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Dependence of green energy markets on big data and other fourth industrial revolution technologies

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ABSTRACT

This paper analyzes the dependence and connectedness among fourth-industrial revolution technology markets (including big data and artificial intelligence, blockchain, and financial technology) and global and regional (US, Europe, and Asia) green energy markets. In particular, we consider the dynamic dependence among these markets in terms of both returns and volatility across different market conditions and investment horizons using the cross-spectral coherence and Quantile-VAR connectedness approach. Three main results emerge from our analysis. First, the return dependence is relatively stronger than volatility dependence and is stronger across most time scales among the technology markets and the European and Asian regional green energy indexes. Second, the return and volatility connectedness is stronger during extreme than normal market conditions. Unless under bullish market times, volatility connectedness appears smaller than return connectedness, implying that market volatility risks spread less forcefully among these markets than return risks under normal and bearish market periods. Third, geopolitical risks, business environment, economic policy, fixed-income, and oil and gold markets' uncertainties are significant predictors of the degree of return and volatility connectedness. Overall, our findings offer crucial insights for short- and long-term investors interested in portfolios with modern technology and green assets. They also emphasize the roles of market and macroeconomic factors in shock propagation and their implications for low-carbon transition.

1. Introduction

The looming climate crisis has pressured the global economy to transition to a more resilient and sustainable environment. Many studies have noted that climate change-related risks have become a major menace to the world's most crucial support systems (see e.g., Verbruggen, 2008; Enwo-Irem and Urom, 2024). As a result, countries and corporations are increasingly encouraged to minimize environmental degradation and carbon footprints. Attaining this fit requires a mix of instruments, of which financial instruments form an intrinsic part. Mobilizing the huge financial flows necessary to mitigate climate challenges has become the world's main priority (Naeem et al., 2021; Ndubuisi and Owusu, 2022). Over the years, various financial instruments, such as green bonds and green equity, have emerged and grown in scope, size, and prominence. Often called "green" financial instruments,

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they offer investment opportunities to investors and portfolio managers while providing the financial means for entrepreneurs and policymakers to upscale ecologically friendly economic activities (Arif et al., 2022). Akin to this, unlike market-based instruments such as carbon tax, they do not negatively affect the revenues and assets value of corporations, especially those in the hard-to-abate industries, and consequently, the value of the portfolios of investors exposed to them (Monasterolo and Raberto, 2018). Hence, extant studies have argued in favor of green financial instruments as the choice instrument to finance climate change mitigation (Sartzetakis, 2021). These benefits have led to expansive literature on green financial instruments. As investors always desire to combine different classes of assets in their portfolio for diversification and hedging purposes, this literature has, among others, analyzed how green financial instruments relate to other financial instruments or assets.

One of the prominent aspects of the above strand of literature focuses on the nexus between green financial instruments and technology stocks (e.g. Kumar et al., 2012; Sadorsky, 2012; Managi and Okimoto, 2013; Inchauspe et al., 2015; Bondia et al., 2016; Ahmad, 2017; Ferrer et al., 2018; Nasreen et al., 2020; Niu, 2021; Urom et al., 2022a). This literature has examined the market responses and volatility spillovers among green energy and technology stocks. The results from this literature show significant evidence of dependence, causality, and spillovers among these variables, although the strength of the correlation and directional predictability varies across studies. Whereas this literature provides important insights into how green financial instruments and technology stocks are related, the available evidence is largely based on the green equity market and aggregate technology index. Unlike green financial assets, investing in green bonds is a recent phenomenon. However, they have gained significant prominence since its introduction in 2007. Indeed, extant studies consider it a strong financial pillar for attaining the much-required low-carbon future (Monasterolo and Raberto, 2018; Sartzetakis, 2021; Reboredo et al., 2020). Akin to this, the global economy is revolutionized by modern technological advancement, and their applications in industrial processes are significantly reducing carbon footprints.

This paper aims to expand the above literature by jointly considering the returns, volatility dependence, and connectedness between the green bond and green equity markets and different technologies that characterize modern technological advancement. Our analysis pays particular attention to how these markets' dependence structure and connectedness vary across market conditions and investment horizons. As per the investment horizon, such insights are particularly relevant to traders and speculators who are more concerned with short- and intermediate-term investment horizons and institutional investors who are more concerned with long-term investment horizons. To address our research objectives, therefore, we employ both the quantile cross-spectral (QCS) dependence technique proposed by Baruník and Kley (2019) and the quantile-based Vector Auto-Regressive (QVAR) spillover index proposed by Ando et al. (2022). In particular, the QCS technique enables us to explore the structure of dependence among these assets across different market situations and investment horizons, such as the short and long term. As per the QVAR, we employ it to examine how shocks are propagated across these assets under the relevant market situations.

More specifically, this paper contributes to the extant literature in three main ways. First, it focuses on the dependence among the stocks of global green bonds and regional green energy and the fourth industrial revolution technology markets. Indeed, the connectedness between the green bond markets and the green equity market has generated interest among scholars, with studies documenting important differences between these markets (Liu et al., 2021b; Pham, 2021; Ferrer et al., 2021; Chai et al., 2022; Tiwari et al., 2022). For instance, Pham (2021) analyzed the time–frequency connectedness between the green bond and green equity market and found they are only strongly connected during extreme market movements. Ferrer et al. (2021) examine the return and volatility connectedness of green bonds and those of other financial markets. Their results show limited evidence of connectedness between the green bond market and the green energy equity market regardless of the time horizon considered. More recently, Tian et al. (2022) considered the propagation of shocks across the "Carbon-Commodity-Finance" system and found that green bonds are the main receivers of shocks from this system. The preceding suggests that although both markets may have a similar objective in financing climate change mitigation, their respective market fundamentals and market participants' behaviors are likely different. Hence, both markets may react differently to changes in other markets, such as those in the technology that is the focus of this paper. Both markets may react differently to different technology types due to their varying importance to green financing.

Secondly, this paper considers how green bond and green equity markets are related to three technologies vis-à-vis Blockchain, Big Data and Artificial Intelligence, and financial technologies (FinTech) that characterize modern technology advancement. Albeit nascent and often discussed within the broader context of fourth industrial revolution technologies, the hedging and portfolio diversification benefits of these technologies are gaining significant traction (see Huynh et al., 2020; Demiralay et al., 2021; Le et al., 2021a,b; Tiwari et al., 2021). Compared to legacy technologies, these fourth industrial revolution technologies are, in principle, believed to be environmentally friendly either inherently or in their application to daily (non-)economic activities that lower carbon footprints (Song et al., 2017; Dubey et al., 2019; Salam, 2020; Tao et al., 2022; Parmentola et al., 2022). Hence, like green financial instruments, they are pivotal in facilitating the global transition to a low-carbon future. From a business model perspective, therefore, this suggests that the investment opportunities these modern technologies offer may represent better portfolio diversification options for investors and portfolio managers interested in investments that address environmental issues and provide financial returns. Whereas this merits rigorous empirical studies, the few extant studies have focused independently on each technology market and how each relates specifically to the green bond market. For instance, Le et al. (2021a) focused on the nexus between FinTech and the green bond market while focusing on AI, robotics, and the green bond market. The innovation of our study in this regard is that we are the first, to the best of our knowledge, to consider the returns and volatility connectedness of both the green bond and green equity markets to three markets. In this way, our study provides a more comprehensive view of the dependence structure and connectedness among the green financial markets and the technology market of fourth industrial revolution technologies.

Thirdly, this paper uses a comprehensive set of macroeconomic variables to predict both time-varying return and volatility connectedness among three key fourth industrial revolution technology indexes and green market indexes at both global and regional market levels across different market conditions. In addition to macroeconomic indicators, we also show how the COVID-19 pandemic and risks associated with geopolitical risks predict the evolution of return and volatility connectedness among these assets across different market conditions. To our best knowledge, while existing literature explores the risk spillovers between FinTech, green bonds, and cryptocurrencies (Le et al., 2021a), the volatility connectedness among AI and robotics stocks, green bonds, and other assets (Huynh et al., 2020), and the effects of COVID on the interdependence between AI and Robotics stocks and traditional and alternative assets (Demiralay et al., 2021) as well as the effects of EPU, the VIX and the COVID-19 pandemic on the dependence structure between artificial intelligence and carbon prices (Tiwari et al., 2021), our study is the first to provide a comprehensive set of macroeconomic variables to predict both time-varying return and volatility connectedness among three key fourth industrial revolution technology indexes and green market indexes at both global and regional market levels across different market conditions.

As a preview of our main findings, we document significant evidence of market dependence between green financial markets and those of fourth industrial revolution technologies, which varies across market conditions and investment horizons. Both return and volatility dependence among these markets are positive across most market conditions and time scales. It is strongest for the European and Asian regional green energy markets in the medium- and long term. Regarding the results from the QVAR-based connectedness technique, the degrees of return connectedness among these markets are relatively moderate during normal times but stronger during extreme market conditions. Moreover, except for the bullish market condition, the volatility connectedness levels are smaller than return connectedness, implying that market risks and volatility shocks among these markets spread less forcefully than return shocks during normal and bearish market conditions. Lastly, we show that the COVID-19 pandemic, business conditions, and uncertainties in the equity and oil markets positively drive return and volatility connectedness among these markets across all market conditions

The rest of the paper unfolds as follows: The next section presents a review of the related literature. The data and empirical strategy are described in section three. Section four presents and discusses the results of the empirical analysis, while section five presents the study's conclusion.

2. Related literature

Our paper is related to the broad literature on the interdependence and co-movements among different financial assets. Indeed, this literature is humongous, and its exhaustive survey is outside the purview of our study. Within this broad literature, however, our research speaks more directly to a strand of literature that focuses on the dependence structure, co-movements, and connectedness among technology and clean energy stocks. The view held in this literature is that investors may perceive clean energy stocks to be similar to those of technology companies, as the success of clean energy companies depends upon the successful breakthrough or adoption of specific technologies (Bondia et al., 2016). Consequently, the stock prices of technology firms drive those of clean energy firms. Henriques and Sadorsky (2008) are among the earliest studies to examine this relationship. The authors employed a four-variable vector autoregression model to examine the relationship between clean energy stock prices, technology stock prices, oil prices, and interest rates. Their results suggest that technology stock prices and oil prices Granger cause the stock prices of clean energy companies. Simulation results from the study also showed that a shock to technology stock prices has a larger impact on clean energy stock prices than a shock on oil prices.

Following this study, extensive empirical analyses have been conducted using various samples, empirical designs, and econometric techniques to explore the aforementioned relationship. Sadorsky (2012), for instance, utilizes multivariate GARCH models to reveal that clean energy stock prices are more closely linked to technology stock prices than to oil prices. Managi and Okimoto (2013) apply a Markov-switching VAR model and discover that oil and technology stock prices positively influence clean energy stock prices in the period following a structural break, while their findings for the period before the structural break align with those of Henriques and Sadorsky (2008). Inchauspe et al. (2015), using a state–space multifactor model, find that since 2007, the impact of oil prices on clean energy stock returns has increased and that technology stocks have a stronger effect on clean energy stocks than oil prices. Besides, Urom et al. (2022b) analyzed oil prices and sectoral clean energy assets using wavelets, Cross-Quantilogram and Time-Varying Parameter (TVP-VAR) techniques to examine directional predictability from oil price uncertainty to these clean energy sectors across different investment horizons/market conditions and to characterize the level of spillovers among them. The study demonstrates strong evidence of heterogeneous dependence and predictability from oil market uncertainty to clean energy sectors across different market conditions and investment horizons. Also, it shows stronger risk spillovers the intermediate- and long-term.

Additionally, Bondia et al. (2016) determine that while technology stock and oil prices affect clean energy stock prices in the short term, this relationship does not hold in the long term. Ferrer et al. (2018) find evidence of short-term pairwise connectedness between clean energy and technology stock prices. Zhang and Du (2017) examine the dynamic relationships among the stock prices of new energy, high-technology, and fossil fuel companies, finding a stronger correlation between the stock prices of new energy companies and high-technology firms compared to coal and oil stocks. Maghyereh et al. (2019) use wavelet and multivariate GARCH (MGARCH) techniques to identify significant bidirectional return and risk spillovers from oil and technology markets to the clean energy market, with these transmissions being more pronounced over longer time horizons. Nasreen et al. (2020) employ wavelet coherency, phase differences, and spillover analysis to investigate the dynamic connectedness between oil prices and the stock returns of clean energy and technology companies, concluding that technology stock returns are the main source of volatility transmission to both oil and clean energy markets.

Overall, the studies mentioned provide strong evidence of dependence, causality, and spillovers among these variables, although the correlation strength and predictability vary across different studies. However, these studies are limited as they primarily focus on the green equity market and the aggregate technology index. Specifically, green bonds have emerged as a new financial instrument to aid the transition to a low-carbon future. Unlike conventional bonds, green bonds are fixed-income securities designed to finance and refinance projects, assets, or commercial activities that offer both economic and environmental benefits (Liu et al., 2021a). Hence, they offer financial returns alongside contributing to environmental performance by fostering green innovations and long-term green investments (Flammer, 2021). Although the first green bond was launched in 2007 by the European Investment Bank, it has become one of the fastest-growing segments of the international capital markets in the space of a decade (Ferrer et al., 2021). This fast growth was largely orchestrated by the publication of the Green Bond Principles (GBP) by the International Capital Markets Association in 2014. In particular, this document contributed to the liquidity, transparency, and integrity of green bonds as distinct financial assets by establishing standardized rules for labeling bonds as green, which further attracted individuals, institutional investors, and issuers, as well as the subsequent inclusion of green into different stock exchanges around the world (Reboredo, 2018; Reboredo and Ugolini, 2020; Ferrer et al., 2021). The view shared largely among scholars is that the green bond is a strong financial pillar for attaining the much-required low-carbon future (Monasterolo and Raberto, 2018; Sartzetakis, 2021; Reboredo et al., 2020).

Regarding the technology market, the global economy is witnessing an unprecedented rise of new technologies often lumped together under the term fourth industrial revolution technologies. These technologies include blockchain, Internet of Things (IoT), artificial intelligence, big data and cloud computing, advanced robotics, and additive manufacturing (3D printing). Outcomes of these technologies, such as the financial technologies (FinTech) that are currently revolutionizing the financial sector space have also been added to the list by some scholars (see e.g., Le et al., 2021a; Jiao et al., 2021; Elheddad et al., 2021; Abakah et al., 2023; Tiwari et al., 2023; Urom, 2023). For instance, Urom (2023) provides new evidence on the dynamic dependence and connectedness between FinTech investments and green assets across different market conditions and investment horizons using wavelets coherency and quantile-based connectedness methods. It demonstrates that the co-movement between FinTech and green bonds and clean energy stocks is strongest in the long-term and that the level of connectedness is stronger at both tails of return distribution. Moreover, Henriques and Sadorsky (2024) examines the potentials of clean energy stocks in the diversification of FinTech stocks related risks using a Q-VAR technique in the estimation of dynamic return connectedness between these stocks. It documents that connectedness is dynamic and stronger at the tails with FinTech stocks as net transmitters of shocks across clean energy sub-sectors. Similarly, considering an important aspect of FinTech, Dang (2024) explores the lead–lag interactions between major cryptocurrency markets and green bonds using wavelets and spectral Granger-causality tests. The results show strong and dynamic correlations between these markets and the existence of a bi-directional causality between cryptocurrencies prices and green bonds.

In principle, these technologies are believed to be environmentally friendly either inherently or in their application to daily (non-)economic activities that lower carbon footprints (Song et al., 2017; Dubey et al., 2019; Wang et al., 2021; Salam, 2020; Tao et al., 2022; Parmentola et al., 2022). For instance, big data and artificial intelligence are now increasingly applied in the different energy sectors to achieve higher energy efficiency, cost reductions in low-emission energy conversion, and improvements in fossil energy conversion as well as predictive maintenance, among others (Dubey et al., 2019; Wang et al., 2020; Tiwari et al., 2021). Blockchain technologies have also been intrinsic in ensuring transparency and traceability in dirty industries and making supply chains more sustainable (Parmentola et al., 2022). Additive manufacturing has also, among others, contributed significantly to lowering energy consumption and comprising shorter manufacturing processes (Khosravani and Reinicke, 2020). Hence, these technologies have also been considered important in facilitating the global transition to a low-carbon future like green financial instruments. From a business model perspective, therefore, this suggests that the investment opportunities these modern technologies offer may represent better portfolio diversification options for investors and portfolio managers interested in investments that address environmental issues and provide financial returns.

In line with the preceding, this paper relates closely with the evolving literature that focuses particularly on risk spillovers, co-movement, dependence, and diversification opportunities among green bonds and those of technology markets indexes (see, e.g., Huynh et al., 2020; Demiralay et al., 2021; Le et al., 2021a,b). However, we differ from these studies in several ways. First, we analyze the interactions among green equity stocks and the technology market indices in addition to the green bond index. Second, we deviate from the conventional use of aggregate technology index and consider the dependence and connectedness among the green market on three technology market indexes, including big data and artificial intelligence, blockchain technology, and FinTech. Each listed related study focused only on different aspects of the fourth industrial revolution technologies. For instance, Le et al. (2021a,b) focused on the global FinTech index, while Huynh et al. (2020) and Demiralay et al. (2021) are concerned with the role of artificial intelligence and robotics stocks, and green bonds on portfolio diversification. Indeed, these studies are also limited in using only the global green bonds index, such as the S&P Green Bond index, which tracks the performance of global green-labeled bonds. Thus, these studies fail to capture other aspects of the green economy and possible asymmetries in the interactions among them and technology stocks at the regional level. In addition to the global green bonds index, this study includes regional green equity market indexes to capture regional differences in the dependence and risk spillovers among these markets in the presence of technology stocks. Lastly, methodologically, we also differ from these studies in that we are first to employ both the cross-quantile spectra and the QVAR model to analyze the dynamic dependence structure and connectedness among these markets as well as the drivers of this dynamic connectedness, which have not been covered in any existing study.

