Energy 328 (2025) 136483

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Time-frequency connectedness and volatility spillovers among green equity sectors: A novel TVP-VAR frequency connectedness approach

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ARTICLE INFO

Keywords:
Time-frequency connectedness
Volatility spillovers
Green equity sectors
TVP–VAR frequency connectedness
COVID-19

ABSTRACT

Investment in green equity market is growing more specifically after COVID-19 due to rising awareness of climate and environmental issues. Investors and policymakers require updated information about the connectedness and shock spillover pattern among green sectors to manage portfolios effectively. The novel TVP–VAR frequency connectedness approach is applied to daily volatility series of green equity indices to explore the volatility spillover dynamics in the time-frequency domain. The findings demonstrate strong interlinkages among green sectors that have become more pronounced during crisis events, with water, energy efficiency, green building and recycling as the largest transmitters of volatility shocks, being considered as systemically important sectors. In contrast, bio-clean fuels, healthy living, advanced materials and natural resources are primary risk absorber sectors. The dynamic analysis reveals the heterogeneous behavior of sectors during turmoil periods. Additionally, the frequency decomposition analysis reveals that volatility spillover is mainly concentrated in the short run, suggesting diversification opportunities for investors in the long run. Empirical findings help investors and policymakers to manage risk in the green equity market. Understanding how sectors influence market instability is crucial. Policymakers must closely and systematically monitor important sectors to prevent systemic risk, as shocks in these sectors can spread to others.

Nomenclature

Abbreviation	Description
ADCC	Asymmetric–Dynamic conditional correlation
ADF	Augmented Dickey–Fuller
BEKK	Baba, Engle, Kraft and Kroner
CCC	Conditional correlation
DCC	Dynamic conditional correlation
ESG	Environmental, social and governance
GARCH	Generalized autoregressive conditional heteroskedasticity
GFEVD	Generalized forecast error variance decomposition
JB	Jarque–Bera
NPDC	Net pairwise directional connectedness
NPDC	Net pairwise directional connectedness
SD	Standard deviation
SDGs	Sustainable Development Goals
SIC	Schwarz Information Criterion
TCI	Total connectedness index
TVP–VAR	Time-varying parameter vector autoregressive
TVP–VMA	Time-varying parameter vector moving average
VAR	Vector autoregression
X_t	Vectors of endogenous variables at time t
X_{t-1}	Vectors of lagged endogenous variables
ε_t	Vector of an error term
Φ_{it}	Time-varying coefficients of the VAR model
$\sum_t$	Time-varying variance covariance matrix.
$\tilde{\theta}_{ijt}(H)$	It measures the input of the variable j to the variance of the forecast error of the variable i at the time horizon H.
$S_x(w)$	The spectral density of variable X_t at specific frequency ω
$\theta_{ijt}(\omega)$	It refers to the portion of the spectrum pertaining to the ith variable at a specific frequency ω that induces a shock in the jth variable.

(continued on next column)

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https://doi.org/10.1016/j.energy.2025.136483
Received 21 March 2024; Received in revised form 6 May 2025; Accepted 7 May 2025
Available online 9 May 2025

1. Introduction

The planet's natural environment is threatened by climate change, deforestation, clean water scarcity, air, soil and water pollution, and depletion of the ozone layer [1]. To tackle these unprecedented issues, inter alia, the United Nation's Sustainable Development Goals (SDGs) and the Paris Agreement in 2015 are more viable actions. These efforts motivate investors to prioritize environmental aspects in their investment decisions rather than just considering returns [2]. This pro-environmental behavior by investors is in line with the philosophy expressed in the theory of planned behavior of Ajzen [3,4], as cited in Chan et al. [5] and the value-belief-norm theory proposed by Stern et al. [6]. This growing trend of green investment serves as a road map toward sustainable development and efficiently reduces pollution emissions [7].

Green equity investment is among several modes of eco-friendly investments and comprises the stocks of companies whose basic business activities benefit the environment. These companies are attached to various industrial sectors such as renewable energy, material and energy efficiency, water and waste management, recycling, and clean transportation [8]. In the present era, the green equity market is on a fast-growing track due to the rising interest of investors and policymakers, more specifically after COVID-19 [9], which is confirmed by an upward trend in green equity sectoral prices as shown in Fig. 1. Although environmental consciousness has steadily increased over the years, the COVID-19 pandemic served as a trigger, hastening this movement and highlighting environmental concerns due to observing pollution reduction, media coverage, and/or a shift in preferences [10–14].

On the other hand, financial markets experienced several major episodes of financial instability and crises e.g., global financial crisis (2008), the European debt crisis (2010–2012), the oil market crash (2014–2016), and the recent COVID-19 pandemic. These risks spillover among financial markets, sectors and individual companies. Like traditional markets, the green equity market, although demonstrating growing resilience, behaves differently in calm and turbulent times. During stable periods, green equities experience lower levels of shock spillover, but this spillover becomes more pronounced during stressful times, such as during the COVID-19 pandemic [15]. Notably, volatility transmits from one economic sector to others due to their connectedness [16,17]. Generally, economic sectors are connected due to upward and downward supply chain relationships and investors' asset allocation patterns across sectors [18] and cause risk spillover across industries [19]. Market participants leverage the interconnectedness of financial assets for improved portfolio selection, effective risk management, real-time crisis monitoring, and business cycle analyses [20].

However, contemporary literature mostly focuses on connectedness and volatility spillovers between green and conventional markets (assets)[1] at aggregate level, while ignoring investigation of inter-sector volatility spillovers in the green equity market. However, exploring the green equity market is essential in the present era due to several aspects, such as the rising demand for green investment, including green equities [21]. Expansion in these markets presents significant growth and profit potential [9,22,23]. Indeed, these markets possess inherent risk mitigation characteristics that provide a safe haven for investors during crises [24,25] and benefit from government support packages and reforms for green industries, such as The European Green Deal [26]. Additionally, regulatory agreements such as the SDGs and Paris Agreement [27] and advancement in green technologies have addressed environmental challenges by promoting a transition to a green economy [25] and supporting meeting the SDGs [28]. However, in contrast to traditional financial markets, green equity markets offer investors the chance to earn optimal returns and meet their environmental commitments [29]. Therefore, it is crucial to invest in sustainable initiatives across essential economic sectors to shift the global economy towards green and sustainable practices [30]. The green economic sectors include advanced materials, bio/clean fuels, energy efficiency, green building, green transportation, healthy living, lighting, natural resources, pollution mitigation, recycling, renewable energy generation, and water [31]. Understanding the connectedness and volatility spillovers at the sectoral level is beneficial for portfolio diversification, forming policies to reduce overall market risk, and designing targeted industrial development plans by considering systematically important sectors with volatility transmission [32]. So, it is paramount to uncover the dynamics of connectedness and volatility spillovers across green equity sectors to assist diverse groups of economic agents and market participants.

