncratic risk. When TCI is elevated, same-day shocks dominate, and only orthogonal exposures (e.g., carbon allowances, selective energy exposures, and explicit tail hedges) preserve protection. Given the small but present lagged channels (notably via BTC and AI), next-day rules, such as derisking AI after BTC surges, can marginally improve drawdown control without sacrificing upside.

## Conclusions and policy implications

This study uses daily data from December 2017 to November 2023 to examine the changing relationships between AI, carbon finance, green energy, and cryptocurrency markets during the CV19 pandemic and the RUW. It reveals a high level of interconnectedness, especially during crises, utilizing advanced analytical techniques, with a significant portion attributed to concurrent market dynamics. The study also found that environmentally friendly assets mitigate risks during turbulent times.

The significant HE exhibited by environmentally sustainable assets during market turbulence suggests a strategic realignment toward incorporating these assets into investment portfolios for investors and fund managers. Not only does this strategy effectively mitigate risk, but it also aligns with the principles of sustainable and ethical investment. The significance of incorporating green investments into portfolios to stabilize them during crises underscores the necessity for policy measures that promote and provide incentives for investments in green energy and carbon finance.

The evidence of high contemporaneous spillovers highlights the systemic interdependence between sustainability-driven and digital asset markets. For policymakers, this indicates the need to integrate carbon-pricing instruments and green-technology incentives within a coordinated macroprudential framework. For investors, understanding these linkages allows dynamic portfolio rebalancing strategies that anticipate spillovers from digital asset shocks to climate-finance instruments. Policymakers must establish real-time monitoring systems to promptly address market fluctuations that impact these interrelated sectors. Mitigating the effects of global crises on these volatile markets is of utmost importance. Moreover, sustainable finance policies can foster investment practices characterized by increased stability and adherence to ethical principles.

Moreover, the intricate nature and swift progression of these markets underscore the significance of continuous education and training for investors and fund managers. Gaining a comprehensive understanding of the intricacies inherent in each sector is crucial for making informed and prudent investment choices. Moreover, considering the worldwide scope and susceptibility of these markets to global occurrences, it is essential to enhance international cooperation in developing policies and managing crises.

Ultimately, the utilization of cutting-edge technologies to enhance market analysis and the prioritization of ethical and sustainable investment practices are of utmost importance. These strategies will help effectively address the challenges arising from the interconnected nature of these markets and capitalize on the potential they offer in an increasingly connected global economy. Policymakers must take swift action to foster investors' understanding of the benefits and risks associated with investing in renewable assets and digital currencies. Targeted educational initiatives and widespread public awareness campaigns can empower the public with the insights needed to make informed, prudent decisions. This more informed populace is better positioned to navigate constantly changing conditions within these complex markets. Moreover, technology designers must work closely with regulatory bodies to ensure that continued development aligns with ideals of fairness and consumer safeguards. Such cooperation can facilitate the adoption of emerging technologies, such as blockchain, for carbon offsets and renewable energy transactions, increasing openness and reliability within these fields. By addressing these pressing needs, leaders can foster sustainable growth and stability across these interrelated areas, ensuring that each contributes to the overall value of economic and environmental well-being.

Further research will focus on the adaptation effect in investment markets and the contribution of sustainable assets to risk mitigation and strategic advantage for portfolio resilience during periods of instability. Future researchers can and should include a comparison involving gold to specifically illustrate how these traditional and nontraditional assets perform in relative terms in hedging portfolios against systemic risks. These studies would provide a broader understanding of how the new asset classes can coexist or enhance existing hedging mechanisms across various investment environments.

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**Author contributions**
J.C.F.: Conceptualization, Formal analysis; H.A.: Software, Methodology; M.R.: Data curation, Resources, Validation, Writing original draft; B.D.: Investigation, Reviewing and Editing.