3. Data and empirical strategy

3.1. Data

Following our research objectives, we use daily equity market indexes that capture the performance of firms whose business models are associated with fourth industrial technologies, including Big data and Artificial Intelligence, Blockchain, and Financial

Table 1
Descriptive statistics.

Variable	Mean	Std. Dev.	Skew.	Ex. Kurt.	J–B	LB-Q(10)	LB-Q^2(10)	ADF
Return								
BDAIR	0.0007	0.0137	−1.0342	10.895	4412.1***	59.170***	513.776***	−18.031***
BLKCHNR	0.0005	0.0125	−1.4443	18.122	12081.4***	66.198***	381.319***	−17.822***
FNTCHR	0.0004	0.0176	−0.72704	8.4865	2659.6***	25.344***	491.516***	−18.454***
SPGBIR	0.0001	0.0031	−1.0928	10.823	4373.7***	59.710***	265.079***	−23.477***
CLNUSR	0.0006	0.0167	−0.53885	10.479	3981.3***	104.640***	788.778***	−20.394***
CLNEUR	0.0005	0.0145	−1.2809	14.721	8009.5***	16.332***	180.140***	−19.299***
CLNASIAR	0.0007	0.0165	−0.34229	4.9456	894.28***	17.061***	143.897***	−18.223***
Volatility								
BDAIV	0.0002	0.0007	10.817	142.79	748231***	513.776***	250.443***	−10.650***
BLKCHNV	0.0002	0.0007	13.386	210.35	161305***	381.319***	171.709***	−11.540***
FNTCHV	0.0003	0.0010	10.351	132.97	649682***	491.516***	278.835***	−10.667***
SPGBIV	0.0000	0.0000	11.996	172.91	109308***	265.079***	164.654***	−21.539***
CLNUSV	0.0003	0.0010	9.9343	120.21	532489***	788.778***	379.676***	−9.6035***
CLNEUV	0.0002	0.0009	17.985	404.11	590484***	180.140***	13.604**	−17.551***
CLNASIAV	0.0003	0.0007	7.2538	75.618	212687***	143.897***	31.084***	−15.360***

** Significance at 5% level.

*** Significance at 1% level.

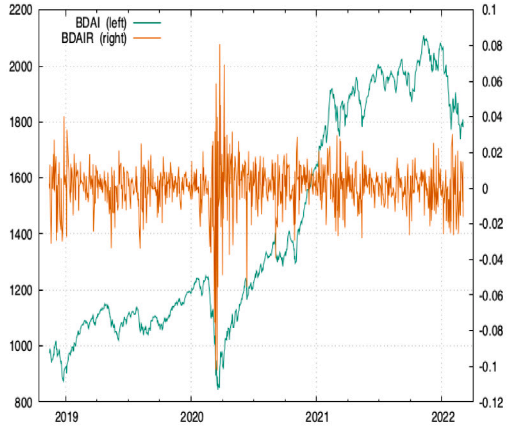
Note: Skew., Ex. Kurt., J–B, LB-Q and ADF denote the Skewness, Kurtosis, Jarque–Bera, Ljung–Box Q and Augmented Dickey–Fuller tests for skewness, normality, autocorrelation and stationarity. "R" and "V" denote return and volatility series, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.

technologies, as well as four green market indexes such as the global green bond index and three regional green market indexes for the period from November 13, 2018, to March 3, 2022. This time is due to the big data and AI index data, which were only available on November 13, 2018. In particular, we use the Nasdaq Yewno Global Big Data and Artificial Intelligence index as a proxy for Big Data and AI (BDAI). This index was created to measure the performance of firms whose businesses involve cybersecurity, deep learning, cloud computing, big data, natural language processing, image recognition, speech recognition, and chatbots. For blockchain technology, we rely on the Indxx Blockchain Index (BLKCHN), which is created to measure the performance of firms that either actively use, invest in, develop, or have products designed to rely on the application of blockchain technology. In contrast, we use Indxx Global Financial technology and Decentralized Finance Index (FNTCH), which captures the performance of companies offering technology-driven financial services while promoting a decentralized finance infrastructure disrupting existing business models in the financial services industry.

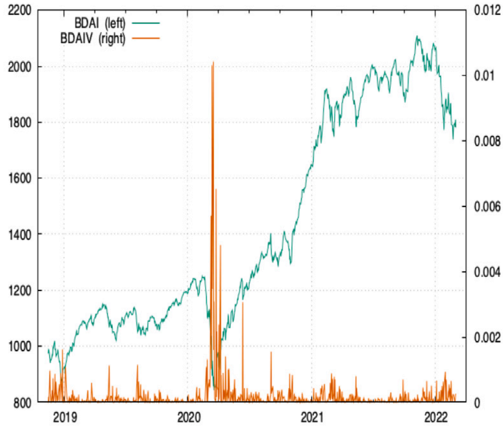
Regarding our measures of global and regional green energy markets, we use the $S\&P$ Green Bond Index (SPGBI), which measures the performance of the global green bond index by maintaining a stringent gauge that includes only green-labeled bonds whose payoff is used to fund environmentally friendly projects. To account for the green energy market at the regional level, we use the NASDAQ OMX Green Economy Index Family, which comprises green energy equity indexes at regional levels. Specifically, for the U.S., Europe, and Asian regional green energy markets, we utilize the NASDAQ OMX Green Economy U.S Index (CLNUS), NASDAQ OMX Green Economy Europe Index (CLNEU), and NASDAQ OMX Green Economy Asia Index (CLNASIA), respectively. These three regional indexes were created to track the market returns of firms within the spectrum of industries whose business models are situated around sustainable development in the U.S., Europe, and Asia. By covering firms from diverse economic sectors, these indexes offer an extensive perspective of the performance of regional green energy markets in the U.S., Europe, and Asia.

In line with our research objectives, all the equity indexes are converted into daily returns using the natural logarithm of daily price changes, that is, $\ln(P_t/P_{t-1})$. We also convert all daily returns to daily volatility by taking the square of the respective daily return series. Therefore, for Big data and AI, BDAIR and BDAIV denote daily return and daily volatility series, respectively. Fig. 1 and Table 1 present the evolution of all daily prices, returns, and volatility series for the variables and their descriptive statistics, respectively. As expected, Fig. 1 shows the clear impact of the COVID-19 pandemic on prices, returns, and volatility levels due to the pandemic-related risks across the global equity market, especially during the first wave of the crisis in 2020. Table 1 shows that among the return series, BDAIR and CLNASIAR jointly possess the highest mean return, while FNTCHV, CLNUSV, and CLNASIAV jointly have the highest mean for the volatility series. Also, Table 1 shows that the highest standard deviation for the return series is attributed to FNTCHR. In contrast, FNTCHV and CLNUSV jointly possess the highest standard deviation among the volatility series. Results of the Skewness (Skew.), Kurtosis (Ex. Kurt.), Jarque–Bera (J–B), Ljung–Box Q (LB-Q), and Augmented Dickey–Fuller (ADF) tests for skewness, normality, autocorrelation, and unit roots are also presented in Table 1. These results show that all return series are negatively skewed while the respective volatility series are positively skewed. Also, it shows the presence of autocorrelation in all series and that the hypothesis of normality and unit roots can be rejected.

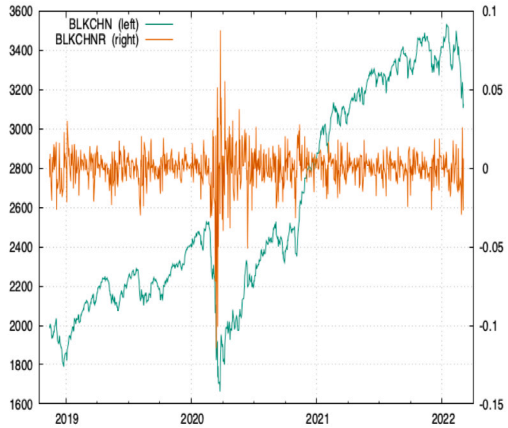
Furthermore, before executing the quantile dependence and connectedness techniques, there is a need to examine if all the variables possess nonlinear features. Table 2 presents the results of the Brock–Dechert–Scheinkman (BDS) test for non-linearity using the VAR model's filtered residuals for all the time series across different dimensions ($i.e.$, $m = 2, 3, \ldots, 6$). As seen in Table 2, the null hypothesis of linearity is rejected for all the variables, indicating that all the variables exhibit nonlinear features. Thus,



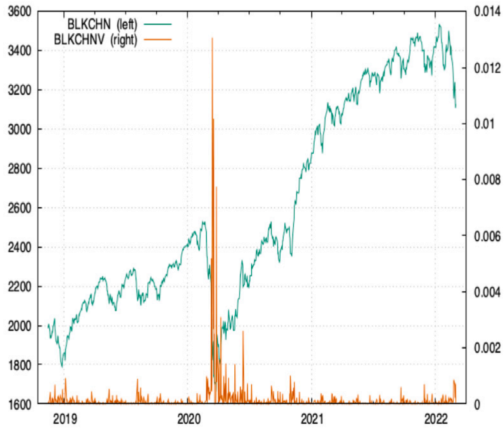
(i) BDAI prices and returns



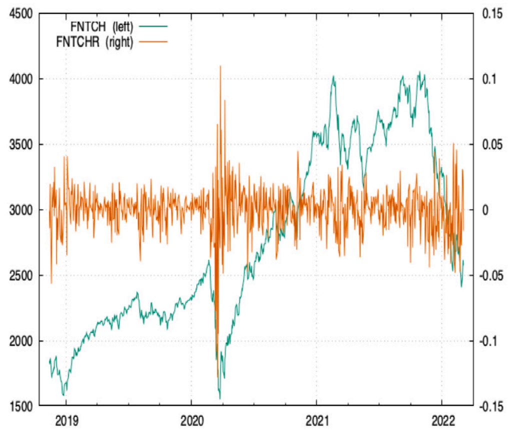
(ii) BDAI prices and volatility



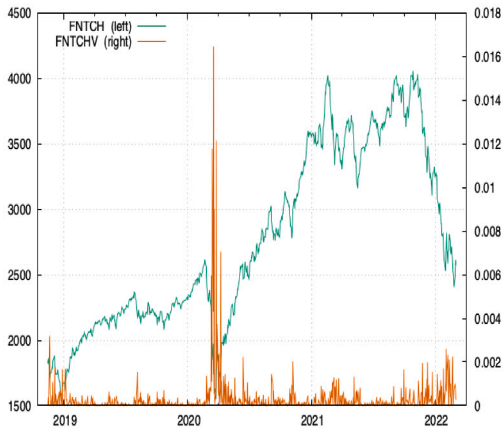
(iii) BLKCHN prices and returns



(iv) BLKCHN prices and volatility

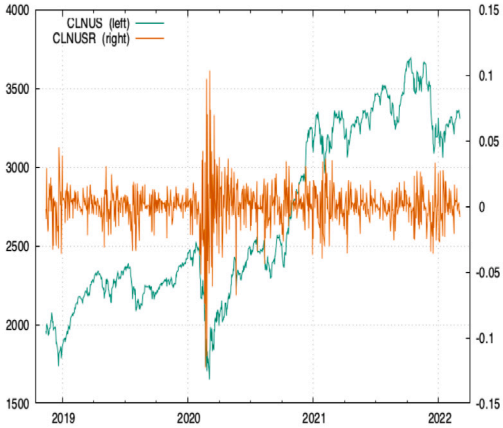


(v) FNTCH prices and returns

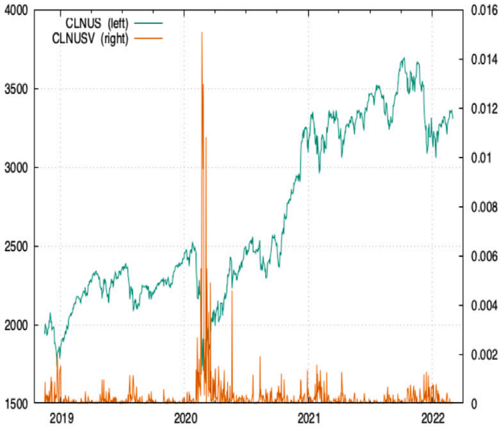


(vi) FNTCH prices and volatility

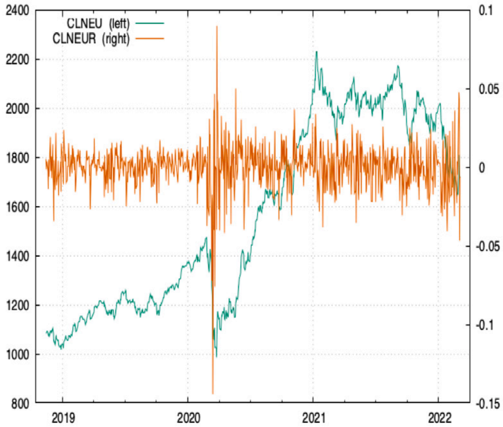
Fig. 1. Plots of prices, returns and volatility series for fourth generation technology and green energy market indexes.
Note: "R" and "V" denote return and volatility series, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



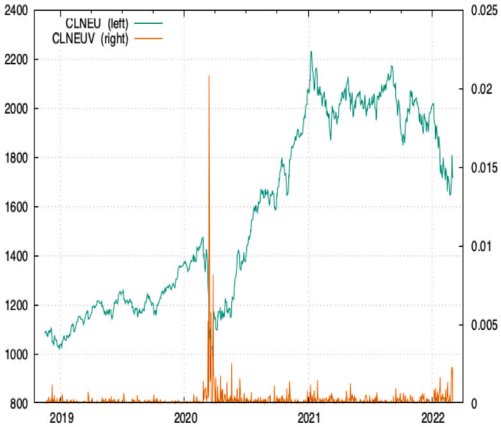
(i) CLNUS prices and returns



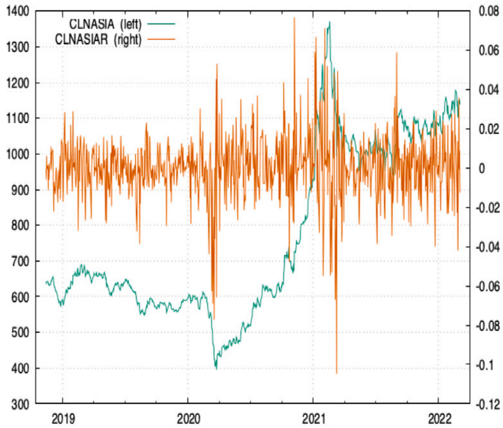
(ii) CLNUS prices and volatility



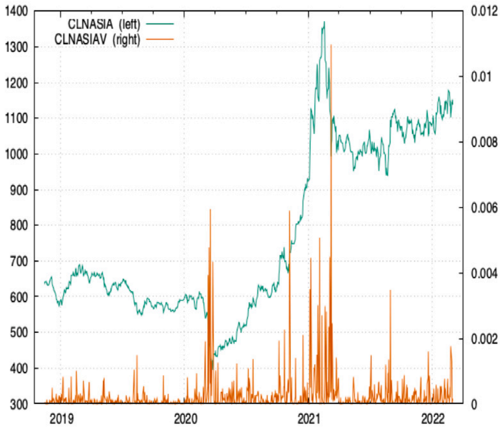
(iii) CLNEU prices and returns



(iv) CLNEU prices and volatility

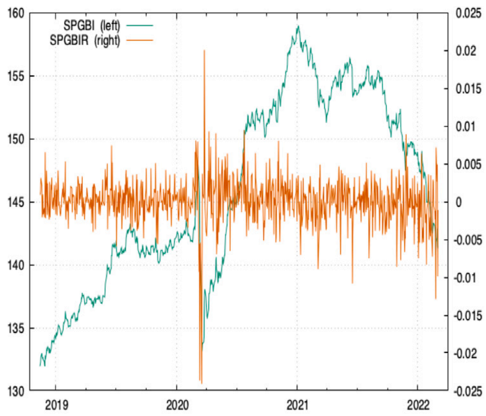


(v) CLNASIA prices and returns

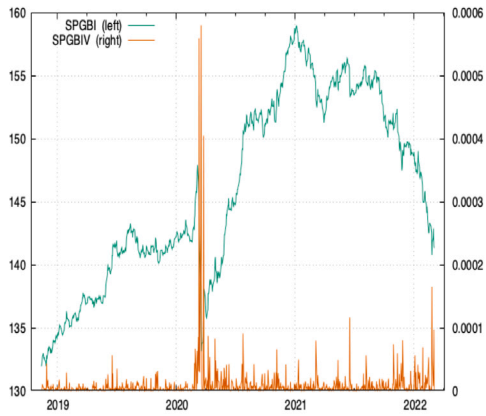


(vi) CLNASIA prices and volatility

Fig. 1. (*continued*).