Therefore, the objective of the study is to explore the main sources of risks or market instability and examine which green sectors are playing the role of volatility transmitters and which sectors are shock receivers with the help of connectedness and volatility spillover analysis. Furthermore, it is important to investigate the volatility connectedness in time domain and explore the heterogeneous behavior of green sectors during crisis events by capturing the time-varying spillover features. In addition, investors with different investment horizons and policymakers are interested in getting volatility spillover information over different frequencies. For that reason, it is imperative to examine volatility spillover over time and frequency domain to support the decisions of various groups of investors and policymakers.

This study makes a multiple contribution to the existing literature. Firstly, it extends the literature (e.g., Ref. [33]) by exploring the volatility spillover structure between green equity sectors in the time and frequency domain. The identification of systematically important sectors with volatility transmission, a potential source of risk contagion, and market moments are useful for policymakers to make targeted industrial development plans as well as take steps to prevent overall market failure [19,34]. In addition, investment across sectors provides more diversification opportunities due to the rising integration among international stock markets [35,36]. However, connectedness and volatility spillovers among sectors have not gained as much attention as aggregate market analysis, as discussed by Mensi et al. [37]. Therefore, knowledge about shock transmission within sectors allows investors and portfolio managers to make risk assessments and design portfolio diversification strategies [37].

Secondly, this study adds to the literature that explores the impact of COVID-19 on volatility spillover patterns within or across various green and traditional markets (for example, [38,39]) by investigating the changes in the green sector's connectedness and spillover pattern caused by a recent health crisis. Knowledge about this phenomenon is beneficial for regulators and policymakers in making plans to protect the green economy from the harmful impact of the crisis and helpful to investors for timely restructuring of portfolios and designing suitable trading schemes. Thirdly, there is evidence that the pro-environmental behavior of investors is playing a leading role in shifting their interests towards eco-friendly investments which are based on the ideology expressed in the theory of planned behavior of Ajzen [3,4] and the value-belief-norm theory suggested by Stern et al. [6]. Therefore, this study is grounded on behavioral change theories, which is a significant theoretical contribution to extant literature.

Finally, the stream of literature that has focused on exploring the volatility spillovers between green and conventional markets has extensively used Diebold and Yilmaz [40,41]. Predominately, the literature used Baruník and Křehlík [42], an updated version of Diebold and Yilmaz's [40,41] approach to observe spillover in the time and

[1] For instance, extended literature explores volatility spillovers between oil prices and renewable energy markets (e.g., (W. [43,56–58]), among green and conventional asset markets (e.g., (G. [38,60]; W. [59,61–63]; J. [9,15,45,107]), across green bond and conventional markets (e.g., (Y. [44,64–68]; M. P. [47]), within sustainable and clean energy markets (e.g., ([39,70]; R. [108]; W. [69]), and within renewable energy sectors and sub-sectors of the green equity market (e.g., Ref. [33].

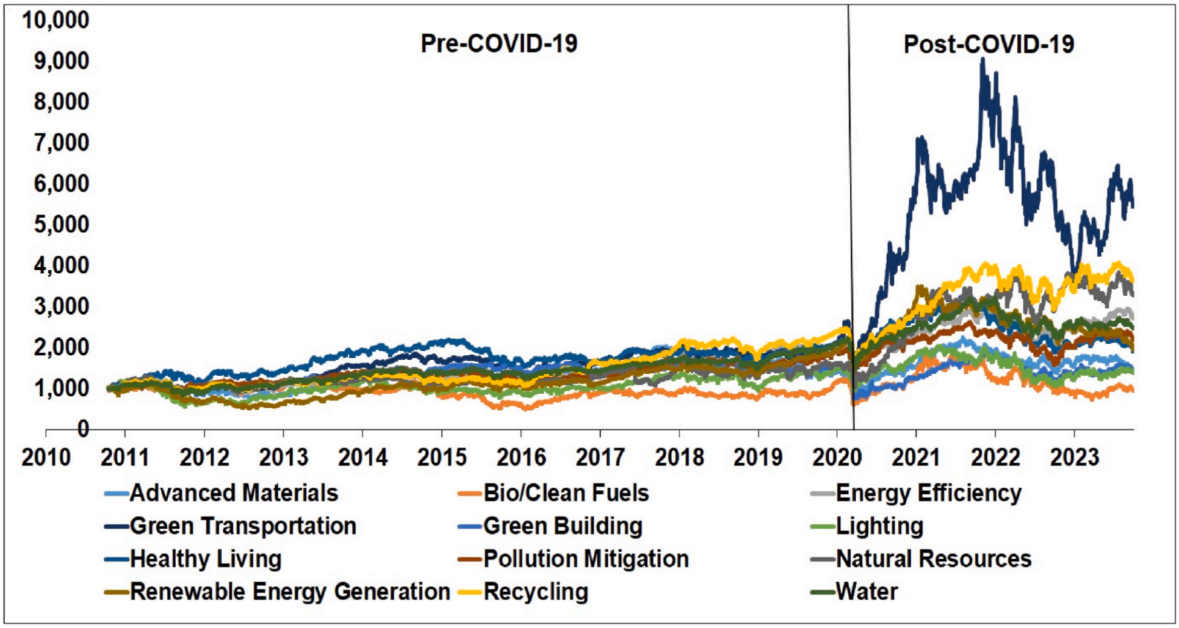

Fig. 1. Index values of green equity sectors from October 2010 to September 2023.
Source: created by the authors.

frequency domain (e.g., Ref. [43,44]). Similarly, some scholars applied both techniques for spillover analysis in the time and frequency domain (e.g., Ref. [45–47]). However, for the analysis of static and dynamic connectedness, these methods utilize the VAR framework, which is subject to outliers, has issues with optimal window size, and losses information due to the rolling window size, making it unsuitable for high-frequency data [32]. These limitations were addressed by the TVP–VAR model proposed by Antonakakis et al. [48], which eliminates the rolling window problem and estimates parameters at each time point using Bayesian techniques to capture dynamic connectedness among variables. Consequently, full sample data is utilized since there is no need for an arbitrary window size. Chatziantoniou et al. [49] introduced a novel TVP–VAR-based framework for frequency connectedness to explore static and dynamic interactions in both the time and frequency domains, integrating the methods of Baruník and Krehlík [42] and Antonakakis et al. [48] to address the rolling window challenge. The present study applied this innovative method to examine volatility spillover patterns across time and frequency domains.