## Declarations

**Conflict of interest**
There are no competing interests.

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**References**

Abakah EJA, Tiwari AK, Ghosh S, Doğan B (2023) Dynamic effect of Bitcoin, fintech and artificial intelligence stocks on eco-friendly assets, Islamic stocks and conventional financial markets: another look using quantile-based approaches. Technol Forecast Soc Change. https://doi.org/10.1016/j.techfore.2023.122566

Abubakr M, Chatziantoniou I, Gabauer D, Karim S (2024) Measuring the G20 stock market return transmission mechanism : evidence from the $R^2$ connectedness approach. Int Rev Financ Anal 91:102986

Abuzayed B, Al-Fayoumi N (2023) Diversification and hedging strategies of green bonds in financial asset portfolios during the COVID-19 pandemic. Appl Econ 55(36):4228–4238. https://doi.org/10.1080/00036846.2022.2128178

Adekoya OB, Oliyide JA, Saleem O, Adeoye HA (2022) Asymmetric connectedness between google-based investor attention and the fourth industrial revolution assets: the case of FinTech and robotics & artificial intelligence stocks. Technol Soc 68:101925. https://doi.org/10.1016/j.techsoc.2022.101925

Adrian T, Working MKB (2016) CoVar. Am Econ Rev 106(07):1–23

Arfaoui N, Naeem MA, Boubaker S, Mirza N, Karim S (2023) Interdependence of clean energy and green markets with cryptocurrencies. Energy Econ 120:106584. https://doi.org/10.1016/j.eneco.2023.106584

Balli F, Balli HO, Dang THN, Gabauer D (2023) Contemporaneous and lagged $R^2$ de-composed connectedness approach: new evidence from the energy futures market. Financ Res Lett. https://doi.org/10.1016/j.frl.2023.104168

Baur DG, Lucey BM (2010) Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. Financ Rev 45(2):217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