(vii) SPGBI prices and returns



(viii) SPGBI prices and volatility

Fig. 1. (*continued*).

Table 2
BDS test for non-linearity.

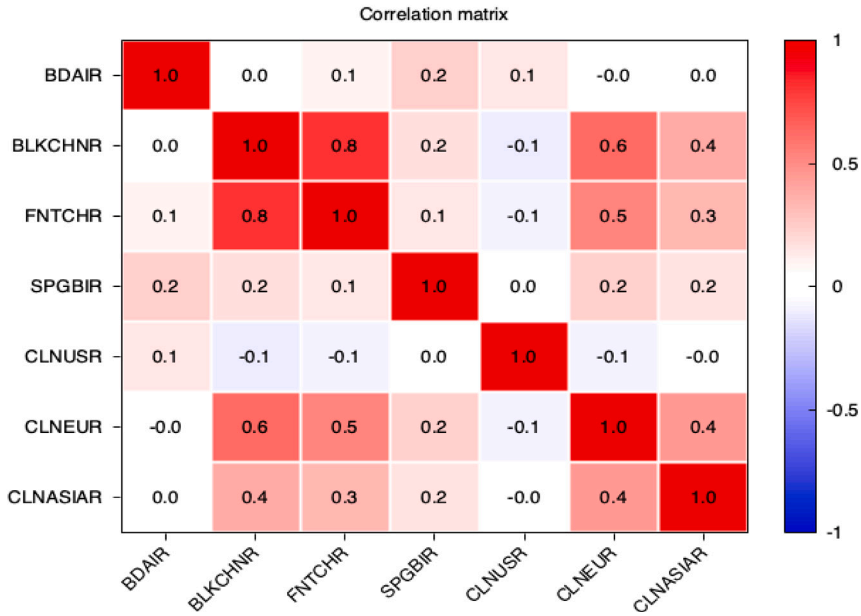
Variable	Dimension				
	m = 2	m = 3	m = 4	m = 5	m = 6
Return					
BDAIR	6.838***	9.335***	11.331***	13.215***	14.571***
BLKCHNR	7.671***	9.741***	11.476***	11.476***	11.476***
FNTCHR	7.394***	10.221***	12.346***	14.395***	15.949***
SPGBIR	3.883***	5.973***	6.805***	7.112***	7.547***
CLNUSR	9.325***	12.425***	13.771***	15.062***	16.585***
CLNEUR	5.937***	7.912***	9.183***	10.445***	11.578***
CLNASIAR	6.558***	7.731***	8.916***	9.846***	10.713***
Volatility					
BDAIV	4.983***	6.528***	7.787***	9.019***	10.017***
BLKCHNV	6.194***	7.168***	8.358***	8.892***	9.413***
FNTCHV	6.051***	8.806***	10.466***	12.077***	13.168***
SPGBIV	3.395***	4.814***	5.3701***	5.315***	5.315***
CLNUSV	6.015***	8.334***	8.983***	9.831***	11.081***
CLNEUV	4.922***	6.486***	7.463***	8.728***	9.772***
CLNASIAV	5.265***	5.912***	7.025***	7.704***	8.348***

*** Significance at 1% level.

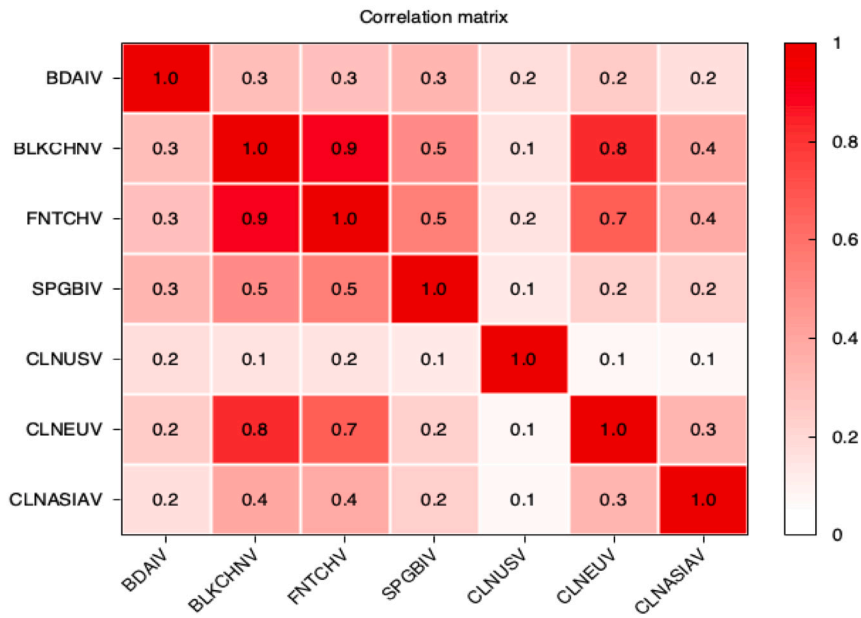
Notes: This table presents the BDS test statistics of Broock et al. (1996) for non-linear independence. The null hypothesis of the BDS test is that the time series is independent and identically distributed (i.i.d.) against an unspecified alternative. "R" and "V" denote return and volatility series, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.

nonlinear models such as quantile-cross spectral and quantile-based connectedness techniques applied in this study are appropriate for examining the dependence between technology stocks and the green market. As a preliminary analysis, Fig. 2 shows the correlation between returns of fourth industrial technologies and green financial markets and the correlation among the volatility of these markets using correlation heat-maps. Fig. 2 Panel A shows that for the return series, the correlation is strongest between FNTCHR and BLKCHNR. ref confirms this fig:corrheatmap Panel B, which shows the highest volatility correlation between FNTCHR and BLKCHNR. Fig. 2 shows that correlations are stronger and generally positive among technology and green energy markets' volatility than among their returns.

Given that, another contribution of our study is to examine how crucial global macroeconomic and geopolitical indicators influence the return and volatility connectedness level among green energy markets and fourth industrial revolution technologies under different market conditions. To achieve this, we use the volatility indexes for equity (VIX), crude oil (OVX), Gold (GVZ), and the Merrill Lynch Option Volatility Estimate (MOVE) to account for the effects of stocks, oil, gold, and the fixed-income markets on both return and volatility connectedness. Furthermore, we include the U.S. Economic Policy Uncertainty index (EPU); Brent crude oil price (Oil); the Aruoba–Diebold–Scotti Business Conditions Index (ADS) of Aruoba et al. (2009); the term spread (Term), which measures the difference between 10 year and 3-month U.S. sovereign bonds maturities; and the Geopolitical Risk Index (GPRI) of Caldara and Matteo (2021) to represent the evolution of global macroeconomic and geopolitical conditions. All the listed variables



(a) Correlation among price returns



(b) Correlation among volatility

Fig. 2. Correlation among price returns and volatility of green energy markets and fourth industrial generation technology.
Note: "R" and "V" denote return and volatility series, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.

were accessed from the database of St. Louis FRED, except the ADS and GPRI, which were taken from the Federal Reserve Bank of Philadelphia database and policyuncertainty.com, respectively. Finally, we account for the potential effects of the COVID-19 pandemic-induced high market volatility on both return and volatility connected, especially during the first wave of the health crisis. To do this, we use a dummy variable with a value of 1 from January 1, 2020, to August 1, 2020, and 0 for other periods.

3.2. Empirical strategy

This subsection introduces the three empirical methodologies we used in this study, which includes the quantile cross-spectral coherency, quantile-VAR-based connectedness and linear regression techniques. We briefly describe the basics of these methodologies in terms of their specific application in this paper as well as their merits and limitations before we proceed to detail their basic equations. First, we use the quantile cross-spectral coherency to examine dynamic dependence across various market states including the bearish, normal and bullish as well as investment horizons such as short-, medium- and long-term. As noted in Baruník and Kley (2019), the main limitation of this technique is that the set of two variables whose degree of coherency is measured must be strictly stationary. So, it fails when both (or any) of the variables are (is) non-stationary. Secondly, we employ the quantile-VAR-based connectedness to examine the levels of risk transmission mechanism for different market conditions for both return and volatility of the chosen assets. Although this recent technique improves on previous measures of risks spillover that implicitly assume that the relationship which prevails at the conditional mean may be generalized to the entire conditional distribution, it is also limited by the strict stationarity condition as in quantile cross-spectral coherency. Lastly, we explore the potential predictive powers of relevant macroeconomic and geopolitical indicators on the dynamic connectedness among these assets within an OLS regression framework. Despite its wide usage, Brossart et al. (2011) argue that the OLS regression approach has important limitations including the potentials of small departures from normality condition, and the presence of outlier data points to produce lower, inaccurate and unstable results, especially in multiple regression frameworks.

3.2.1. Quantile cross-spectral coherency technique

To analyze the dependence structure among the green energy market and the fourth industrial technology markets, we rely on the quantile cross-spectral (coherency) technique proposed by Baruník and Kley (2019). This method permits us to examine the dependence between the variables across different quantiles of the joint distribution and across frequencies. Following Baruník and Kley (2019), assume that $(R_t)_{t\in Z}$ represents a set, comprising two aptly stationary times series, constituted as follow: $R_t = (R_{t,j1}, R_{t,j2})$. The coherence between these two processes across different quantiles, represented by $(R^{j_1 j_2})$ may be written as:

$$\mathfrak{R}^{j_1 j_2}(\omega;\tau_1,\tau_2) := \frac{f^{j_1 j_2}(\omega;\tau_1,\tau_2)}{(f^{j_1 j_1}(\omega;\tau_1,\tau_1)f^{j_2 j_2}(\omega;\tau_2,\tau_2))^{1/2}} \tag{1}$$

where ω denotes the time–frequency relating to $\omega\xi 2\pi 1/5; 1/22; 1/250$ respectively. Basically, the coherency (co-dependence) across these three frequencies is associated with the short- (1 week), the intermediate- (1 month) and the long-term (1 year). Also, π corresponds to the periodic intervals corresponding to $\omega\xi(-\pi < \omega < \pi)$; τ_1 and τ_2 denotes the consecutive τth quantiles of R_{t,j_1} and R_{t,j_2} (i.e., 0.5, 0.05 or 0.95), while $(\tau_1,\tau_2) \in [0,1], f^{j_1 j_2}, f^{j_1 j_1}$ and $f^{j_2 j_2}$ denote the quantile cross-spectral density and the quantile spectral densities of processes R_{t,j_1} and R_{t,j_2}, which are respectively generated from the Fourier transform of the quantile cross-covariance kernels matrix, represented by $\Gamma(\tau_1,\tau_2) := (f\omega;\tau_1\tau_2)_{j_1 j_2}$, where:

$$\gamma^{j_1 j_2} := Cov\left(I\{X_{t+k,j_1} \le q_{j_1(\tau_1)}\}, I\{X_{t+k,j_2} \le q_{j_2(\tau_2)}\}\right) \tag{2}$$

Furthermore, for $j_1, j_2 \in \{1,\dots,d\}, k \in Z, \tau_1, \tau_2 \in [0,1]$ and $I\{A\}$ represent the indicator function of event A. To generate details for serial and cross-sectional dependence, K is varied while $j_1 \neq j_2$ is restricted. The quantile cross-spectral density kernels matrix, $f(\omega;\tau_1,\tau_2) := (f(\omega;\tau_1,\tau_2))_{j_1 j_2}$, is generated from the frequency domain where:

$$f^{j_1 j_2}(\omega;\tau_1,\tau_2) := (2\pi)^{-1}\sum_{k=-\infty}^{\infty}\gamma_k^{j_1,j_2}(\tau_1,\tau_2)e^{-ik\omega} \tag{3}$$

Furthermore, quantile coherency is generated by the smoothed quantile cross-periodogram, defined as:

$$\hat{G}_{n,R}^{j_1,j_2}(\omega;\tau_1,\tau_2) := \frac{2\pi}{n}\sum_{s=1}^{n-1} W_n\left\{\omega - \frac{2\pi s}{n}\right\} I_{n,R}^{j_1,j_2}\left\{\frac{2\pi s}{n},\tau_1,\tau_2\right\} \tag{4}$$

where $I_{n,R}^{j_1,j_2}$ denotes the rank-based copula cross periodograms (CCR-periodograms) matrix while W_n corresponds to a series of weight functions. Thus, the estimator for the quantile coherency may be written as:

$$\mathfrak{R}_{n,R}^{j_1 j_2}(\omega;\tau_1,\tau_2) := \frac{\hat{G}_{n,R}^{j_1,j_2}(\omega;\tau_1,\tau_2)}{\left\{\hat{G}_{n,R}^{j_1,j_1}(\omega;\tau_1,\tau_1)\hat{G}_{n,R}^{j_2,j_2}(\omega;\tau_2,\tau_2)\right\}^{\frac{1}{2}}} \tag{5}$$

Lastly, we explore the coherency matrices for three quantiles such as 0.05, 0.5 and 0.95, which is associated with the lower-, intermediate- and upper-quantiles, respectively, and the combined quantile levels including 0.05|0.05, 0.5|0.5, 0.95|0.95. This enables use to examine dependence under the left, intermediate and right tails of the distributions. Besides, as in Baruník and Kley (2019), the core of the quantile cross-spectral density, $\{f^{j_1 j_2}(\omega;\tau_1,\tau_2)\}$ in Eq. (1) may be dissociated into real and imaginary parts. As in Maghyereh and Abdoh (2020), the real parts presented in this study denote the co-spectrum of the following processes: $(I\{R_{t,j_1} \le q_{j_1}(\tau_1)\})_{t\in Z}$ and $(I\{R_{t,j_2} \le q_{j_2}(\tau_2)\})_{t\in Z}$.

3.2.2. The QVAR-based connectedness analysis

Inspired by the second aim of this paper, we rely on the recently proposed Quantile-VAR connectedness technique of Ando et al. (2022), which improves on the VAR-based spillover approach of Diebold and Yilmaz (2012). The empirical design of this methodology enables us to explore risk spillover mechanism among green energy markets and the chosen fourth industrial revolution technology assets across different return and volatility quantiles. The key primacy of this technique relates to its flexibility that permits us to explore variations in shocks conveyance across various market situations. Empirically, as noted in Abid et al. (2024), this methodology evades the empirical distress associated with random choice of window sizes that are needed to retrieve the dynamic connectedness measures.

The Q-VAR(p) model, which yields all the connectedness estimates may be defined as follows:

$$y_t = \nu(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau) y_{t-j} + \upsilon_t(\tau). \tag{6}$$

where y_t, and y_{t-j} are $m \times 1$ dimensional vectors denoting the returns (volatility) of green energy and fourth industrial revolution technology markets; τ is of range [0, 1], representing the quantile of interest; p is the QVAR model lag length; $\nu(\tau)$ relates to an $m\times 1$ dimensional vector of conditional mean while $\vartheta_j(\tau)$ is an $m \times m$ dimensional matrix of QVAR coefficients. Moreover, $\upsilon_t(\tau)$ denotes an $m \times 1$ dimensional vector of random error terms that corresponds to a $m \times m$ dimensional variance–covariance matrix of $\sum(\tau)$.

The QVAR(p) model defined above may be transformed into a Quantile VAR Moving Average (QVMA)(∞) following the Wold's theorem expressed below:

$$y_t = \nu(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau) y_{t-j} + \upsilon_t(\tau) = \nu(\tau) + \sum_{i=0}^{\infty} \varphi_i(\tau) \upsilon_{t-i}$$

Further, the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD), which may be expressed as the impact that a shock on variable j imposes on another variable i, may be defined as follows:

$$\psi_{ij}^{g}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' \varphi_h(\tau) \Sigma(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i' \varphi_h(\tau) \Sigma(\tau) \varphi_h(\tau)' e_i)} \tag{7}$$

$$\tilde{\psi}_{ij}^{g}(H) = \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij}^{g}(H)}$$

e_i may be normalized into a zero vector with unity on the ith term. This process yields the following equalities: $\sum_{j=1}^{k} \tilde{\psi}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{k} \tilde{\psi}_{ij}^{g}(H) = K$.

Moreover, the total directional connectedness *TO* others, which denotes the overall impact that variable *i* exerts on the remaining variables *j* may be expressed as:

$$C_{i\to j}^{g}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{ji}^{g}(H) \tag{8}$$

Likewise, the total directional connectedness *FROM* others, which captures the total effect on variable *i* from shocking other variables *j* in the system, may be written as:

$$C_{i\leftarrow j}^{g}(H) = \sum_{j=1, i\neq j}^{k} \tilde{\psi}_{ij}^{g}(H) \tag{9}$$

Following this, the net total directional connectedness *NDC* shows the variance of *TO* others and *FROM* others, which is associated with the net effect that variable *i* imposes on the concerned network. This is expressed as:

$$C_i^{g} = C_{i\to j}^{g}(H) - C_{i\leftarrow j}^{g}(H) \tag{10}$$

where $C_i^g > 0; (C_i^g < 0)$ suggests that variable *i* is a net transmitter (receiver) of shocks, showing that it affects other variables more (less) than it is influenced by them.