The results indicate that the water, energy efficiency, green building, and recycling sectors are key transmitters of volatility within the network. In contrast, the bio/clean fuels, healthy living, advanced materials, and natural resources sectors are the primary industries that absorb risks. Additionally, volatility spillover tends to occur mainly in the short term, indicating that the green equity market quickly processes information and disseminates risk among green sectors within a very short timeframe. It has been noted that the volatility connectedness among green sector equities is time-varying, with the Total Connectedness Index (TCI) ranging from 49 % to 91 % between October 2010 and September 2023. For example, the TCI value was 89 % in early 2020, likely influenced by the COVID-19 pandemic, but it dropped to 49 % by the end of 2021 due to government measures to stabilize the economies. This value then rose to 73 % in 2022 because of the Russia–Ukraine conflict.

2. Literature review

This study adopted a multi-theory approach (i.e., value-belief-norm theory, theory of planned behavior, and risk contagion, and modern portfolio theory) to investigate the research problem at hand. At first, value-belief-norm theory[2] explains the investor's behavioral change and postulates that an individual's environmentally sensitive decision-making behavior is explained by awareness of negative consequences to a valuable object (environment), recognizing responsibility, and considering their obligation to be involved in environmental protection [6,50]. The proponents of this theory believe that the intention behind this environmentally sensitive behavior is the well-being of society. Second, the theory of planned behavior of Ajzen [3,4], as cited in Ref. [5]) states that human attitude, perceived behavioral control, and subjective norms serve as factors affecting the intention to be involved in specific behavior. Consequently, awareness, attitude, and responsibility towards the planet's environment is increasing. Therefore, investors' behavior towards green investment has changed.

Third, the theoretical basis of risk contagion and propagation across markets or sectors can be traced back to the work of Engle et al. [51], who proposed the "heat wave" and "meteor shower" hypotheses and described the volatility spillover phenomena. Although there is no agreed definition of contagion, Dornbusch et al. [52] best described the contagion as "a significant increase in cross-market linkages after a shock to an individual country (or group of countries)". It can be explained that a shock to one sector can be transmitted to other sectors due to the interconnectedness between them, which causes an excessive increase in the overall level of systemic risk [34]. Dornbusch et al. [52] listed the causes of contagion in two categories, i.e., fundamental causes (financial and trade links, common shocks) and investor behavior. Fourth, Markowitz (1952) introduced a mean–variance model that is extensively utilized for selecting securities within a portfolio, helping investors minimize risk through diversification. Diversifying a portfolio involves lowering investment risk while maintaining a relatively stable return [53]. This framework laid the groundwork for Modern Portfolio Theory. According to Markowitz [54], as referenced in Leković [55], a portfolio should comprise assets that exhibit low correlation with one another to achieve diversification benefits, and the author recommended that investors allocate their funds across various industries rather than concentrating on a single sector, as companies from different

[2] Value-belief-norm theory is introduced by Stern et al. [6] and is an extension of the norm activation model of Schwartz [109].

sectors tend to have low correlations. He maintained that unsystematic risk could be mitigated through diversification by selecting an optimal mix of uncorrelated securities within a portfolio.

It may be concluded that investors' environmentally conscious behavior encourages them to be involved in sustainable forms of investment. In times of crisis, the levels of connectedness rise, leading to a heightened volatility spillover within green sectors, which could elevate the likelihood of risk contagion and potentially trigger a systemic risk event. In addition, combination of least connected green sectors in a portfolio can offer best risk-adjusted returns to environment-friendly investors.

After discussing the theoretical literature, the empirical literature on green and sustainable equity markets can be divided into four research streams. The first investigates volatility spillover among oil prices and renewable energy markets. The second stream deals with volatility connectedness between conventional and green asset markets. The third focuses on spillover and connectedness between green bonds and other conventional asset markets. The fourth group emphasizes connectedness and volatility spillover within sustainable markets and green equity sectors.

First of all, a significant number of studies explore volatility spillover between oil prices and the renewable energy market, which is a part of the green equity market. Sadorsky [56] analyzed the volatility spillover and correlation between oil prices and clean energy and technology company stock prices using numerous GARCH family models i.e., BEKK, CCC, and DCC. The results revealed short and long-run volatility persistence and association among stocks of clean energy and technology companies. Ahmad [57] also investigated return and volatility spillover between crude oil prices, clean energy and technology company stock prices. The results of Diebold and Yilmaz [40] and the GARCH family models i.e. BEKK, CCC, and DCC explained that technology and clean energy companies play a dominant role in spillovers to crude oil prices. Similarly, Ferrer et al. [43] explored the time-frequency connectedness between equity prices of US clean energy, and crude oil prices and found interdependence in the short run while association, in the long run, is not noticeable with the help of Barunik and Krehlik's (2018) methodology. Tan et al. [58] also highlighted the risk of spillover between oil and clean energy stocks.