Ben JabeurGozgor SG, Rezgui H, Mohammed KS (2024) Dynamic dependence between quantum computing stocks and Bitcoin: portfolio strategies for a new era of asset classes. Int Rev Financ Anal 95(PB):103478. https://doi.org/10.1016/j.irfa.2024.103478
Billio M, Getmansky M, Lo AW, Pelizzon L (2012) Econometric measures of connectedness and systemic risk in the finance and insurance sectors. J Financ Econ 104(3):535–559. https://doi.org/10.1016/j.jfineco.2011.12.010
Bouri E, Molnár P, Azzi G, Roubaud D, Hagfors LI (2017) On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Financ Res Lett 20:192–198. https://doi.org/10.1016/j.frl.2016.09.025
Broadstock DC, Chatziantoniou I, Gabauer D (2022) Minimum connectedness portfolios and the market for green bonds: advocating socially responsible investment (SRI) activity. Appl Energy Financ. https://doi.org/10.1007/978-3-030-92957-2_9
Bughin J, Hazan E, Ramaswamy S, Chui M, Allas T, Dahlström P, Henke N, Trench M (2017) Artificial intelligence the next digital frontier. McKinsey and Company Global Institute 47(3.6). http://large.stanford.edu/courses/2017/ph240/kim-j1/docs/mckinsey-jun17.pdf.
Charfeddine L, Benlagha N, Maouchi Y (2020) Investigating the dynamic relationship between cryptocurrencies and conventional assets: implications for financial investors. Econ Model 85:198–217. https://doi.org/10.1016/j.econmod.2019.05.016
Cifuentes-Faura J, Mohammed KS, Alofaysan H (2024) The connectedness and structural changes among green and conventional markets energy with $CO_2$ emissions in the United States. Econ Anal Policy. https://doi.org/10.1016/j.eap.2024.06.009
Cortez MC, Andrade N, Silva F (2022) The environmental and financial performance of green energy investments: European evidence. Ecol Econ 197:107427. https://doi.org/10.1016/j.ecolecon.2022.107427
Czarnitzki D, Fernández GP, Rammer C (2023) Artificial intelligence and firm-level productivity. J Econ Behav Organ 211:188–205. https://doi.org/10.1016/j.jebo.2023.05.008
Dawar I, Dutta A, Bouri E, Saeed T (2021) Crude oil prices and clean energy stock indices: lagged and asymmetric effects with quantile regression. Renew Energy 163:288–299. https://doi.org/10.1016/j.renene.2020.08.162
Demiralay S, Gencer HG, Bayraci S (2021) How do artificial intelligence and robotics stocks co-move with traditional and alternative assets in the age of the 4th industrial revolution? Implications and insights for the COVID-19 period. Technol Forecast Soc Change 171:120989. https://doi.org/10.1016/j.techfore.2021.120989
Demiralay S, Gencer HG, Bayraci S (2022) Carbon credit futures as an emerging asset: hedging, diversification and downside risks. Energy Econ 113(July):106196. https://doi.org/10.1016/j.eneco.2022.106196
Di Febo E, Ortolano A, Foglia M, Leone M, Angelini E (2021) From Bitcoin to carbon allowances: an asymmetric extreme risk spillover. J Environ Manage 298:113384. https://doi.org/10.1016/j.jenvman.2021.113384
Diebold FX, Yilmaz K (2012) Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast 28(1):57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006
Diebold FX, Yilmaz K (2014) On the network topology of variance decompositions: measuring the connectedness of financial firms. J Econom 182(1):119–134. https://doi.org/10.1016/j.jeconom.2014.04.012
Dutta A, Bouri E, Rothovius T, Uddin GS (2023) Climate risk and green investments: new evidence. Energy 265(December 2022):126376. https://doi.org/10.1016/j.energy.2022.126376
Ederington LH (1979) The hedging performance of the new futures markets. J Finance 34(1):157–170. https://doi.org/10.1111/j.1540-6261.1979.tb02077.x
Engle R (2002) Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. J Bus Econ Stat 20(3):339–350. https://doi.org/10.1198/073500102288618487
Felten EW, Raj M, Seamans R (2018) A method to link advances in artificial intelligence to occupational abilities. In: AEA Papers and Proceedings. 2014 Broadway, Suite 305, Nashville, TN 37203: American Economic Association. Vol 108, pp 54–57
Gabauer D, Chatziantoniou I, Stenfors A (2023) Model-free connectedness measures. Financ Res Lett 54(February):103804. https://doi.org/10.1016/j.frl.2023.103804
Genizi A (1993) Decomposition of $R^2$ in multiple regression with correlated regressors. Stat Sin 3:407–420
Gronwald M (2019) Is Bitcoin a commodity? On price jumps, demand shocks, and certainty of supply. J Int Money Finance 97:86–92. https://doi.org/10.1016/j.jimonfin.2019.06.006
Hanif W, Ko HU, Pham L, Kang SH (2023) Dynamic connectedness and network in the high moments of cryptocurrency, stock, and commodity markets. Financ Innov 9(1):84. https://doi.org/10.1186/s40854-023-00474-6
Hassan MK, Hasan MB, Halim ZA, Maroney N, Rashid MM (2022) Exploring the dynamic spillover of cryptocurrency environmental attention across the commodities, green bonds, and environment-related stocks. North Am J Econ Finance 61:101700. https://doi.org/10.1016/j.najef.2022.101700
Huynh TLD, Hille E, Nasir MA (2020) Diversification in the age of the 4th industrial revolution: the role of artificial intelligence, green bonds and cryptocurrencies. Technol Forecast Soc Change 159:120188. https://doi.org/10.1016/j.techfore.2020.120188
Huynh ANQ, Duong D, Burggraf T, Luong HTT, Bui NH (2022) Energy consumption and Bitcoin market. Asia-Pac Financ Mark 29(1):79–93. https://doi.org/10.1007/s10690-021-09338-4
Karim S, Naeem MA (2022) Do global factors drive the interconnectedness among green, Islamic and conventional financial markets? Int J Manag Finance 18(4):639–660. https://doi.org/10.1108/IJMF-09-2021-0407
Karim S, Lucey BM, Naeem MA, Uddin GS (2022) Examining the interrelatedness of NFTs, DeFi tokens and cryptocurrencies. Finance Res Lett 47:102696. https://doi.org/10.1016/j.frl.2022.102696
Kenett DY, Tumminello M, Madi A, Gur-Gershgoren G, Mantegna RN, Ben-Jacob E (2010) Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. PLoS ONE 5(12):1–14. https://doi.org/10.1371/journal.pone.0015032
Kenett DY, Huang X, Vodenska I, Havlin S, Stanley HE (2015) Partial correlation analysis: applications for financial markets. Quant Financ 15(4):569–578. https://doi.org/10.1080/14697688.2014.946660