Finally, the Total Connectedness Index (TCI), which ideally represents the mean share of error variance in one variable's forecast that is associated with all other variables. Expressed differently, this captures the extent that a shock in one variable is caused by all other variables on average. This measure may be interpreted as an indicator of market risk. This is because a higher TCI shows a higher level of network interconnectedness. This may be expressed as:

$$TCI(H) = \frac{\sum_{i,j=1, i\neq j}^{m} \tilde{\psi}_{ij}^{g}(H)}{m} \tag{11}$$

3.2.3. Drivers of return and volatility connectedness

To examine how some crucial macroeconomic indicators drive the degree of total return and volatility connectedness between green energy and fourth industrial revolution technologies markets, we specify the following regression model:

$$TCI_t = \alpha + \gamma X_t + \nu_t \tag{12}$$

TCI_t represents the total Q-VAR return (volatility) connectedness index for the normal, bearish and bullish market conditions estimated in Eq. (11), while X_t represents a set of macroeconomic variables including (i) equity, oil, and gold market volatility captured by the implied volatility indexes (VIX, GVZ and OVX); (ii) Economic Policy Uncertainty (EPU) represented by the U.S. economic policy uncertainty index; (iii) fixed income market uncertainty proxied by the Bank of America Merril Lynch MOVE index; (iv) Brent oil returns (Oil); (v) the term spread between the ten-year and three-month Treasury Bonds (Term); (vi) the ADS business condition index (ADS)); and (vii) geopolitical risk index (GPRI). Lastly, α and γ are the regression coefficients, while ν_t denotes the error term.

4. Results and discussion

This section proceeds in three steps. First, we present and discuss the results from the QCS estimation. Second, we present and discuss the results from the QVAR connectedness approach. The third section does the same for the analysis focusing on the drivers of time-varying quantile connectedness among the green energy markets and the fourth industrial revolution technology markets.

4.1. The dependence structure between fourth industrial revolution technology and green energy markets

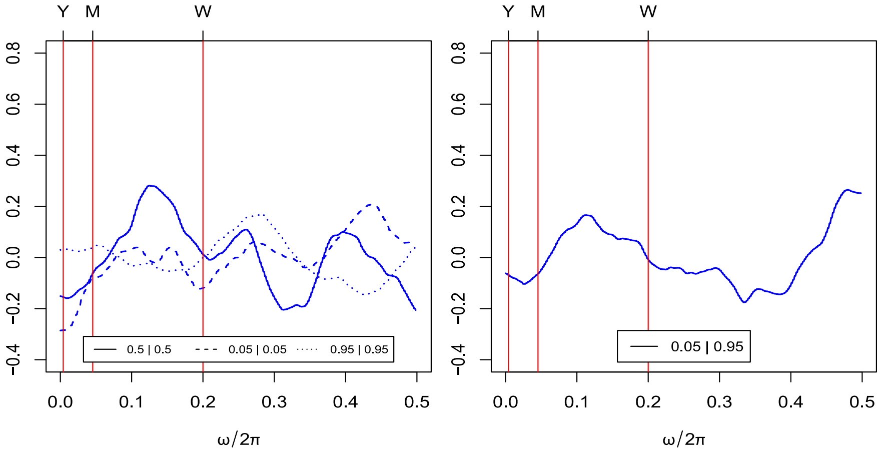
Figs. 3–8 present the estimates of quantile coherency between green energy market indexes and each fourth industrial technology returns and volatility realized from the quantile cross-spectral at the lower, middle, and upper quantiles across three frequencies. In particular, Fig. 3 presents the quantile return coherency between each green energy market indicator with BDAI while Figs. 4 and 5 show the quantile return coherency with BLCHN and FNTECH, respectively. Similarly, Fig. 6 presents the quantile volatility coherency between each green energy market indicator with BDAI while Figs. 7 and 8 show the quantile volatility coherency with BLKCHN and FNTECH, respectively. Following past studies such as Maghyereh and Abdoh (2021) and Maghyereh et al. (2019), the horizontal axis displays the daily cycles over the interval, while the measures of co-dependence of green energy market indexes and each fourth industrial technology returns and volatility are presented in the vertical axis. The weekly (W), monthly (M), and yearly (Y) frequency cycles in the upper label of the horizontal axis show how each pair of the time series is dependent under the short-, medium- and long-term, respectively, across the combinations of quantile levels such as 0.05|0.05 (bear market), 0.5|0.5 (normal market) and 0.95|0.95 (bull market) in the graphs on the left. In addition, we consider a combination of extreme quantile levels (0.05|0.95), which enables us to explore the dependence between the lower quantile of each fourth industrial technologies index and the upper quantile of each green energy market index, as shown in the right figures.

4.1.1. Fourth industrial revolution technology and green energy markets: Return dependence

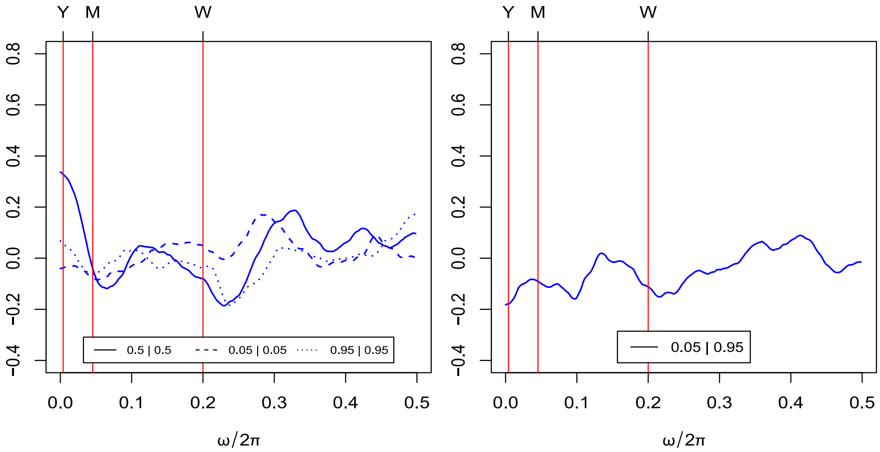
As may be seen in Fig. 3 Panel a–d, results show that return dependence between green energy market indexes and BDAI is positive and strongest for regional green energy market indexes for Europe and Asia in the medium- and long-term, especially in the long-term for Europe during the bearish market condition. However, dependence is mostly negative in the short term, irrespective of market conditions for the European and Asian green energy markets. For the global green bond (SPGBI) and U.S. green energy markets, dependence is mixed for all time scales and market conditions. For instance, when the market condition is bullish or normal in the long term, dependence is positive for the U.S. green energy market. At the same time, it is negative during normal and bearish markets for the global green bond market. Across both medium- and short-term, dependence is mixed but strengthens mainly during normal market periods, especially for SPGBI. The results of dependence on BDAI emphasize that if the bearish market condition persists in the long term, dependence is positive between BDAI and regional green energy markets, especially the European and Asian green energy markets. However, the dependence between BDAI and SPGBI is negative under this market condition and time scale.

Regarding dependence from the combination of extreme quantile levels (0.05|0.95) as displayed by graphs on the right, results show some interesting patterns. First, we find that for SPGBI, dependence is mostly negative both in the short-term and as the time–frequency increases towards the long-term, while for the U.S and Asian regional green energy markets, dependence is mostly negative across all the investment horizons, except in the U.S market, where dependence is mixed in the short-term. Similarly, for the European regional green energy market, dependence is mostly positive in the short term with brief periods of negative dependence but positive across the medium- and long term. These results suggest that except for medium- and long-term dependence across extreme quantiles for the European green energy market, the dependence between extreme quantiles of BDAI and the remaining green energy market indexes is mostly negative across the various investment horizons considered in this study. According to Maghyereh and Abdoh (2020), extreme events in the BDAI market may have the opposite effect on extreme events in the green energy market.

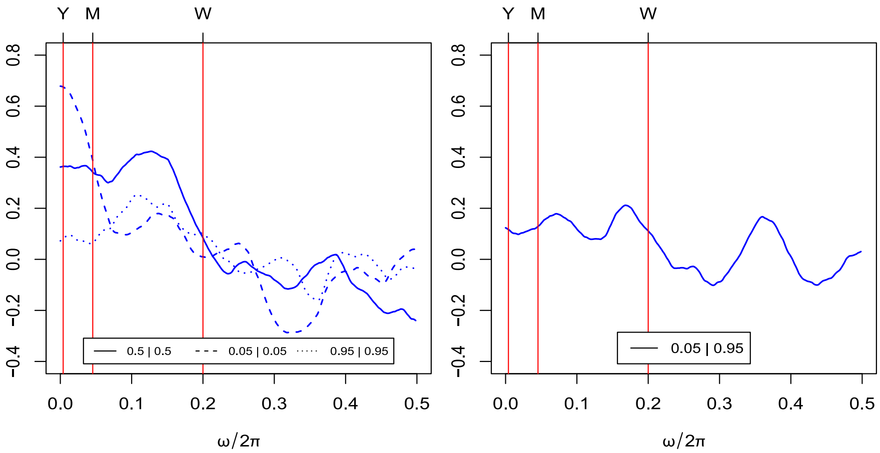
As shown in Fig. 4 Panel a–d, similar results may be drawn regarding the dependence between green energy market indexes and Blockchain technology (BLKCHN) across quantiles and investment horizons. For instance, for regional green energy markets in Europe and Asia, dependence is positive across the short-, medium- and long-term under all three market conditions, especially under the market period for the European regional green energy market. Results are mixed for SPGBI and the U.S. regional green energy market. For SPGBI, dependence under the bullish market condition is consistently low relative to the levels of dependence under both normal and bearish market periods across all time scales. In the short term, the dependence is mostly positive for all bearish and normal market conditions, with notable periods during which it switched to negative. However, dependence under bearish market conditions is negative, persisting through the medium term to become stronger in the long term, while under normal market conditions, dependence is positive and stronger in the medium term but decreases towards the long term. For the U.S. regional green



(a)BDAI vs SPGBI returns

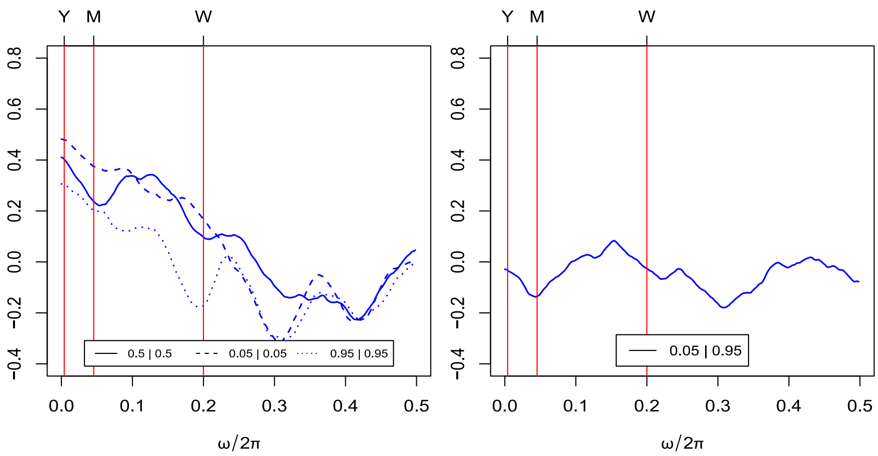


(b)BDAI vs CLNUS returns



(c)BDAI vs CLNEU returns

Fig. 3. Quantile coherency between BDAI and green energy returns. Estimates are for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution. Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The —— , - - - and ...... line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



(d)BDAI vs CLNASIA returns

Fig. 3. (*continued*).

energy market, the direction of dependence with BLKCHN is mostly negative in the short-run for all market conditions, except for a notable period of positive dependence under a bullish market state.

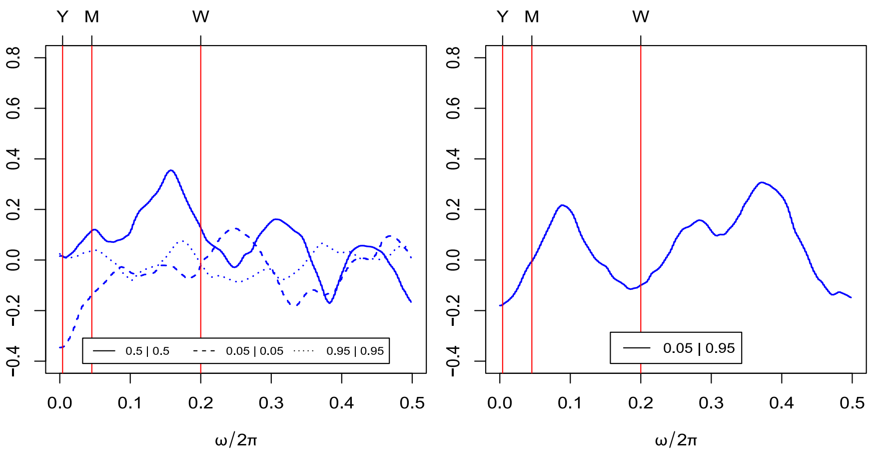
However, dependence is mainly negative in the medium- and long-term but under normal and bullish market states, it becomes positive in the long-term, especially for the normal market condition. Intuitively, positive dependence indicates that a positive (negative) event may follow a positive (negative) event in the BLKCHN market in the respective green energy market. Meanwhile, results from the combination of extreme quantile levels (0.05|0.95) of the joint distributions shown in the graphs on the right suggest that in the short term, dependence is mostly positive and stronger for SPGBI and the Asian regional green energy market. Although dependence is also positive for the European and U.S. markets, it is relatively small, especially for the U.S. green energy market. For European and Asian regional markets, dependence is mostly positive in both medium- and long-term, especially for the European market. Regarding the SPGBI, although dependence changes from negative to positive before the end of the medium term, it becomes negative and relatively stronger in the long term. In contrast, for the U.S. regional green energy market, dependence becomes negative towards the end of the medium-term until the long-term, during which it becomes positive.

Further, Fig. 5 Panel a–d shows the dependence between green energy markets and financial technology (FNTCH) across market conditions and investment horizons. Here, results show that the dependence between FNTCH and European and Asian regional green energy markets is positive across all the frequencies, becoming stronger when market conditions are bearish, especially for Europe. For SPGBI, dependence across all market conditions is mainly positive but with a short-lived period of negative dependence under normal and bearish market states. However, dependence across all market conditions is positive during the medium term. At the same time, it becomes relatively weak, except under normal market conditions, where it becomes negative and relatively stronger in the long term. These suggest long-term diversification benefits for a portfolio with these assets. Regarding SPGBI, dependence is mostly positive in the short- and medium-term for most market conditions. At the same time, in the long-term, it is negative and stronger under normal market conditions but relatively low and negative (positive) under bullish (bearish) market conditions.

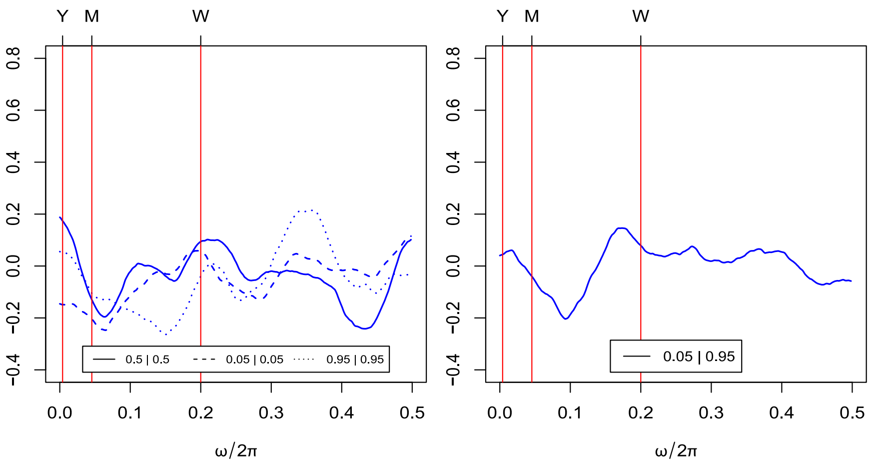
Regarding the U.S. regional green energy market, the direction of dependence under bearish market conditions is mixed. It is relatively weak in the short- and medium-term but becomes positive and relatively strong in the long term. Similarly, dependence under bullish and bearish market conditions is mixed across the short- and medium-term. In the long term, dependence becomes positive for the bullish market but negative for the bearish market states. As shown in the graphs on the right, the dependence between extreme quantiles of FNTCH and the three regional green energy markets is mostly positive in the short term. At the same time, it is dominantly negative for the SPGBI market. Similarly, dependence is generally positive across the markets considered in the medium term. However, although dependence remains positive long-term for both SPGBI and the European regional market, it becomes negative long-term, especially for the Asian regional green energy market. As noted earlier, negative dependence suggests that an opposite event may follow a negative event for the FNTCH market in the concerned green energy market.