The second part of the literature investigates the volatility spillover pattern among green and conventional asset markets. Liu and Hamori [45] focused on finding the return and volatility spillover from fossil energies and other traditional variables to the renewable equity market in Europe and the US in the time and frequency domain. Using the approaches of Diebold and Yilmaz [40,41], and Barunik and Krehlik (2018), they reported that these spillovers are conditional on frequency and intensify due to sudden price fluctuations or specific events. Time-frequency volatility spillover analyses performed by Sharma et al. [9] concluded that connectedness increases among green and conventional indexes after the COVID-19 outbreak, and the bi-directional relationship between both indices is confirmed by the Granger causality test. Khalfaoui et al. [59] examine the connectedness and spillover effects between the green stock market, the US stock market, and Bitcoin with the help of the Quantile VAR network approach. Similarly, Chen et al. [60] examined return connectedness and hedge effectiveness between 12 NASDAQ green economic equities and the natural gas market with the help of TVP–VAR methodology during various crisis episodes. They found that various green equities can provide better hedge effectiveness against the risk of the natural gas market and some equities offer hedge features similar to the US dollar and gold during different turmoil events. Hanif et al. [38] identified that COVID-19 triggered the spillovers and co-movements between rare earth metals and the renewable energy market with the help of wavelet analysis and Diebold and Yilmaz's [40] spillover index methodology.

Furthermore, Jiang et al. [61] analyzed the COVID-19 impact on spillovers between green finance, renewable and non-renewable energy, and carbon markets in China. The total connectedness increases notably during the outbreak and varies with stressful events. Non-renewable energy affected carbon prices post-COVID-19, with spillovers mainly in the short run tied to investor sentiments. Similarly, Li et al. (2023) examined the spillover connections among metal, traditional energy, and clean energy markets at the sub-sector level (energy efficiency, renewable energy, and clean fuels).Following Diebold and Yilmaz [40, 41], their analysis revealed that the energy efficiency market serves as the main risk transmitter across various market scenarios, with metal and traditional energy markets being the recipients of such risks. Lan et al. [62] investigated the volatility spillover among the renewable energy, non-renewable energy, carbon, and high-tech markets and the climate policy uncertainty index. The BEKK–GARCH model identified climate policy uncertainty as the main risk transmitter. However, full sample results in the frequency domain explained the shock-receiving role of the non-renewable and carbon market. Moreover, Karkowska and Urjasz [63] studied volatility spillovers in green and conventional equity markets across Europe, the USA, and China. The TVP–VAR results indicated that the US market drives volatility transmission while China's green market absorbs shocks. Additionally, Trancoso and Gomes [15] used the TVP–VAR model to analyze how green equities affect the stock market, noting a shift from shock transmission to reception as green finance grows.

The third stream of studies examined the volatility spillover and connectedness between green bonds and other conventional asset markets. Pham [64] conducted the volatility analysis among green and conventional bonds using a multivariate DCC–GARCH framework. He reported volatility clustering in the green bond market while receiving volatility shocks from the conventional bonds market. Park et al. [65] using bivariate GARCH i.e., BEKK, DCC, ADCC, concluded on the asymmetric volatility features in the green bond market and identified spillover effects between the green bond and equity market. The studies by Gyamerah et al. [66], Tang et al. [44], Yadav et al. [47], and Huang et al. [67] mainly emphasized the volatility spillover among green bonds, in the renewable energy market using various generalized forecast error variance decomposition methods based on VAR as well as M–GARCH family approaches. However, Chen et al. [68] using the TVP–VAR model, found that green bonds mostly act as shock transmitters, showing more spillover to conventional bonds than stocks, commodities, or foreign exchange.

Finally, there is growing concern about the connectedness and volatility spillover within sustainable markets and green equity sectors. Zhang et al. [69] investigated the volatility spillovers between various sustainable financial indexes and provided hedge ratios along with portfolio weights using DCC–GARCH and DCC–GARCH t-copula approaches. In the same pattern, Lu et al. [39] also studied the dynamic connectedness across numerous green finance markets using the TVP–VAR extended joint connectedness approach. They explained the role of each market in volatility spillover and found a significant increase in dependence after the outbreak of COVID-19. The study by Zhou et al. [33] explored the risk spillover path across the various renewable energy markets that are part of the green economy sectoral index family. Applying the BEKK model, they observed that volatility spillovers at high dimensions across these markets mostly transmit risk from solar and fuel cell energy markets to other renewable markets. Moreover, Wu and Qin (2024) studied asymmetric volatility spillover among China's ESG, new energy, green bonds, and carbon markets. The results revealed persistent asymmetric volatility transmission over 40 days, with ESG and new energy connected more than green bonds and the carbon market. It is also found that green bonds and ESG act as net shock transmitters, and carbon and new energy as receivers. They observed that bad volatilities dominated good ones in the post-COVID-19 period. Similarly, the dynamic connections among clean energy, sustainable, and green markets were explored by Ozkan et al. [70]. Results show strong integration, with clean energy markets transmitting shocks, whereas green markets receive them. However, sustainable markets play both roles as shock transmitters senders and receivers.

Despite abundant research on connectedness and volatility spillover among green and conventional markets, studies examining the volatility spillover within green equity sectors are scarce. However, understanding the inter-sector volatility spillover structure not only helps policymakers to identify the leading sector in volatility transmission in order to minimize overall market risk and make development plans to support volatility-absorbing sectors ([19]; Chirila, 2022) but can also be used to predict and manage extant crises (Laborda & Omlo, 2021). Furthermore, investors and portfolio managers can use spillover structures for portfolio diversification and risk management [37,71]. Volatility spillover at different frequencies over different time frames may facilitate the decisions of investors with different investment horizons as well as policymakers in designing time-specific development plans. Therefore, this study fills this gap by exploring the volatility spillover dynamics in the time and frequency domain to assist policymakers, investors, and portfolio managers.

3. Data and empirical methodology

3.1. Data and preliminary analysis

To explore the connectedness and volatility spillover dynamics of green equity sectors in the time and frequency domain, this study utilized the daily closing prices of the NASDAQ OMX green economic index family, following Pham [23], Ferrer et al. [8], Sharma et al. [9]. This index family measures the financial performance of various global green economic sectors, which were introduced in October 2010 with a base value of 1000 and are calculated in US dollars. The reason for selecting these indices as a proxy for green equity sectors is their worldwide popularity and data availability. Green sectoral equity indices include advanced materials, bio/clean fuels, energy efficiency index, green building, green transportation, healthy living, lighting, natural resources, pollution mitigation, recycling, renewable energy generation, and water index (Appendix 1 provides a complete description of indices). Daily closing index values are extracted from October 15, 2010, to September 30, 2023, from the website of investing.com. The initial date is selected due to the availability of green equity sectoral data [8]. To find the sectoral volatility spillover structure, this study defines the price volatility of each sector index in terms of absolute returns by following the studies of Corbet et al. [72], and Costa et al. [73], as follows:

$$V_{i,t} = \left| \ln p_{i,t} - \ln p_{i,t-1} \right| \tag{1}$$

Where, $p_{i,t}$, $p_{i,t-1}$ refers to the closing price of index i at time t and t-1, respectively.