Khalfaoui R, Mefteh-Wali S, Viviani JL, Jabeur SB, Abedin MZ, Lucey BM (2022) How do climate risk and clean energy spillovers, and uncertainty affect US stock markets? Technol Forecast Soc Change 185:122083. https://doi.org/10.1016/j.techfore.2022.122083
Khurshid A, Khan K, Cifuentes-Faura J, Chen Y (2024) Asymmetric multifractality: comparative efficiency analysis of global technological and renewable energy prices using MFDFA and A-MFDFA approaches. Energy 289:130106. https://doi.org/10.1016/j.energy.2023.130106
Kroner KF, Jahangir S (1993) Time-varying distributions and dynamic hedging with foreign currency futures. J Financ Quant Anal 28(4):535–551
Li Z, Meng Q (2022) Time and frequency connectedness and portfolio diversification between cryptocurrencies and renewable energy stock markets during COVID-19. N Am J Econ Finance 59:101565. https://doi.org/10.1016/j.najef.2021.101565
Lorente DB, Si Mohammed K, Cifuentes-Faura J, Shahzad U (2022) Dynamic connectedness among climate change index green financial assets and renewable energy markets:n evidence from sustainable development perspective Daniel. Renew Energy. https://doi.org/10.1016/j.renene.2022.12.085
Magdalena R, Sharif Karimi M, Si Mohammed K, Dumitru M, Hagiu A (2025a) Pioneering sustainable energy: a dynamic analysis of AI and green patents in renewable and nuclear power. J Appl Econ. https://doi.org/10.1080/15140326.2025.2519068
Magdalena R, Si Mohammed K, Nassani AA, Dascalu N (2025b) Evaluating the environmental effects of Bitcoin mining on energy and water use in the context of energy transition. Sci Rep 15(1):1–12. https://doi.org/10.1038/s41598-025-92314-z
Mnif E, Jarboui A, Mouakhar K (2024) Strategic insights into carbon markets, digital finance and geopolitical risks for advancing green sustainability investments. Manag Environ Qual 35(7):1622–1649. https://doi.org/10.1108/MEQ-10-2023-0369
Mohsin K (2021) Cryptocurrency & its impact on environment. Int J Cryptocurrency Res. https://doi.org/10.2139/ssrn.3846774
Naeem MA, Lucey BM, Karim S, Ghafoor A (2022) Do financial volatilities mitigate the risk of cryptocurrency indexes? Finance Res Lett 50:103206. https://doi.org/10.1016/j.frl.2022.103206
Nasir O, Javed RT, Gupta S, Vinuesa R, Qadir J (2023) Artificial intelligence and sustainable development goals nexus via four vantage points. Technol Soc 72(August 2022):102171. https://doi.org/10.1016/j.techsoc.2022.102171
Pesaran HH, Shin Y (1998) Generalized impulse response analysis in linear multivariate models. Econ Lett 62(1):85–90. https://doi.org/10.1016/s0165-1765(98)00214-6
Porter ME, Reinhardt FL (2007) Grist: a strategic approach to climate. Harv Bus Rev 85(10):21–44
Rao A, Gupta M, Sharma GD, Mahendru M, Agrawal A (2022) Revisiting the financial market interdependence during COVID-19 times: a study of green bonds, cryptocurrency, commodities and other financial markets. Int J Manag Financ 18(4):725–755. https://doi.org/10.1108/IJMF-04-2022-0165
Ratner M, Chiu CCJ (2013) Hedging stock sector risk with credit default swaps. Int Rev Financ Anal 30:18–25. https://doi.org/10.1016/j.irfa.2013.05.001
Rehman MA, Pata UK (2025) Quantile spillover connectedness among $CO_2$ emission sources: an empirical analysis in European Union. Gondwana Res. https://doi.org/10.1016/j.gr.2025.06.021