4.1.2. Fourth industrial revolution technology and green energy markets: Volatility dependence

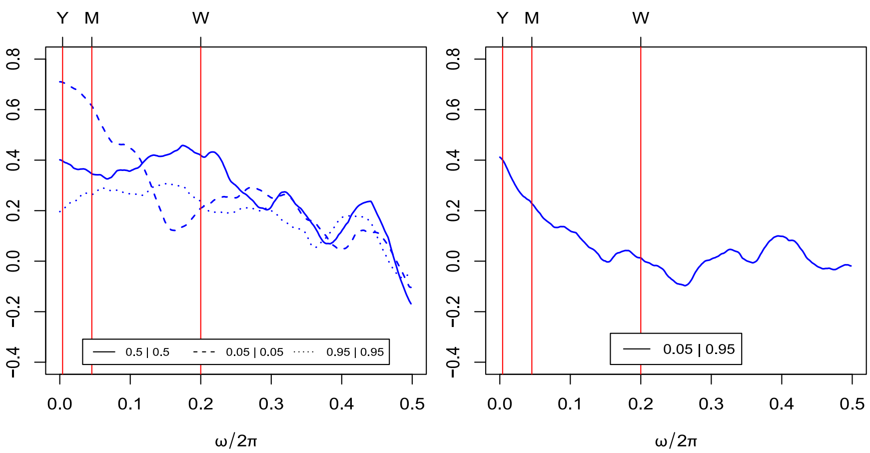
Fig. 6 presents the quantile volatility coherency between each green energy market indicator with BDAI while Figs. 7 and 8 shows the quantile volatility coherency with BLCHN and FINTECH, respectively. Similar to returns dependence between BDAI and fourth industrial technology markets, Fig. 6 Panel a–d indicates that the dependence between BDAI and fourth industrial technology volatility is strongest for the BDAI and Asian green energy market in the long-term when the market condition is bullish. This is closely followed by the volatility dependence between BDAI and the European green energy market in the long term when market conditions are bearish. In both cases, however, volatility dependence is mainly positive across all market conditions in the medium-term but negative in the short term. These results indicate that a decrease may follow an increase in the volatility of BDAI in the



(a)BLKCHN vs SPGBI returns



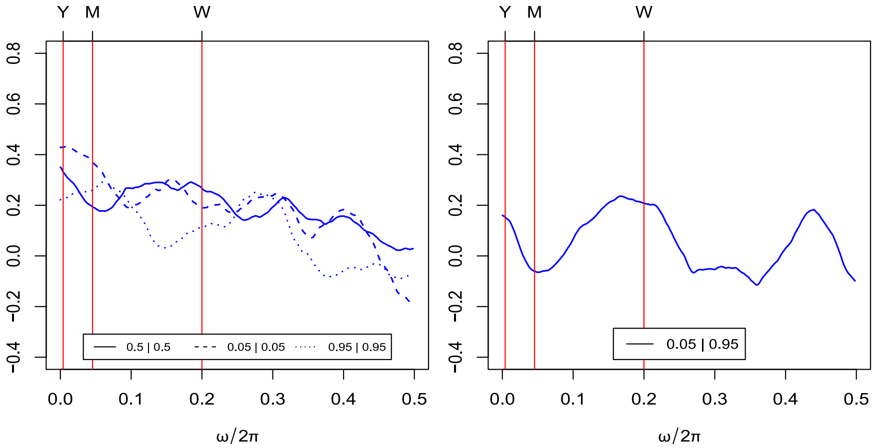
(b)BLKCHN vs CLNUS returns



(c)BLKCHN vs CLNEU returns

Fig. 4. Quantile coherency between BLKCHN and green energy returns. Estimates are for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution.

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ——, - - - and ...... line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



(d)BLKCHN vs CLNASIA returns

Fig. 4. (*continued*).

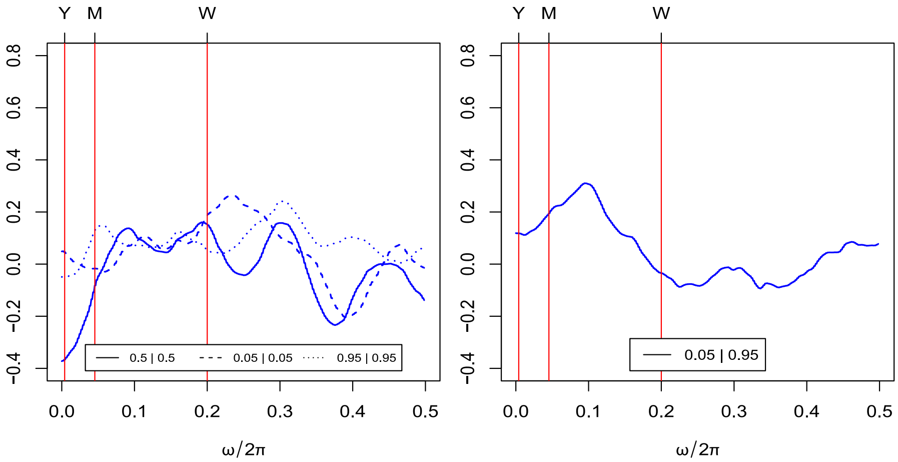
volatility of European and Asian green energy markets in the short term, while in the long term, an increase in the volatility of BDAI may trigger an increase in the volatility of both European and Asian green energy markets.

Similar patterns of volatility dependence may be seen in the case of BDAI and the global green bond market (SPGBI), but on a lower scale. However, for the BDAI and the U.S. green energy market, across all time scales, volatility dependence is negative during the bearish market; it is positive under other market conditions but relatively lower than in other regional green energy markets. Regarding dependence from the combination of extreme volatility quantiles, as shown by the graphs on the right, results show that across all the green energy markets, extreme volatility dependence is negative in the long term. However, it is positive in the medium term for European and Asian markets and negative for the U.S. green energy market. In the medium term, dependence is positive but becomes negative in the long term. Besides, in the short-term, extreme volatility dependence is negative for all markets but changes to positive as the frequency scale is increased towards the medium term, except for the U.S. green energy market. In contrast, extreme volatility dependence is positive for the U.S. green energy market at the start of the short term. However, it becomes negative as the frequency scales are increased towards the medium- and long-term.

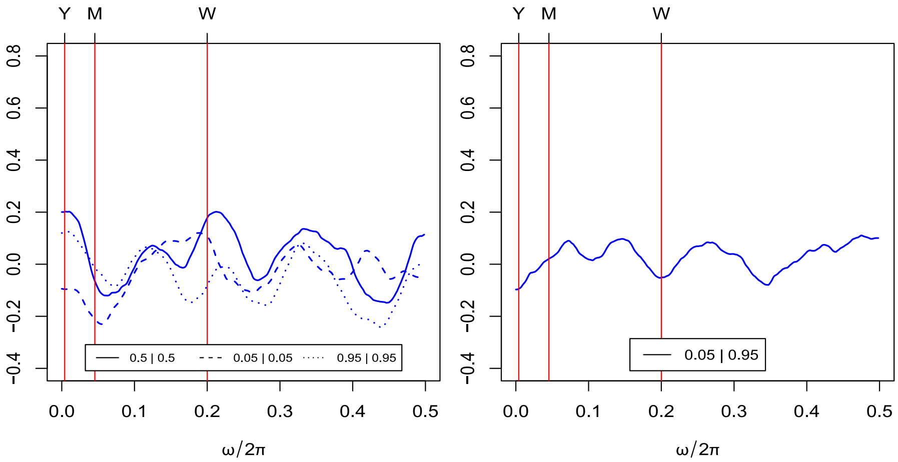
Fig. 7 Panel a–d presents the quantile volatility coherency between BLKCHN and each green energy market, demonstrating interesting patterns. First, contrary to the decreasing levels of return dependence between BLKCHN and SPGBI towards the long-term, it shows that volatility dependence increases sharply under all market conditions as the time–frequency scale increases towards the medium- and long-term, especially under the normal market periods. A similar pattern may also be observed in the volatility dependence between BLKCHN and the European and Asian green energy markets across the three market conditions and time scales, except for the Asian green energy market where dependence under a bearish market period is negative and weak, especially in the medium-term. For the U.S. green energy market, volatility dependence with BLKCHN is generally weak across all time scales and market conditions, except under normal market periods, during which dependence is positive and relatively strong as the time frequency is increased to the long term. Considering the combination of extreme volatility quantiles, results are relatively similar across all green energy markets, time scales, and market conditions. In particular, volatility dependence is relatively weak and negative across both short- and medium-terms but strengthens long-term, especially for European and Asian green energy markets. There are, however, periods of strong negative volatility dependence between the global green bond and Asian green energy markets.

As can be seen in Fig. 8 Panel a–d, when compared to return dependence, volatility dependence between FNTCH and the global green bond market is relatively weak in the short-term but stronger as the time–frequency is increased to the medium-term under all market conditions. However, in the long term, volatility dependence under both tails of the volatility distribution becomes stronger, but under normal market conditions, it becomes weaker. Relative to return dependence, similar levels of moderate dependence between FNTCH and the U.S. green energy market under all market conditions can be seen in the medium term, while for the European and Asian markets, results show stronger short-term volatility dependence. While a similar degree of volatility dependence can be seen across all market conditions in the medium term among FNTCH and the European and Asian markets, volatility dependence is slightly weaker than return dependence, especially under bullish market conditions. In particular, for the Asian green energy market, volatility dependence under bullish market conditions dominates dependence under other market conditions across all frequency scales. In contrast, this phenomenon is noticeable only in the short term for the European market as volatility dependence under bearish market conditions dominates in the long term.

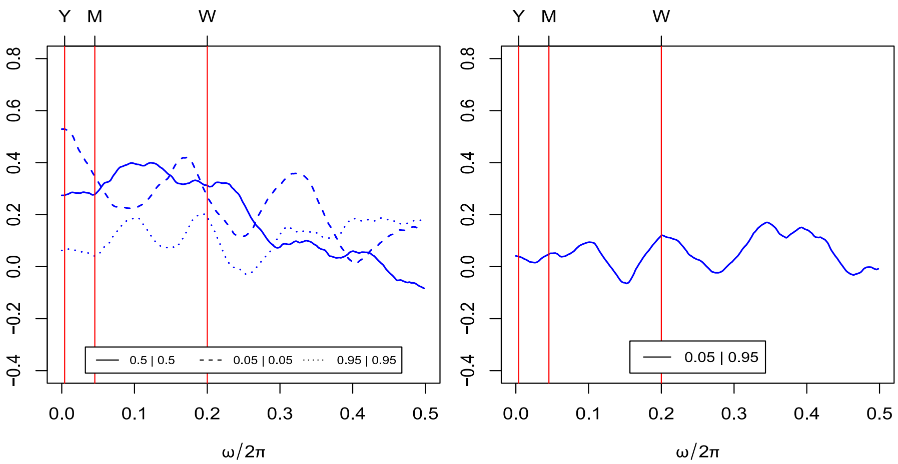
Lastly, the combination of extreme volatility quantiles of FNTCH and green energy market indexes shown in graphs on the right demonstrates that for all time scales, extreme volatility dependence is mainly negative for the FNTCH and Asian green energy market pair. For the European market, it is mainly positive in the short- and medium-term but becomes negative and stronger as the time scale increases towards the long-term. The extreme volatility quantile dependence between FNTCH and the global green bond market is stronger but changes from negative to positive as the time scales increase towards the medium term. While this dependence



(a)FNTCH vs SPGBI returns

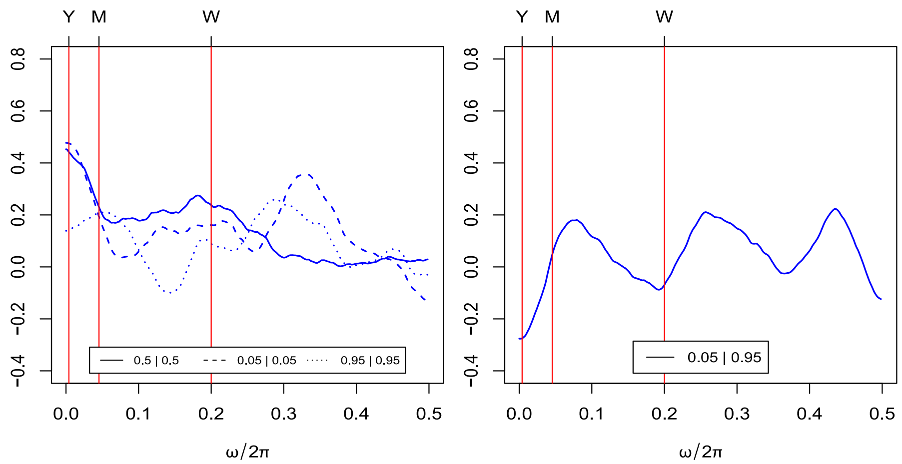


(b)FNTCH vs CLNUS returns



(c)FNTCH vs CLNEU returns

Fig. 5. Quantile coherency between FNTCH and green energy returns. Estimates are for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution. Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The —— , - - - and ...... line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



(d)FNTCH vs CLNASIA returns

Fig. 5. (*continued*).

remains positive throughout the medium term, it becomes very weak in the long term, indicating that Financial technology exhibits a very low degree of volatility dependence on the global green bond market at the extreme quantiles. Lastly, the dependence between extreme volatility quantiles between FNTCH and the U.S. green energy market is mainly negative in the short- and long term-but positive in the medium. Across all time scales, extreme volatility quantile dependence between FNTCH and the U.S. green energy market is relatively stronger than their extreme return volatility dependence.

4.2. Connectedness among fourth industrial revolution technology and green energy markets

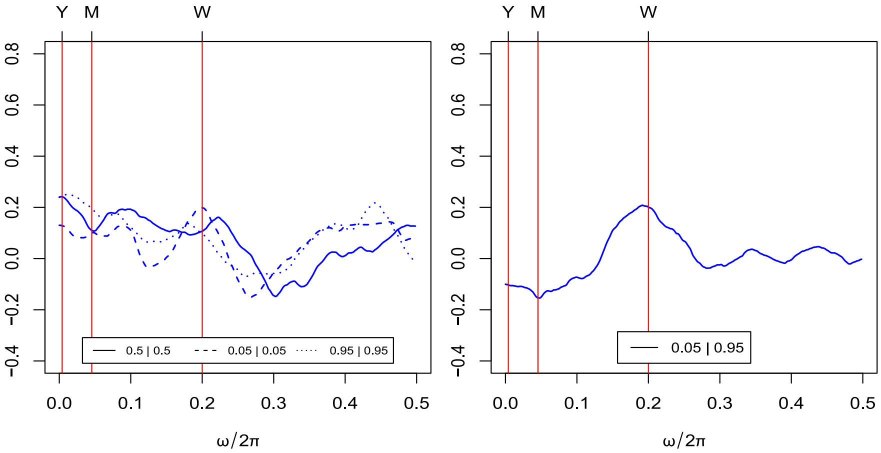
Tables 3 and 4 present the results on the degree of connectedness among the green financial and technology markets. In particular, Table 3 reports the return connectedness among these markets, while Table 4 reports their volatility connectedness. Each table reports the degree of connectedness among the green financial and technology markets under three market conditions vis-à-vis the normal, bearish, and bullish market conditions corresponding to 0.5, 0.05, and 0.95 quantiles of the return distribution, respectively.

4.2.1. Fourth industrial revolution technology and green energy markets: Return connectedness

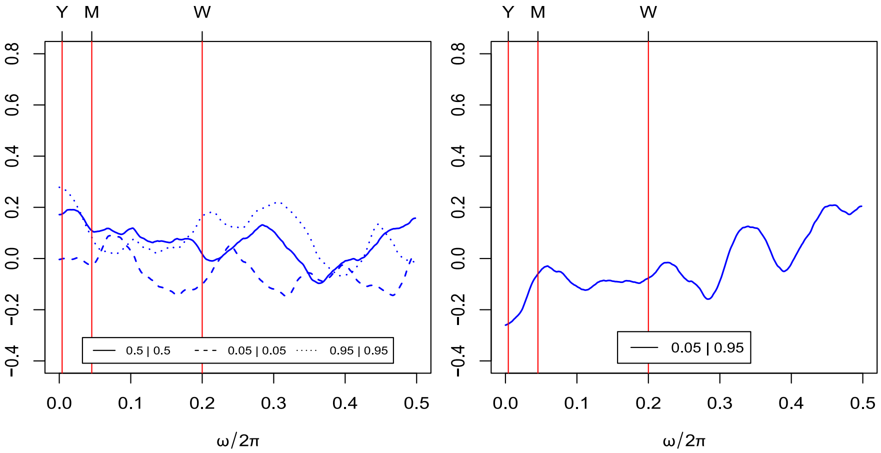
As shown in Table 3, the total connectedness index (TCI) among the variables during the normal period is approximately 40.1%, and 89%, and 88% during the bearish and bullish periods, respectively. The TCI illustrates how much a shock or market risk in one variable influences all other variables in the system, on average. Hence, the obtained TCI values indicate that the return connectedness between the green financial market and the technology market is relatively moderate during normal times but stronger during extreme market conditions, especially when the market is bearish. The result is in line with previous studies that show higher connectedness among financial markets during extreme market conditions (e.g., Pham, 2021; Liu et al., 2021a), especially during bearish market states.

For each market, the net directional connectedness (NDC) measures the difference between how much of a shock it spilled over to all other markets and how much of a shock in all other markets is spilled over to that specific market. Hence, it illustrates the power of each market as it demonstrates which markets are increasingly contributing to the market interconnectedness and which are contributing less. Evidence from Table 3 shows that during normal market conditions, the returns on BDAIV (66.4%) and SPGBIV (11.2%) are the net shock transmitters, suggesting that they are driving the market risks during this period, and hence influence others more than others are influencing them. The returns on BLKCHNV, FNTCHV, CLNUSV, CLNEUV, and CLNASIAV, on the other hand, are net shock receivers, implying that they are driven by the market risks with FNTCHV (−28.4%) and BLKCHNV (−16.9%) being the top in that list. When we consider the two extreme conditions, some notable differences occur. In particular, we observe that while the returns on BDAIV (BLKCHNV, FNTCHV, CLNUSV, and CLNASIAV) remain net shock transmitters (receivers) during bearish and bullish market conditions, the returns on SPGBIV become a net shock receiver during both extreme market conditions. On the other hand, the returns on CLNEUV become a net transmitter during both extreme conditions. Besides these, the results also indicate that the return spillovers received from or contributed to the system are significantly higher during extreme market conditions compared to the normal period for each market.