Table 1 presents the summary statistics of the daily volatilities belonging to equities of 12 green sectors and Fig. 2 shows their evolution during the sample period. First of all, high values of mean volatility and standard deviation highlight that the bio/clean fuels followed by lighting and green transportation sectors appear to be the riskiest sectors, which is an indication of big price swings. The possible reasons for the high level of volatility in the bio/clean fuels sector may include policy uncertainty and investor hesitation due to uncertainty in revenue and the cost of clean fuel production, which comes from the unpredictability of conventional fuel markets [74]. Contrary to this, the smaller value of average volatility related to water, renewable energy generation, and pollution mitigation sectors shows them to be less risky sectors, with signs of stable price movements. Fig. 2 shows many upward movements in the sector's volatilities during the period studied, which may be the result of different financial, economic, and geopolitical events i.e., the European debt crisis (2010–2012), the oil market collapse (2014–2016), the US-China trade war (2018–2019), the COVID-19 pandemic (2020), and the Russia–Ukraine conflict (2022).

The results of diagnostic tests for the validity of employing the TVP–VAR frequency connectedness approach revealed that skewness and kurtosis for all series are right skewed and leptokurtic distribution with shape peak and thick tail. These findings are confirmed by the Jarque–Bera test which explains that all volatility series do not follow a normal distribution. Secondly, a stable time series is the prerequisite for application of the TVP–VAR frequency connectedness approach, which is confirmed by the Augmented Dickey–Fuller (ADF) test. The results of the ADF test revealed that all series are stationary at the level and fulfill the requirements of empirical methodology.

3.2. TVP–VAR frequency connectedness approach

To study the connectedness and volatility spillover dynamics in the time and frequency domain, this study applied the novel TVP–VAR-based frequency connectedness approach of Chatziantoniou et al. [49], who combined the models of Barunik and Krehlik (2018) and Antonakakis et al. [48]. TVP–VAR with lag order p can be expressed as:

$$x_t = \phi_{1t}x_{t-1} + \phi_{2t}x_{t-2} + \ldots + \phi_{pt}x_{t-p} + \xi_t, \xi_t \sim N(0, \Sigma_t) \tag{2}$$

Where, X_t, $X_{t-1,}$ and $\mathcal{E}_t$ are N × 1 dimensional vectors, Φ_{it} represents the time-varying coefficients of the VAR model and $\sum_t$ denotes the time-varying variance covariance matrix. However, both Φ_{it} and $\sum_t$ are N × N dimensional matrices.

The generalized forecast error variance decomposition (GFEVD) can be written as:

$$\theta_{ijt}(H) = \frac{(\Sigma_t)_{jj}^{-1} \Sigma_{h=0}^{H} \left((\psi_h \, \Sigma_t)_{ijt} \right)^2}{\Sigma_{h=0}^{H} \left(\psi_h \, \Sigma_t \, \psi_h' \right)_{ii}} \tag{3}$$

$$\widetilde{\theta}_{ijt}(H) = \frac{\theta_{ijt}(H)}{\Sigma_{K=1}^{N} \theta_{ijt}(H)} \tag{4}$$

Here, $\widetilde{\theta}_{ijt}(H)$ measures the input of the green sector j to the variance

Table 1
Descriptive statistics of the volatilities of green equity sectors.

	Mean	SD	Skewness	Kurtosis	Jarque–Bera	ADF
Advanced Materials	0.0103	0.0105	2.729	16.58	29819	−8.893
Bio/Clean Fuels	0.0127	0.0133	3.636	30.73	114466	−10.74
Energy Efficiency	0.0088	0.0093	3.039	21.32	51876	−8.114
Green Building	0.0085	0.0101	4.828	50.63	328917	−7.628
Green Transportation	0.0109	0.0130	2.973	16.48	30211	−7.129
Healthy Living	0.0083	0.0089	3.495	25.01	74290	−8.495
Lighting	0.0112	0.0109	2.342	12.53	15695	−8.563
Natural Resources	0.0108	0.0127	6.552	116.78	1826498	−9.087
Pollution Mitigation	0.0082	0.0083	2.938	22.90	59965	−8.612
Recycling	0.0084	0.0087	3.120	22.46	58176	−8.072
Renewable Energy Generation	0.0081	0.0085	3.768	38.22	180664	−8.815
Water	0.0071	0.0075	3.421	26.18	81326	−7.788

Notes: Jarque–Bera and ADF test results for all sectors are significant at a 1 % level.