Rehman MA, Chopra R, Yadav A (2024) Co-moment insights from environmental sustainability with financial markets dynamics. Comput Econ 66(4):2959–2985. https://doi.org/10.1007/s10614-024-10814-y
Ren B, Lucey B (2022) A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies. Energy Econ 109:105951. https://doi.org/10.1016/j.eneco.2022.105951
Rudebusch GD (2021) Climate change is a source of financial risk. FRBSF Econ Lett 3:1–6
Schinckus C, Canh NP, Ling CH (2020) Crypto-currencies trading and energy consumption. Int J Energy Econ Policy 10(3):355–364
Selmi R, Mensi W, Hammoudeh S, Bouoiyour J (2018) Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. Energy Econ 74:787–801. https://doi.org/10.1016/j.eneco.2018.07.007
Shahzad U, Kamel Si Mohammed MSK (2025) Dynamic connectedness between a corporate bond market with WTI, geopolitical and financial volatility: spillover from post-COVID-19 and Russian-Ukrainian clash. Int J Financ Econ. https://doi.org/10.1002/ijfe.70037
Shahzad U, Asl MG, Panait M, Sarker T, Apostu SA (2023) Emerging interaction of artificial intelligence with basic materials and oil & gas companies: a comparative look at the Islamic vs. conventional markets. Resour Policy 80:103197. https://doi.org/10.1016/j.resourpol.2022.103197
Sharma S, Aggarwal V, Dixit N, Yadav MP (2023) Time and frequency connectedness among emerging markets and QGREEN, FinTech and artificial intelligence-based index: lessons from the outbreak of COVID-19. Vision. https://doi.org/10.1177/09722629221141553
Standford University (2023) Artificial Intelligence Index Report Introduction to the AI Index Report 2023. Human-Centered Artificial Intelligence. 1–386
Tiwari AK, Abakah EJA, Le TL, de la Leyva- Hiz DI (2021) Markov-switching dependence between artificial intelligence and carbon price: the role of policy uncertainty in the era of the 4th industrial revolution and the effect of COVID-19 pandemic. Technol Forecast Soc Chang 163:120434. https://doi.org/10.1016/j.techfore.2020.120434
Tu Z, Xue C (2019) Effect of bifurcation on the interaction between Bitcoin and Litecoin. Financ Res Lett. https://doi.org/10.1016/j.frl.2018.12.010
Urom C, Ndubuisi G, Guesmi K, Benkraien R (2022) Quantile co-movement and dependence between energy-focused sectors and artificial intelligence. Technol Forecast Soc Chang 183:121842
Webster C, Ivanov S (2020) Future tourism in a robot-based economy: a perspective article. Tourism Rev 75(1):329–332
Wu M, Wang L, Yang H (2024) Heterogeneity in the volatility spillover of cryptocurrencies and exchanges. Financ Innov 10(1):85. https://doi.org/10.1186/s40854-023-00585-0

Yousaf I, Mohammed KS, Yousaf UB, Serret V (2025) The effect of crypto price fluctuations on crypto mining, and $CO_2$ emissions amid geopolitical risk. Financ Res Lett 72(November 2024):106551. https://doi.org/10.1016/j.frl.2024.106551
Zhang Y, Umair M (2023) Examining the interconnectedness of green finance: an analysis of dynamic spillover effects among green bonds, renewable energy, and carbon markets. Environ Sci Pollut Res 30(31):77605–77621

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