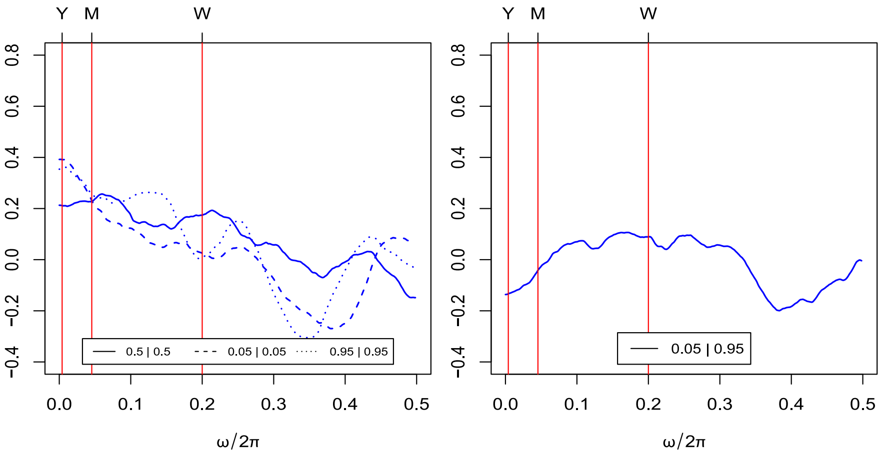
Regarding the pairwise directional connectedness (which shows the bilateral connectedness among the markets), the results show a low pairwise spillover among the markets during the normal market conditions, with the variance of each market return being mainly driven by their own shocks. However, during extreme market conditions, the pairwise spillovers among the respective markets become stronger than in the normal period. Moreover, the magnitude of own shock spillovers in each market is smaller



(a)BDAI vs SPGBI volatility



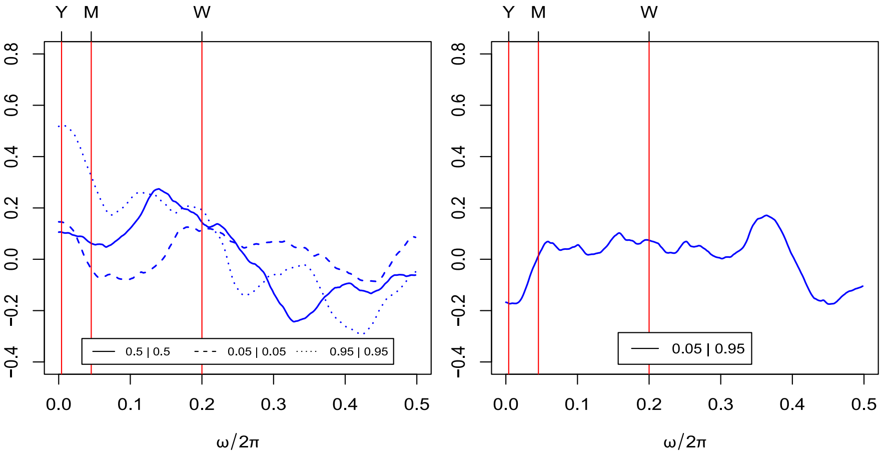
(b)BDAI vs CLNUS volatility



(c)BDAI vs CLNEU volatility

Fig. 6. Quantile coherency between BDAI and green energy market volatility. Estimates are for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution.

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The , and line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



(d)BDAI vs CLNASIA volatility

Fig. 6. (*continued*).

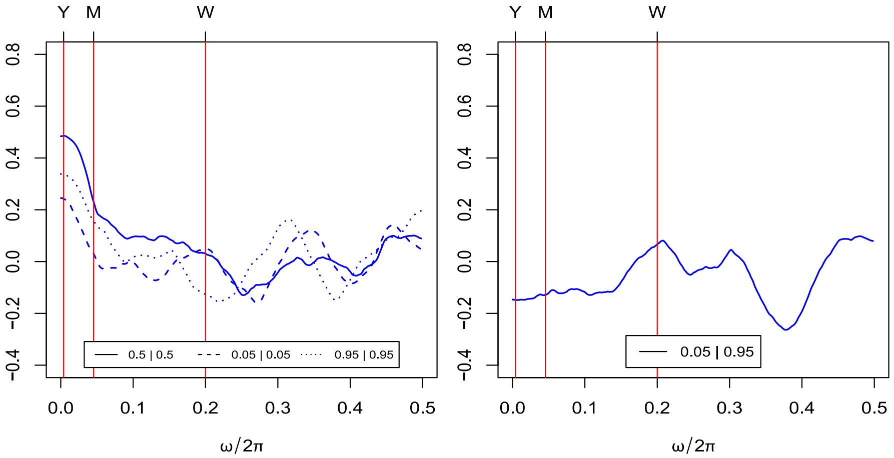
during these periods compared to their initial value during the normal period. They are also lesser than the TCI value, implying these markets' susceptibility to shocks from other markets during extreme market conditions. As Londono (2019) rightly noted, these extreme shocks result from the arrival of unexpected good or bad news, described as beneficial or adverse shocks in the market. Following Diebold and Yilmaz (2014), Fig. 10a–c plot the net pairwise directional connectedness among the markets under study. Blue nodes in the figures illustrate the net transmitters of risks, while yellow nodes illustrate net receivers. The sizes of the nodes represent weighted average net total directional connectedness. Hence, depending on whether a market is a net transmitter or net receiver of risks, the sizes of the node rank the net directional connectedness, with larger nodes being markets with stronger net directional connectedness. As expected, Fig. 10 re-emphasizes that the BDAIR market is the main net shock transmitter across the three market states. Other technology markets, including FNTCHR and BLKCHR, both receive significant shocks from BDAIR during these periods, although the spillover shock receipt by FNTCHR during the bull period is somewhat smaller. As per the green financial markets, the highest shock receipts from the technology markets across the market conditions are from BDAIR and mostly to CLNEUR and CLNASIAR. Whereas CLNUSR only shows evidence of minute connectedness from BDAIR during the bullish state, we find little or no shock receipt or transmission between SPGBIR and either of the technology markets across the market conditions.

Thus far, our discussions have focused on average connectedness among the markets. In reality, however, this relationship may be time-varying due to, among others, economic, political, and social factors. To this end, Fig. 9 displays the dynamic TCI of the three market conditions over our sampling period. Consistent with the average TCI presented in Table 3, the time-varying TCIs of the normal periods lie below those of the bearish and bullish market states. Nevertheless, evidence from the figure indicates time-varying characteristics of the TCI over the sample period, especially during normal periods. For the normal TCI, observable improvements in TCI from September 2019 were short-lived by early January 2020, probably due to the COVID-19 outbreak. While the TCI increased somewhat afterward, it plummeted significantly towards the end of the third quarter of 2020 and until the beginning of the first quarter of 2021. Since then, it has been unable to sustain any improvement levels that put it at par with its pre-pandemic levels. The patterns of TCI of bullish and bearish market states mirror those of the normal market state, although they remain significantly higher during this period.

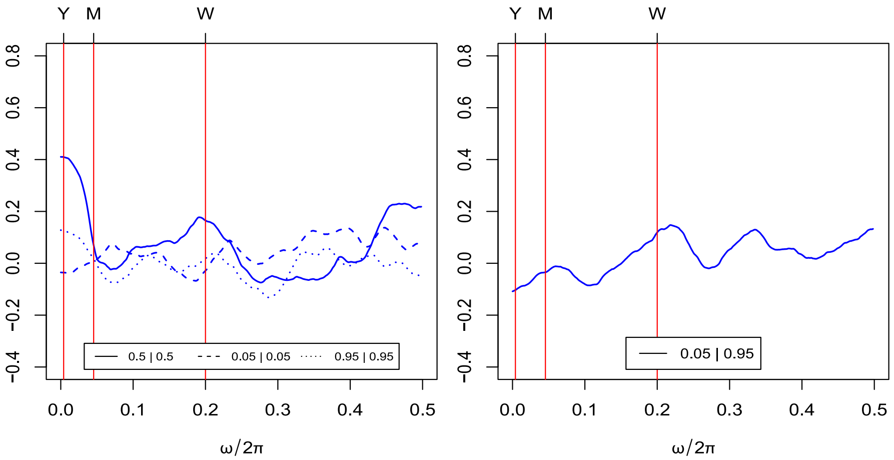
4.2.2. Fourth industrial revolution technology and green energy markets: Volatility connectedness

Table 4 shows the volatility connectedness among the green financial and technology markets. The TCI during the normal market condition is approximately 38.3%, and 46.3% and 84.3% during the bearish and bullish periods, respectively. This result confirms initial findings from the analysis on return connectedness, suggesting that the green financial and technology markets are more connected during bearish and bullish market states than during the normal period. However, the TCI under the different market conditions for the volatility connectedness is lower than their corresponding values for the return connectedness, implying that the return connectedness among these markets is stronger than their volatility connectedness. That is, the return shocks among these markets spread more vigorously than their volatility shocks. This is more pronounced under normal and bearish market conditions where the figures in the diagonal cells representing the magnitude of own volatility shock spillovers are hardly lower than the value of the TCI.

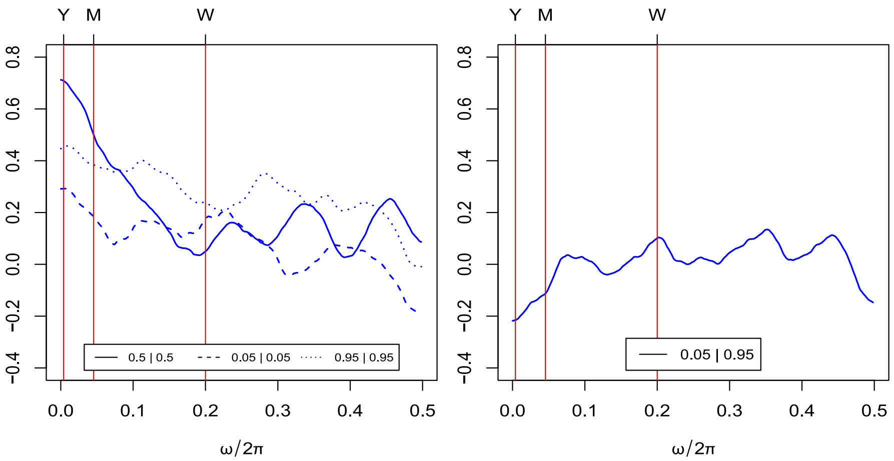
Regarding the NDC, BDAIV (CLNASIA) remains a net transmitter (receiver) across market conditions. SPGBIV also remains a net transmitter during normal periods and a net receiver during extreme market conditions. However, an apparent difference between FNTCHR and BLKCHR is that while they remain net shock receivers during normal and bullish market conditions, they become net shock transmitters during bearish market conditions. For CLNUSV, it becomes a net transmitter during normal and bullish market conditions but remains a net receiver of shock during bearish market conditions. CLNEUV, on the other hand, remains a net shock receiver during normal times while becoming a net shock transmitter during extreme market conditions. Furthermore,



(a)BLKCHN vs SPGBI volatility



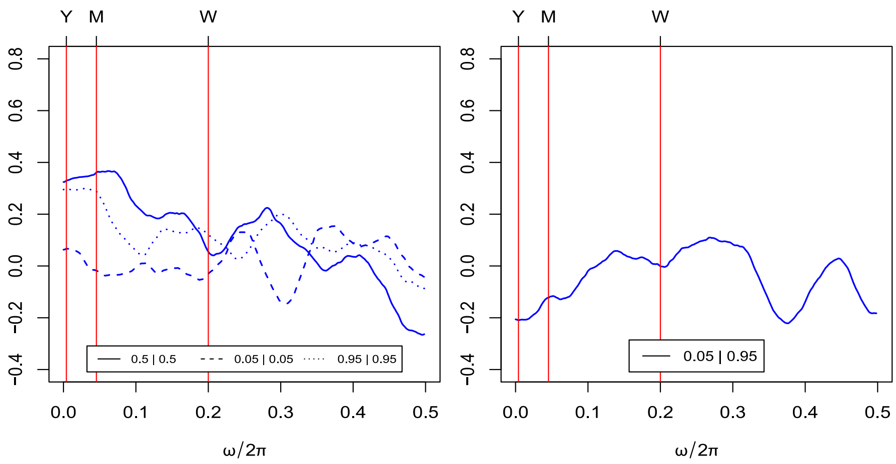
(b)BLKCHN vs CLNUS volatility



(c)BLKCHN vs CLNEU volatility

Fig. 7. Quantile coherency between BLKCHN and green energy volatility. Estimates are for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution.

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ▬ , - - - and ...... line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



(d)BLKCHN vs CLNASIA volatility

Fig. 7. (*continued*).

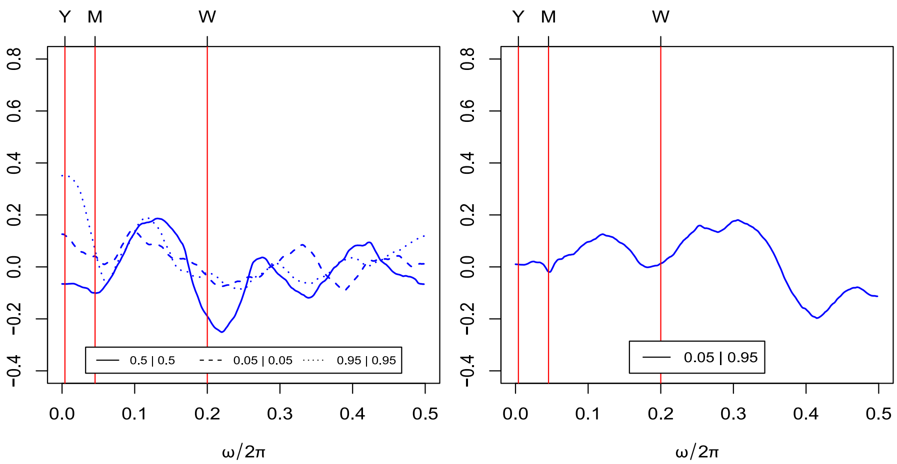
Fig. 11 presents the network system of net directional pairwise connectedness among all the series. The description of the figure is similar to Fig. 9. Insights from Fig. 12 show that during normal and bearish market conditions, BDAIV is the major transmitter of volatility shocks with the FNTCHV and BLKCHNV being the highest receivers of these volatility shocks when it comes to the technology market. The green financial markets show little or no significant evidence of being recipients of these shocks during this period. However, there is some evidence that Blockchain has transmitted some volatility shocks to CLNEUV and CLNASIA during this period. During the bullish period, CLNUSV was the major transmitter of shock, exerting significant volatility shocks on both regional and technology markets as well as the global green bond market. Put together; these results suggest that the market connectedness among the green financial markets and technology market varies not only across market conditions but also whether we focus on return or volatility connectedness among these markets, with the market that are either being driven by others or drive others depending on whether we focus on the returns or volatility connectedness.

Finally, Fig. 11 displays the dynamic TCI of the three market conditions over the sampling periods. The description of the figure is as given for that of the return connectedness. Consistent with the average TCI presented in Table 4, the time-varying TCIs of the bullish market condition remain consistently higher than that of the bearish and normal market conditions, respectively. As per the normal and bearish market conditions, the TCI of the normal market conditions lies consistently lower than that of bearish market conditions except between the end of the first quarter of 2020 and the beginning of the last quarter of that year. There are also somewhat observable improvements in the TCI of bearish market conditions towards the beginning of 2021, while that of normal and bull plummets.

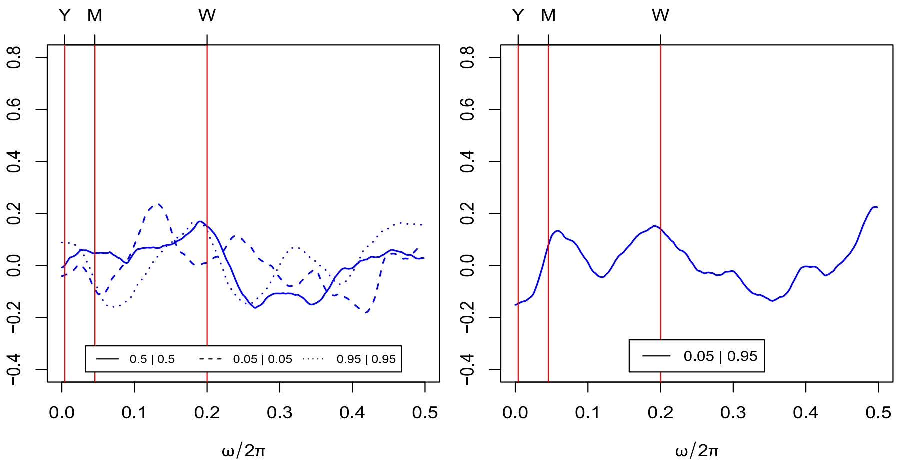
4.3. Drivers of return and volatility connectedness between green energy and fourth industrial revolution technology markets

Table 5 presents the results of predictive powers of the chosen macroeconomic variables on total return and volatility connectedness indexes for the different market conditions. Focusing on the drivers of total return connectedness across the three market conditions, columns 1–3 indicate that risk indicators, including stock volatility (VIX), oil volatility (OVX), gold volatility (GVZ), and Economic Policy Uncertainty (EPU), significantly predict changes in return connectedness across market conditions. In particular, while return connectedness across all market conditions exhibits increasing dependence in response to stock (VIX), oil (OVX), and economic policy uncertainty (EPU), they exhibit increasing dependence in response to gold volatility (GVZ) only under normal market condition but a decreasing dependence when total return connectedness index is at both tails of the distribution, representing the bear and bull market periods. Similarly, Pham et al. (2021) document evidence of positive dependence between the total connectedness of green energy investments, fossil fuels, and cryptocurrencies on stock changes (VIX), oil (OVX), and economic policy uncertainty (EPU), while Tian et al. (2022) show that EPU is the main driver of spillover across the system of carbon, commodity and financial markets.