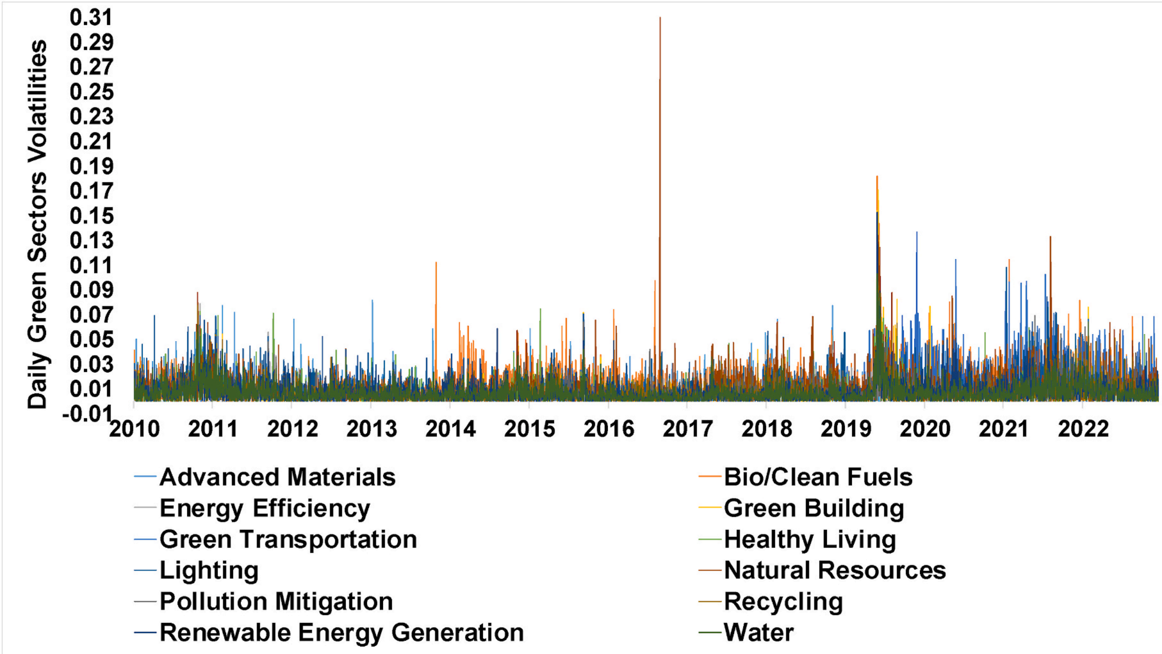

Fig. 2. Volatilities of green equity sectors from October 15, 2010, to September 30, 2023.

of the forecast error of the green sector i at the time horizon H. Furthermore, the rows of $\widetilde{\theta}_{ijt}(H)$ do not sum up to 1 and need to be normalized, which results in $\widetilde{\theta}_{ijt}$. This normalization process provides the following identities:

$$\Sigma_{i=1}^{N}\widetilde{\theta}_{ij}(H)=1, \Sigma_{j=1}^{N}\ \Sigma_{i=1}^{N}\widetilde{\theta}_{ijt}(H)=N. \tag{5}$$

In the next stage, TVP–VAR base connectedness measures are presented. To begin with, an equation of the total directional connectedness (TO) others is provided which measures the volatility spillover from sector i to all other sectors j as:

$$TO_{it}(H)=\Sigma_{i=1,i\neq j}^{N}\ \widetilde{\theta}_{jit}(H) \tag{6}$$

Next, the equation of total directional connectedness (FROM) others explains how much volatility is received by sector i from all other sectors j which is presented as:

$$FROM_{it}(H)=\Sigma_{j=1,i\neq j}^{N}\ \widetilde{\theta}_{ijt}(H) \tag{7}$$

The difference between total directional TO and FROM connectedness shows the (NET) total directional connectedness. It measures the net volatility spillover by sector i on the analyzed network, as below:

$$NET_{it}(H)=TO_{it}(H)-FROM_{it}(H) \tag{8}$$

Hence, if $\mathrm{NET}_{it}>0$ or $\mathrm{NET}_{it}<0$ it shows that sector i impacts or influences all other sectors j more or less than being influenced by them. As a result, it explains the net transmitter or receiver of volatility.

In addition to the above-mentioned connectedness measure, net pairwise directional connectedness (NPDC) is computed as follows:

$$NPDC_{ijt}(H)=\widetilde{\theta}_{ijt}(H)-\widetilde{\theta}_{jit}(H) \tag{9}$$

$NPDC_{ijt}>0$, or $NPDC_{ijt}<0$ represent that sector j impacts sector i more or less than vice versa.

And lastly, the total connectedness index (TCI) explains the degree of total network connectedness. It explains the average impact of a shock in one sector on other sectors and its high value represents high market risk. It is expressed as:

$$TCI_t(H)=N^{-1}\Sigma_{i=1}^{N}TO_{it}(H)=N^{-1}\Sigma_{i=1}^{N}\ FROM_{it}(H) \tag{10}$$

After the explanation of relatedness in the time domain, connectedness in the frequency domain is elaborated. The spectral density of X_t at frequency ω can be stated as the Fourier transformation of the TVP–VMA:

$$S_x(w)=\Sigma_{h=-\infty}^{\infty}\ E\left(x_t x_{t-h}'\right)e^{iwh}=\Psi\left(e^{-iwh}\right)\Sigma_t\Psi'\left(e^{+iwh}\right) \tag{11}$$

The frequency generalized forecast error variance decomposition (GFEVD) is the combination of the GFEVD and spectral density. Just like the normalization of GFEVD in time, the frequency GFEVD also needs to normalize and can be written as:

$$\theta_{ijt}(\omega)=\frac{(\Sigma_t)_{jj}^{-1}\left|\Sigma_{h=0}^{\infty}\left(\Psi\left(e^{-iwh}\right)\ \Sigma_t\right)_{ijt}\right)\Big|^2}{\Sigma_{h=0}^{\infty}\left(\Psi\ \left(e^{-iwh}\right)\Sigma_t\Psi\left(e^{iwh}\right)\right)_{ii}} \tag{12}$$

$$\widetilde{\theta}_{ijt}(\omega)=\frac{\theta_{ijt}(\omega)}{\Sigma_{K=1}^{N}\theta_{ijt}(\omega)} \tag{13}$$

Here, $\widetilde{\theta}_{ijt}(\omega)$ shows the portion of the spectrum of the ith sector at a given frequency ω that results in shock in the jth sector.

Furthermore, to capture connectedness at various frequency bands (short and long run), all frequencies within a specific range are summed up as:

$$\widetilde{\theta}_{ijt}(d)=\int_a^b\widetilde{\theta}_{ijt}(\omega)d\omega \tag{14}$$

In this equation, $d=(a,b): a, b\in(-\pi,\pi), a<b$.

Now, connectedness among sectors can be exactly calculated as in Diebold and Yilmaz [40,41]. However, they refer to frequency connectedness measures in this case and examine the information spillover in a specific frequency range d. Detailed equations are mentioned below:

$$TO_{it}(d)=\Sigma_{i=1,i\neq j}^{N}\ \widetilde{\theta}_{jit}(d) \tag{15}$$

$$FROM_{it}(d)=\Sigma_{i=1,i\neq j}^{N}\ \widetilde{\theta}_{ijt}(d) \tag{16}$$

$$NET_{it}(d)=TO_{it}(d)-FROM_{it}(d) \tag{17}$$

$$NPDC_{ijt}(d) = \widetilde{\theta}_{ijt}(d) - \widetilde{\theta}_{jit}(d) \tag{18}$$

$$TCI_t(d) = N^{-1}\Sigma_{i=1}^{N} TO_{it}(d) = N^{-1}\Sigma_{i=1}^{N} FROM_{it}(d) \tag{19}$$

These equations provide measures of spillover regarding a certain range but do not explain the overall impact. Therefore, Barunik and Krehlik (2018) proposed to weigh all contribution measures in each frequency band d concerning the overall system by, $\Gamma(d) = \Sigma_{i,i=j}^{N} \widetilde{\theta}_{ijt}(d)/N$

$$T\widetilde{O}_{it}(d) = \Gamma(d).\ TO_{it}(d) \tag{20}$$

$$TRO\widetilde{M}_{it}(d) = \Gamma(d).\ FROM_{it}(d) \tag{21}$$

$$NE\widetilde{T}_{it}(d) = \Gamma(d).\ NET_{it}(d) \tag{22}$$

$$NPD\widetilde{C}_{ijt}(d) = \Gamma(d).\ NPDC_{ijt}(d) \tag{23}$$

$$TC\widetilde{I}_t(d) = \Gamma(d).\ TCI_t(d) \tag{24}$$

Finally, the relationship between Diebold and Yilmaz's [40,41] connectedness measure in the time domain and Barunik and Krehlik's (2018) measures in the frequency domain is presented below:

$$TO_{it}(H) = \Sigma_d TO_{it}(d) = \Sigma_d\left(\Sigma_{i=1,i\neq j}^{N} \widetilde{\theta}_{jit}(d)\right) \tag{25}$$

$$FROM_{it}(H) = \Sigma_d FROM_{it}(d) = \Sigma_d\left(\Sigma_{i=1,i\neq j}^{N} \widetilde{\theta}_{ijt}(d)\right) \tag{26}$$

$$NET_{it}(H) = \Sigma_d NET_{it}(d) = \Sigma_d\left\{\left(\Sigma_{i=1,i\neq j}^{N} \widetilde{\theta}_{jit}(d)\right) - \left(\Sigma_{i=1,i\neq j}^{N} \widetilde{\theta}_{ijt}(d)\right)\right\} \tag{27}$$

$$NPDC_{ijt}(H) = \Sigma_d NPDC_{ijt}(d) = \Sigma_d\left(\widetilde{\theta}_{ijt}(d) - \widetilde{\theta}_{jit}(d)\right) \tag{28}$$

$$TCI_t(H) = \Sigma_d TCI_t(d) = \Sigma_d\left(N^{-1}\Sigma_{i=1}^{N} TO_{it}(d)\right) = \Sigma_d\left(N^{-1}\Sigma_{i=1}^{N} FROM_{it}(d)\right) \tag{29}$$

4. Empirical results and discussion

4.1. Total average volatility connectedness

This section highlights the average total connectedness and volatility spillover structure in the time and frequency domain across 12 global green equity sectors from 2010 to 2023. Table 2 presents the total average interaction while Tables 3 and 4 show the short run (1–5 trading days) and long run (5-infinite days) connectedness among sectors. The table columns demonstrate the volatility spillovers by an individual sector to all other sectors and summed up in a row labeled as "TO" excluding the diagonal elements that explain their contribution. Similarly, the rows refer to the volatility received by a green sector from other sectors and are added under the heading "FROM" excluding diagonal components. Lastly, the difference between "TO" and "FROM" is represented as the "NET" contribution of the individual sector made in the connectedness network.

A sector is classified as a net shock transmitter if its net connectedness value is positive, while a sector with a negative net connectedness value is considered a net shock receiver [75]. Generally, net shock receivers and transmitters are also classified as risk absorbers and transmitters because they receive and transmit the shocks to others [76,77].

In Table 2, the total connectedness index (TCI)[3] indicates close linkages among sectors with 69.67 % of volatility forecast error variance coming from connections between sectors. This integration may be due to sharing similar environment protection attributes. It further indicates the possibility of sectoral contagion and systemic risk spillover. The studies of Tan et al. [58] and Pham [23] also found a close relationship among several green equity indices in which they investigated their connectedness with other variables. The remaining portion of TCI (30.33 %) is contributed by idiosyncratic factors of each sector. The frequency decomposition of total connectedness in Tables 3 and 4 elaborates that inter-sector volatility connectedness is mainly driven by shock spillover in the short-run (44.14 %) more than in the long-run (25.52 %). It explains that green sectors quickly absorb and process information in the short-run and most of the shocks are not persistent over a longer period.

Furthermore, it is noticed from the connectedness Table 2 and Fig. 3 that water is the largest net volatility transmitter, followed by energy efficiency, green building, and recycling, sharing 101.12 % shocks to others and receiving 78.83 % volatility from others. Water is the most basic requirement of every society [78], which may be the reason for its greater contribution to the system. Similar attributes of these sectors were found by Chen et al. [60] in the return connectedness between green economic sectors and gold, the US dollar, and natural gas. According to Diebold and Yilmaz [41], these four sectors are considered systematically important due to the highest positive net contributions (NET) and spillovers to (TO) other sectors included in the system. Conversely, the bio/clean fuels sector is the largest net shock receiver (−19.43 %) and least connected in terms of volatility transmission (33.61 %) and absorption from others (53.04 %). Moreover, net shock absorbers which have similar features to the bio/clean fuels sector include healthy living, advanced materials, and natural resources sectors. The possible reasons behind the sector's role as a "risk transmitter" or "risk absorber" include the degree of connectedness, the upward–downward supply chain relationship, investors allocation pattern, and government policies and regulations.

Tables 3 and 4 clarify that most inter-sector volatility connectedness is noticed in the short run except for green transportation and pollution mitigation sectors for which long-run connectedness dominates. Specifically, it is important to note the heterogeneous behavior of the renewable energy generation sector as being the net shock receiver in the short run and volatility transmitter in the long run.