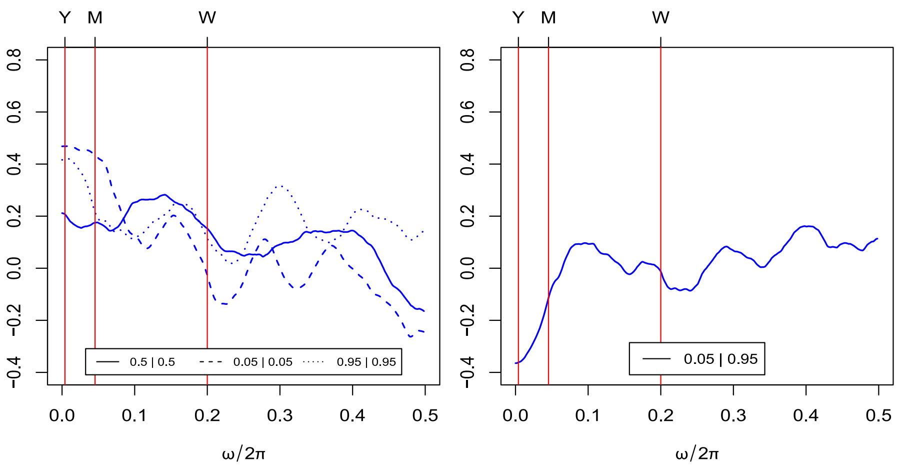
As can be seen in columns 4–6, our findings also emphasize less significant and weaker impacts of stock (VIX), oil (OVX), gold (GVZ), and economic policy uncertainty (EPU) on total volatility connectedness across the three market conditions. Specifically, we find that although volatility connectedness exhibits an increasing significant dependence in response to an increase in equity (VIX) and gold (GVZ) markets' volatility across all market conditions, it only increases during normal and bearish market conditions following an increase in oil market volatility (OVX) while during the normal market period only, volatility connectedness increases in response to an increase in economic policy uncertainty (EPU). Taken together, these results suggest that significant changes in the degree of connectedness between the green energy market and fourth industrial revolution technologies are mainly driven by innovations in the stock (VIX), oil (OVX), and gold (GVZ) markets and economic policy and that these effects are relatively stronger on returns connectedness, especially during normal market periods.



(a)FNTCH vs SPGBI volatility



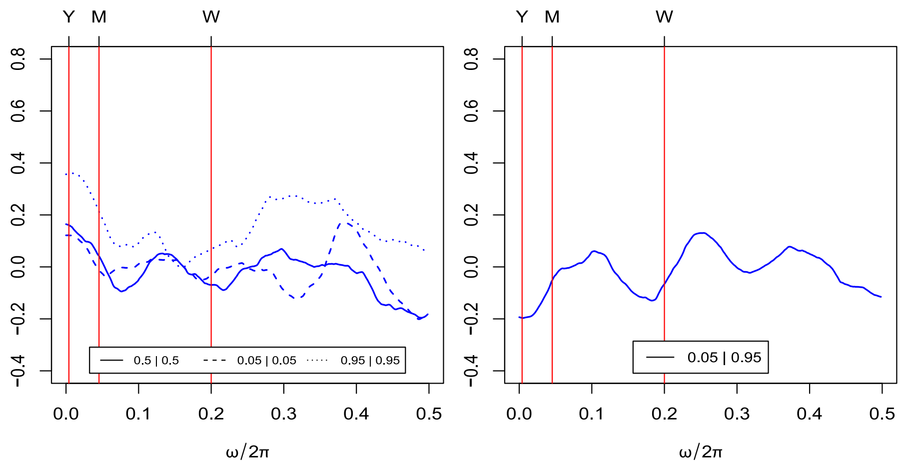
(b)FNTCH vs CLNUS volatility



(c)FNTCH vs CLNEU volatility

Fig. 8. Quantile coherency between FNTCH and green energy volatility. Estimates are for the 0.05|0.05, 0.5|0.5, 0.95|0.95 and the 0.05|0.95 of the joint distribution.

Note: Plots of the real part of the quantile coherency estimates of Baruník and Kley (2019) for 0.05, 0.5, and 0.95 quantiles together with 95% confidence intervals. W, M, and Y denote weekly, monthly, and yearly periods, respectively. The ——, - - - and ...... line corresponds to the 0.5, 0.05 and 0.95 quantiles, respectively. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.



(d)FNTCH vs CLNASIA volatility

Fig. 8. (*continued*).

Table 3
Quantile return connectedness.

	BDAIV	BLKCHNV	FNTCHV	SPGBIV	CLNUSV	CLNEUV	CLNASIAV	FROM others
Normal market								
BDAIR	65.42	10.24	7.86	5.66	1.87	5.64	3.31	34.58
BLKCHNR	26.91	35.39	12.76	4.42	1.39	13.39	5.73	64.61
FNTCHR	25.18	15.44	38.68	3.96	2.01	9.98	4.75	61.32
SPGBIR	7.15	1.70	1.41	83.34	2.36	1.84	2.21	16.66
CLNUSR	2.77	1.80	1.99	2.87	87.85	1.39	1.32	12.15
CLNEUR	22.75	10.89	5.71	7.16	1.47	47.29	4.73	52.71
CLNASIAR	16.17	7.65	3.19	3.78	2.23	5.56	61.41	38.59
TO others	100.93	47.72	32.92	27.86	11.33	37.80	22.05	280.62
Inc. own	166.35	83.11	71.60	111.20	99.18	85.09	83.46	
NDC	66.35	−16.89	−28.40	11.20	−0.82	−14.91	−16.54	TCI = 40.09
Bear market								
BDAIR	20.53	13.38	13.83	13.34	12.70	13.94	12.28	79.47
BLKCHNR	15.95	16.25	14.44	13.07	12.39	15.16	12.74	83.75
FNTCHR	16.14	14.06	17.04	13.36	12.74	13.82	12.84	82.96
SPGBIR	14.29	12.98	12.76	20.74	13.33	13.47	12.43	79.26
CLNUSR	13.30	12.67	12.91	12.39	22.19	14.02	12.54	77.81
CLNEUR	15.17	13.74	13.53	13.53	12.86	18.60	12.56	81.40
CLNASIAR	14.83	13.85	13.30	13.07	12.50	13.84	18.60	81.40
TO others	89.68	80.67	80.77	78.76	76.53	84.25	75.39	566.06
Inc. own	110.21	96.92	97.81	99.49	98.72	102.85	94.00	
NDC	10.21	−3.08	−2.19	−0.51	−1.28	2.85	−6.00	TCI = 80.87
Bull market								
BDAIR	23.93	13.31	14.63	12.46	11.27	13.09	11.31	76.07
BLKCHNR	17.29	17.71	15.24	12.22	10.56	14.40	12.58	82.29
FNTCHR	17.25	14.63	19.36	11.92	11.12	13.85	11.88	80.64
SPGBIR	13.94	12.56	12.16	23.97	11.96	13.03	12.37	76.03
CLNUSR	13.29	11.80	12.10	12.63	25.54	12.13	12.52	74.46
CLNEUR	15.40	13.99	13.40	13.27	10.93	20.27	12.74	79.73
CLNASIAR	15.20	13.30	13.09	12.60	11.44	13.91	20.46	79.54
TO others	92.36	79.59	80.61	75.10	67.28	80.41	73.41	548.76
Inc. own	116.29	97.30	99.97	99.08	92.82	100.68	93.87	
NDC	16.29	−2.70	−0.03	−0.92	−7.18	0.68	−6.13	TCI = 78.39

Notes: TCI denotes the Total Connectedness Index; Inc. own is Including own while NDC is the Net Directional Connectedness. “R” denotes return series. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.

Table 4
Quantile volatility connectedness.

	BDAIV	BLKCHNV	FNTCHV	SPGBIV	CLNUSV	CLNEUV	CLNASIAV	FROM others
Normal market								
BDAIV	65.09	10.11	7.72	5.03	2.65	4.99	4.41	34.91
BLKCHNV	34.14	40.05	7.36	3.99	2.48	8.04	3.94	59.95
FNTCHV	38.98	8.57	34.24	4.59	2.35	5.80	5.48	65.76
SPGBIV	8.18	2.51	2.33	77.75	1.81	3.73	3.68	22.25
CLNUSV	3.10	2.08	1.91	1.68	86.66	2.51	2.07	13.34
CLNEUV	15.44	9.95	5.01	7.62	2.58	55.01	4.39	44.99
CLNASIAV	9.08	3.85	4.82	2.96	2.39	4.06	72.84	27.16
TO others	108.92	37.07	29.14	25.86	14.27	29.13	23.97	268.36
Inc. own	174.00	77.13	63.38	103.61	100.93	84.14	96.81	
NDC	74.00	−22.87	−36.62	3.61	0.93	−15.86	−3.19	TCI = 38.34
Bear market								
BDAIV	52.68	12.71	10.83	6.91	4.31	7.58	4.97	47.32
BLKCHNV	17.93	42.51	15.52	4.65	3.72	10.16	5.51	57.49
FNTCHV	16.62	16.32	40.02	6.08	3.68	9.82	7.46	59.98
SPGBIV	7.53	5.97	7.82	62.82	3.96	6.18	5.71	37.18
CLNUSV	5.72	5.03	5.85	4.19	69.29	5.91	4.02	30.71
CLNEUV	8.73	13.61	11.11	5.49	4.68	49.37	7.00	50.63
CLNASIAV	6.25	8.22	9.79	5.27	3.41	7.61	59.45	40.55
TO others	62.77	61.86	60.93	32.60	23.75	47.26	34.67	323.84
Inc. own	115.45	104.38	100.95	95.42	93.04	96.63	94.12	
NDC	15.45	4.38	0.95	−4.58	−6.96	−3.37	−5.88	TCI = 46.26
Bull market								
BDAIV	15.36	11.50	11.37	12.37	25.14	11.95	12.31	84.64
BLKCHNV	15.42	12.20	11.67	12.52	23.71	12.29	12.19	87.80
FNTCHV	15.42	11.16	12.36	12.58	24.22	11.81	12.45	87.64
SPGBIV	13.94	11.41	11.39	13.74	24.83	12.51	12.19	86.26
CLNUSV	12.71	11.04	10.98	12.53	28.82	11.49	12.43	71.18
CLNEUV	14.23	11.71	11.44	13.00	24.29	13.07	12.26	86.93
CLNASIAV	14.13	11.77	11.64	13.31	22.45	12.44	14.27	85.73
TO others	85.84	68.60	68.49	76.31	144.62	72.49	73.83	590.18
Inc. own	101.20	80.79	80.86	90.04	173.44	85.57	88.10	
NDC	1.20	−19.21	−19.14	−9.96	73.44	−14.43	−11.90	TCI = 84.31

Notes: TCI denotes the Total Connectedness Index; Inc. own is Including own while NDC is the Net Directional Connectedness. "V" denotes volatility series. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia.

Columns 1–3 indicate that for all the market conditions, the coefficients associated with uncertainties in the fixed-income market, as indicated by the Merrill Lynch Option Volatility Estimate (MOVE), are significantly negative. This suggests that an increase in the fixed-income market uncertainty results in a decrease in return connectedness between the green energy market and fourth industrial revolution technologies. We obtain similar results for changes in total volatility connectedness, as shown in columns 4–6, except under bullish market conditions. In particular, innovations in the fixed-income market volatility drive total volatility connectedness in the opposite direction, except when the market condition is bullish. These results indicate that increased volatility in the fixed-income market causes fixed-income investors to look elsewhere, including the green energy and fourth industrial revolution technology markets. This leads to reductions in return-volatility risk spillovers among these assets. In contrast, results in columns 1–3 show that the coefficient on the oil price is only significant under normal market conditions, while columns 4–6 show that none of the coefficients is significant, indicating that an increase in oil price returns is associated with an increase in total return connectedness between these markets under normal market periods only.

Moreover, as shown in columns 1–3, the geopolitical risk index coefficient (GPRI) coefficient is significant and positive under normal market periods. At the same time, it is significant but negative during the bull market conditions. This indicates that uncertainties associated with geopolitics exhibit asymmetric predictive power on the degree of return connectedness between green energy and fourth industrial revolution technologies markets. These findings imply that the total return connectedness between green energy markets and fourth industrial revolution technologies intensifies following an increase in geopolitical risk during a normal market period. However, when the market condition becomes bullish, the degree of return connectedness decreases. In contrast, columns 4–6 show that coefficients associated with the geopolitical risk index (GPRI) are significant and positive across all market conditions, indicating that total volatility connectedness between these markets increases in response to an increase in geopolitical risks. Similar results on the positive effects of geopolitical risk on energy market volatility have emerged in a few studies (e.g., Liu et al., 2021a; Yang et al., 2021). Specifically, Liu et al. (2021a) provide evidence of the significant positive influence of geopolitical uncertainty on long-term energy market volatility, while Yang et al. (2021) document evidence of the pattern of risk spillovers from geopolitical risk to green energy markets across different investment horizons.

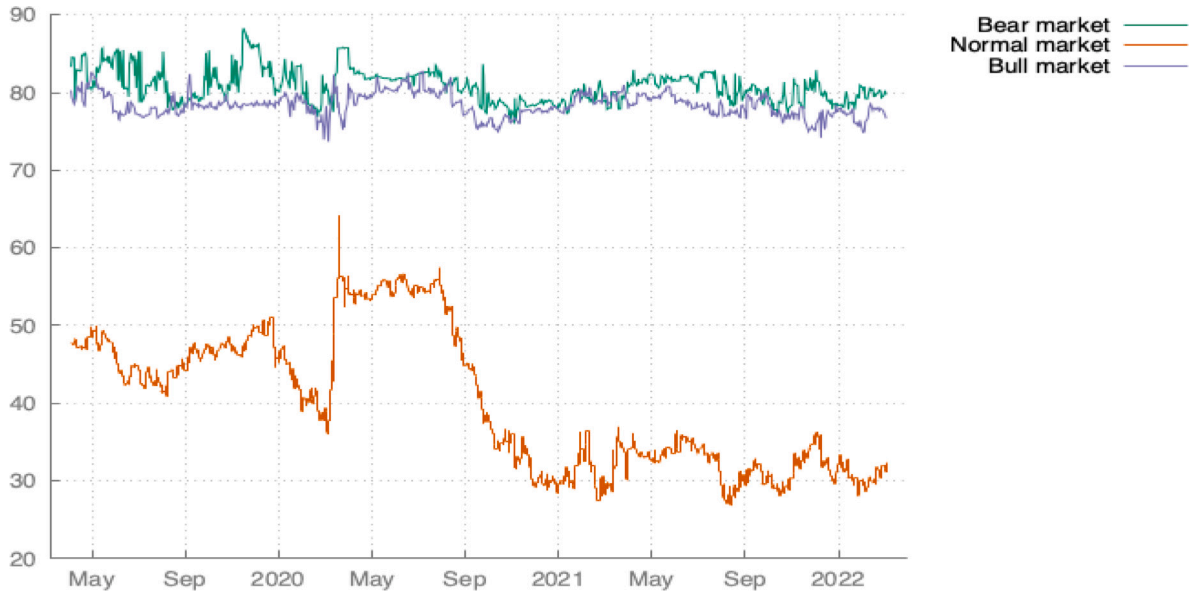


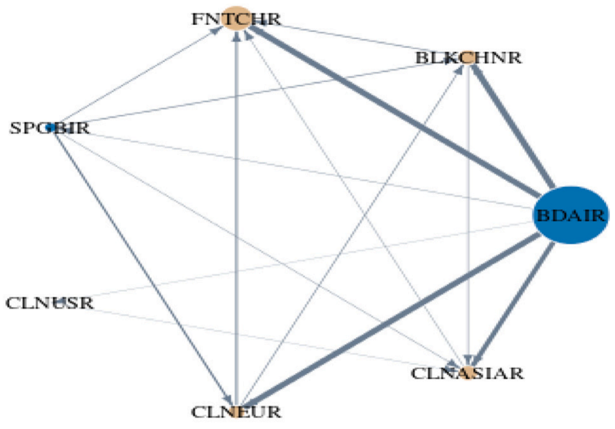
Fig. 9. Plot of total dynamic return connectedness among green energy markets and fourth industrial generation technology.

Furthermore, we find that across all market conditions, both total return and volatility connectedness between green energy and fourth industrial revolution markets exhibit an increasing dependence in response to an increase in the ADS business condition index (ADS). As noted in Aruoba et al. (2009), the mean value of the ADS index is zero, indicating that higher positive values show a higher-than-average business environment, while higher negative values indicate a worse-than-average business environment. This indicates that an increase in better-than-average business conditions is associated with increasing degrees of both total return and volatility connectedness between green energy and fourth industrial revolution technologies markets. On average, the coefficients on ADS indicate that the predictive power of an increase in the better-than-average business conditions is relatively stronger for total volatility connectedness, irrespective of the market condition. Contrarily, the coefficients on the term spread (Term) indicate that the influence of the term spread on total return connectedness between green energy and fourth industrial revolution technologies markets is not significant across all market conditions. However, it is significant and positive for total volatility connectedness under normal and bearish market conditions. As an indicator of investors' insight into future economic and financial market situations, an increase in the term spread signals the expectation of recession shortly. Our results indicate that an increase in the probability of recession in the future does not significantly influence the degree of total return connectedness between green energy and fourth industrial revolution technologies markets across all market conditions. However, the predictive power becomes significant and positive on total volatility connectedness between these markets under normal and bearish market conditions. Lastly, the coefficients on the COVID-19 dummy show that both total return and volatility connectedness between these markets intensified in response to the volatile financial and economic conditions created by the global pandemic.

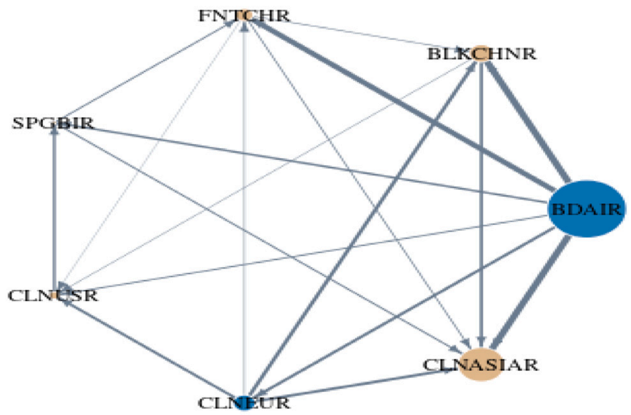
5. Conclusion and policy implications

The quest for a solution to the climate crisis has led to a global transition to environmental sustainability underpinned by possible net-zero carbon emissions. Green financial instruments such as green stocks and bonds and the adoption of fourth industrial revolution technologies have featured prominently as pathways towards attaining this goal. Hence, the main goal of this paper was to determine the dependence structure and connectedness among investments in the green financial market and investments in fourth-industrial technologies. For the former, we focus on global green bonds and regional clean energy markets for the U.S., Europe, and Asia. Concerning fourth industrial revolution technologies, we focus on Blockchain, Financial technology, Big data, and Artificial Intelligence stocks. We addressed our research question by employing the quantile cross-spectral coherency technique proposed by Baruník and Kley (2019) and the quantile-based Vector Auto-Regressive (QVAR) spillover index proposed by Ando et al. (2022). We also used the linear panel model to examine the drivers of return and volatility spillovers among the markets under study across different market conditions.

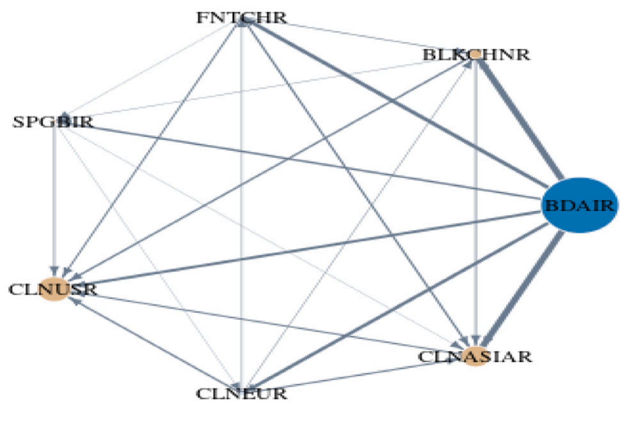
Results from the quantile cross-spectral coherency technique show significant evidence of market dependence between the green financial market and those of fourth industrial revolution technologies, but that vary across market conditions and investment horizons. Concerning the return dependence, dependence between the green energy market and big data and artificial intelligence is positive and strongest for the European and Asian regional green energy markets in the medium- and long term. Similar results may be drawn regarding the dependence between green energy market indexes and Blockchain technology across quantiles and investment horizons. For instance, for regional green energy markets in Europe and Asia, dependence is positive across the short-,



(a) Normal market return connectedness



(b) Bear market return connectedness



(c) Bull market return connectedness

Fig. 10. Network plots of net pairwise directional return connectedness among green energy markets and fourth industrial generation technology.
Note: Blue and yellow nodes denote net transmitter and receiver of shocks, respectively. Also, vertices are weighted using averaged net pairwise directional connectedness measures while the size of nodes represent weighted average of net total directional connectedness. "R" denote return series. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

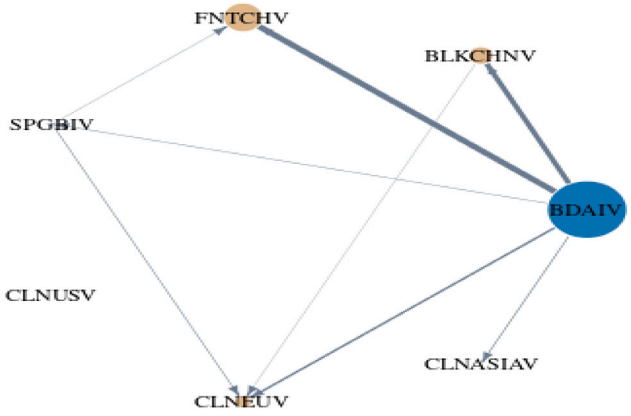
Fig. 11. Plot of total dynamic volatility connectedness among green energy markets and fourth industrial generation technology.

medium- and long-term under all three market conditions, especially under a bearish market period for the European regional green energy market. As per financial technology, its dependence on the European and Asian regional green energy markets is positive across all the frequencies. It is becoming stronger when the market condition is bearish, especially for Europe.

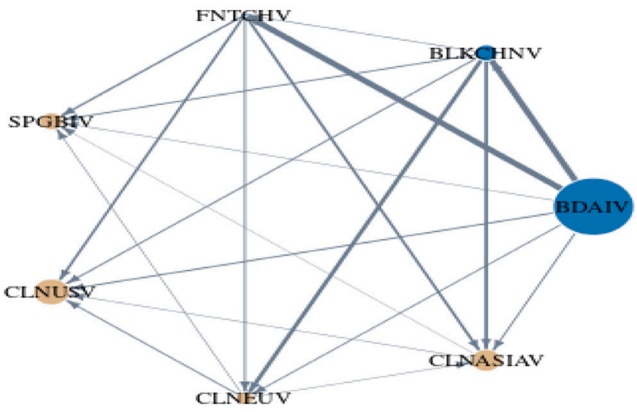
Concerning the volatility dependence, the dependence between big data and artificial intelligence and the green energy market is strongest in the Asian green energy market in the long term when the market condition is bullish. While we find a similar pattern of volatility dependence with green bonds, on a lower scale, there is positive volatility dependence between blockchain technology and the European and Asian green energy markets across the three market conditions and time scales. The exception to this is the Asian green energy market, where dependence under bearish market periods is negative and very low, especially in the medium term. For the U.S. green energy market, volatility dependence on blockchain technology is generally low across all time scales and market conditions, except under normal market periods. Volatility dependence between financial technology and the global green bond market is relatively weak in the short- -term but stronger as the time–frequency is increased to the medium term under all market conditions. We also find moderate dependence between financial technology and the U.S. green energy market under all market conditions in the medium term. In contrast, for the European and Asian markets, results show stronger short-term volatility dependence.

Regarding the results from the QVAR-based connectedness technique, the return connectedness among the green financial market and the fourth industrial revolution technology market are relatively moderate during normal times but become stronger during extreme market conditions. Among the fourth industrial revolution technology markets, big data and artificial intelligence are net transmitters of shock across all market conditions, while the others are net receivers across all market conditions. Big data and artificial intelligence also have the highest net shock transmitters, exerting significant shocks on the green financial market and other technology markets. Among the green financial markets, the USA regional clean stock shows evidence of the least connectedness with the technology market, including big data and artificial intelligence. As per the volatility spillover, the results also show a stronger level of connectedness between the green financial market and the fourth industrial revolution technology market during extreme market conditions compared to normal market conditions. Except for the bullish market condition, however, the level of volatility connectedness is smaller than the return connectedness, implying that market risks and uncertainty shocks among these markets spread less forcefully than return during normal and bearish market conditions. Big data remains a net shock transmitter to other markets but only plays a major role during normal and bearish market conditions where they exert significant risks to other technology markets. During bullish market conditions, the USA regional clean energy stock is the major net shock transmitter, exerting significant influence on other green financial and technology markets.

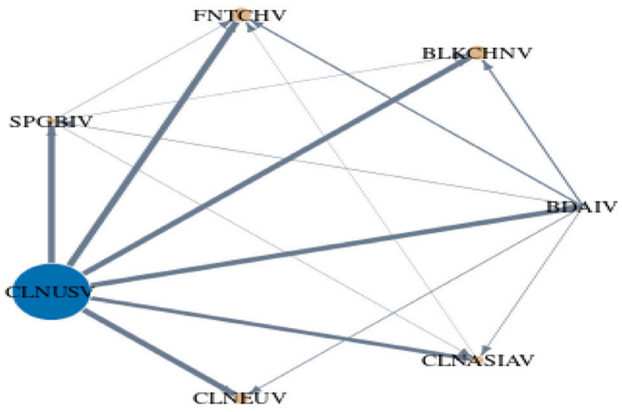
Furthermore, the linear panel models used to assess the drivers of return and volatility connectedness among the green energy and fourth industrial revolution technology markets show that the COVID-19 pandemic, business conditions, and uncertainties about the stock and oil markets drive positively the return and volatility spillovers among the green financial market and the fourth industrial revolution technology market across all market conditions. Except for volatility spillover under bullish market conditions, fixed-income market uncertainty reduces the return and volatility spillovers among the markets across all market conditions. Geopolitical risks and the gold market uncertainty positively predict the volatility connectedness across all market conditions. Similar results are obtained for economic policy uncertainty and term spread between the 10 year and 3-month Treasury bonds (Term) except during extreme market conditions for the former and bullish market conditions for the latter. As per return spillover, gold market uncertainty



(a) Normal market volatility connectedness



(b) Bear market volatility connectedness



(c) Bull market volatility connectedness

Fig. 12. Network plots of net pairwise directional volatility connectedness among green energy markets and fourth industrial generation technology.
Note: Blue and yellow nodes denote net transmitter and receiver of shocks, respectively. Also, vertices are weighted using averaged net pairwise directional connectedness measures while the size of nodes represent weighted average of net total directional connectedness. "V" denotes volatility series. BDAI, BLKCHN, FNTCH, SPGBI represent Big Data, Blockchain, FinTech and S&P green bond indexes while CLNUS, CLNEU and CLNASIA are clean energy indexes for the United States, Europe and Asia. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 5
Impact of macroeconomic indicators on return and volatility connectedness.

	Return connectedness			Volatility connectedness		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Normal	Bear	Bull	Normal	Bear	Bull
Constant	3.779***	4.430***	4.427***	3.009***	3.506***	4.399***
	(0.0674)	(0.0306)	(0.0106)	(0.0799)	(0.0628)	(0.0156)
ln(VIX)	0.174***	0.109***	0.017***	0.056***	0.041***	0.023***
	(0.0279)	(0.0091)	(0.0044)	(0.0029)	(0.0058)	(0.0064)
ln(OVX)	0.024***	0.021**	0.012***	0.073***	0.038*	0.004
	(0.0021)	(0.0082)	(0.0044)	(0.0260)	(0.0205)	(0.0051)
ln(GVZ)	0.211***	−0.042***	−0.016***	0.146***	0.163***	0.026***
	(0.0277)	(0.0105)	(0.0043)	(0.0326)	(0.0256)	(0.0064)
ln(EPU)	0.042***	0.007**	−0.0004	0.027**	−0.003	−0.003
	(0.0093)	(0.0028)	(0.0015)	(0.0109)	(0.0086)	(0.0021)
ln(MOVE)	−0.083***	−0.045***	−0.021***	−0.092***	−0.105***	0.007
	(0.0249)	(0.0103)	(0.0031)	(0.0294)	(0.0231)	(0.0057)
Δln(Oil)	0.188**	−0.004	−0.001	−0.158	−0.113	0.004
	(0.0933)	(0.0138)	(0.0147)	(0.1101)	(0.0865)	(0.0215)
ΔGPRI	0.023**	0.001	−0.005***	0.016**	0.044***	0.006***
	(0.0099)	(0.0023)	(0.0014)	(0.0081)	(0.0086)	(0.0021)
ΔTerm	0.104	−0.007	0.009	0.281***	0.186**	−0.003
	(0.0843)	(0.0218)	(0.0133)	(0.0995)	(0.0782)	(0.0194)
ΔADS	0.069***	0.011**	0.007***	0.071***	0.067***	0.014***
	(0.0131)	(0.0055)	(0.0021)	(0.0154)	(0.0121)	(0.0030)
COVID-19	0.122***	0.032***	0.013***	0.144***	0.032**	0.009***
	(0.0139)	(0.0075)	(0.0022)	(0.0163)	(0.0128)	(0.0032)
Ω Mean	3.667	4.392	4.361	3.608	3.821	4.434
Ω Max.	4.161	4.481	4.415	4.347	4.237	4.528
Ω Min.	3.289	4.331	4.299	3.092	3.441	4.272
Std. Dev.	0.22	0.026	0.019	0.269	0.165	0.027
R-squared	0.747	0.277	0.196	0.763	0.614	0.088

*** Significance at 1% level.

** Significance at 5% level.

* Significance at 10% level.

Note: Robust standard errors are presented in brackets. Ω Mean, Ω Max and Ω Min are the mean, maximum and minimum log values of total return and volatility connectedness indexes for the three market conditions while Std. Dev. is the standard deviation of total return and volatility connectedness indexes for the three market conditions. VIX, OVX and GVZ are the volatility indexes for equity, oil and gold markets while EPU, MOVE, GPRI, ADS, Term and Oil denote the U.S. Economic Policy Uncertainty index, Merrill Lynch Option Volatility Estimate, Geopolitical Risk index, Aruoba–Diebold–Scotti Business Conditions Index, the Term spread and oil prices, respectively.

positively (negatively) predicts return spillover during normal (extreme) market conditions. While economic policy uncertainty only predicts return spillover during normal and bearish periods, the oil market does so only during market normal market conditions. On the other hand, geopolitical risks are a strong predictor of return spillover, but only during normal and bullish market conditions.

The important policy insights from our findings relate to the importance of new information regarding shock propagation across financial markets for both investors and policy agents. As the world beckons on the global financial markets to mobilize the needed capital flows to address the looming climate challenges, information on the structure of interactions between green assets (which is the main channel of climate finance mobilization) and fourth industrial revolution technologies stocks are particularly crucial. Both capital mobilization and modern technological advancement are fundamental to mitigating climate risks. Indeed, the advancement of both depends on the returns and risks associated with investments in them and other features such as diversification potentials. Therefore, our findings on the levels of dependence and connectedness among green and modern technologies and how these change across time and market conditions are crucial for investors. This information can improve dynamic asset allocation that will improve return and risk reductions that are necessary to ensure the continuous flows of capital toward technology advancement and the development of more climate-friendly processes.

In particular, our findings hold useful implications for both short- and long-term investors interested in portfolio optimization involving modern technology and green financial assets based on the reported degrees and patterns of dependence and connectedness. For instance, results of significantly positive return dependence among these assets vary across market conditions and investment horizons, especially with regional green energy markets in Europe and Asia calling for active dynamic portfolio management strategies to effective risk management. In terms of return risk transmission, periods of calm in the global equity markets appear to be the safe periods of combining these assets to mitigate portfolio risks. In contrast, bearish and bullish market periods may not offer this opportunity, as the connectedness measure shows. Therefore, the observed patterns of dependence and connectedness are crucial in diversified portfolio construction and effective risk management. Even more, our analysis of the drivers of connectedness also emphasizes the need for policy-makers to reduce uncertainty in economic policy, as it is among the main factors that exacerbate the propagation of shocks across these crucial asset classes. In this regard, our study has some limitations, particularly in regulatory frameworks and industry-specific dynamics, that may be crucial drivers of dynamic connectedness among these markets. These dynamics are, however, complex and difficult to incorporate into our analysis due to the empirical design of the methods adopted in this study. Hence, we recommend that future studies offer some interesting insights into the effects of regulatory frameworks and industry-specific factors on the dynamic connectedness among the markets considered in this study.

CRediT authorship contribution statement

Ramzi Benkraiem: Writing – review & editing, Methodology, Data curation. **Khaled Guesmi:** Project administration, Formal analysis. **Gideon Ndubuisi:** Writing – original draft. **Christian Urom:** Resources, Methodology, Data curation. **Samuel Vigne:** Supervision, Methodology, Conceptualization.

Data availability

Data will be made available on request.

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