Finally, regarding pairwise connectedness, the highest pairwise connectedness is observed from water to energy efficiency (11.65 %), whereas transmission from energy efficiency to water (11.28 %) is also the second largest. The possible reason for the strong relationship lies in the interdependence between the water and energy sectors, as a rise in water demand also drives an increase in energy demand [79]. Efficient utilization of water and energy resources, and decreased related costs can enhance energy efficiency [79,80]. Consequently, industries focusing on energy-efficient technologies are closely associated with the water sector. Furthermore, water is also highly connected with recycling (11.25 %), while shock spillover from recycling to water (9.96 %) is also noticeable. Additionally, energy efficiency and recycling, water and green building as well as water and renewable energy generation sector are closely connected pairs. The water sector was found to be closely connected with energy efficiency, recycling, green building, and renewable energy generation because of its deep integration with these areas to sustain their business operations [79,81–83]. In this sense, any shock originating in the water sector spills over to other associated sectors and vice versa. Based on the previous discussion and the analysis of gross directional volatility spillovers, it can be inferred that the water, energy efficiency, green building, and recycling sectors are highly interconnected and significantly influence nearly all other sectors. Due to their close relationships, the investors may not benefit from diversification in a portfolio. Conversely, sectors such as advanced materials, bio/clean fuels, healthy living, and natural resources demonstrate the weakest interconnections with other sectors within the system. These areas present opportunities for diversification and can be paired with any closely connected sectors. Furthermore, industries focused on green

[3] TCI represents the average effect of a shock in one variable (sector) on all the other variables (sectors), and a high value indicates greater market risk [49].

Table 2
Average total volatility connectedness between green equity sectors.

	AM	BIO	ENEF	GB	GT	HL	LGT	NR	PM	REC	REG	WTR	FROM
Advanced Materials (AM)	32.13	2.8	9.52	7.24	5.93	3.45	6.38	4.84	6.01	7.5	5.68	8.5	67.87
Bio/Clean Fuels (BIO)	3.59	46.96	5.54	5.71	6.86	3.77	3.62	4.05	3.78	5.61	4.81	5.7	53.04
Energy Efficiency (ENEF)	6.52	2.85	21.48	8.87	7.41	4.53	7.1	5.2	7.69	10.01	6.69	11.65	78.52
Green Building (GB)	5.58	3.38	9.54	24.3	8.07	4.35	5.39	5.14	6.68	9.98	6.96	10.64	75.7
Green Transportation (GT)	4.24	4.77	7.83	8.24	31.55	4.33	5.68	5.07	4.96	7.56	7.18	8.59	68.45
Healthy Living (HL)	4.05	2.79	7.3	6.76	6.22	38.47	5.54	3.83	5.16	6.21	5.96	7.71	61.53
Lighting (LGT)	5.65	2.34	9.41	6.77	6.73	4.6	30.15	3.87	7.27	7.2	7.41	8.6	69.85
Natural Resources (NR)	4.88	3.32	7.87	7.09	6.79	3.49	4.22	37.86	4.58	7.89	4.29	7.73	62.14
Pollution Mitigation (PM)	5.48	2.62	9.82	8.13	5.99	4.27	7.06	4.2	28.49	7.21	6.78	9.96	71.51
Recycling (REC)	5.52	3.06	10.84	9.8	7.6	4.08	5.79	5.48	6.27	23.52	6.8	11.25	76.48
Renewable Energy Generation (REG)	4.9	2.86	8.27	8.03	7.67	4.59	6.84	3.84	6.35	7.94	27.93	10.79	72.07
Water (WTR)	5.59	2.82	11.28	9.68	7.63	4.68	6.31	4.92	7.64	9.96	8.31	21.17	78.83
TO	56.01	33.61	97.23	86.3	76.9	46.13	63.93	50.43	66.38	87.07	70.88	101.1	835.99
Net	−11.86	−19.43	18.7	10.6	8.45	−15.4	−5.91	−11.71	−5.13	10.59	−1.19	22.29	TCI = 69.67

Notes: The results of the TVP–VAR connectedness approach are based on VAR lag order 1 (SIC) and 100 steps ahead generalized forecast error variance decomposition.

Table 3
Average short-term volatility connectedness [1–5 trading days].

	AM	BIO	ENEF	GB	GT	HL	LGT	NR	PM	REC	REG	WTR	FROM
Advanced Materials (AM)	24.67	1.69	6.59	4.85	3.38	2.24	4.15	3.24	4.01	5.17	3.7	5.75	44.77
Bio/Clean Fuels (BIO)	2.34	33.95	3.58	3.36	3.59	2.57	2.42	2.38	2.47	3.58	3.12	3.72	33.13
Energy Efficiency (ENEF)	4.31	1.72	15.22	5.79	4.21	2.88	4.6	3.26	5.18	6.68	4.13	7.71	50.47
Green Building (GB)	3.56	1.93	6.17	16.29	4.07	2.72	3.35	3.15	4.35	6.42	4.07	6.8	46.59
Green Transportation (GT)	2.5	2.49	4.88	4.53	19.84	2.65	3.49	2.96	3.09	4.61	4.12	5.21	40.53
Healthy Living (HL)	2.45	1.87	4.82	4.21	3.51	29.18	3.5	2.32	3.34	4	3.7	4.96	38.66
Lighting (LGT)	3.85	1.57	6.48	4.32	3.8	3.09	22.45	2.47	4.94	4.92	4.84	5.82	46.09
Natural Resources (NR)	3.06	1.78	5.09	4.36	3.58	2.17	2.53	27.96	2.85	5.24	2.64	5.04	38.34
Pollution Mitigation (PM)	3.43	1.47	6.45	5.04	3.3	2.55	4.49	2.52	20.4	4.59	4.16	6.41	44.41
Recycling (REC)	3.65	1.89	7.23	6.34	4.31	2.6	3.73	3.68	4.08	16.9	4.18	7.39	49.09
Renewable Energy Generation (REG)	3.2	1.86	5.52	5.08	4.44	2.87	4.59	2.56	4.4	5.16	19.75	7.07	46.75
Water (WTR)	3.64	1.72	7.56	6.34	4.33	2.98	3.99	3.32	5.1	6.67	5.19	14.77	50.85
TO	35.98	20	64.37	54.22	42.52	29.33	40.85	31.85	43.81	57.03	43.87	65.86	529.7
Net	−8.79	−13.13	13.9	7.62	1.99	−9.33	−5.24	−6.49	−0.6	7.94	−2.88	15.01	TCI = 44.14

Notes: Results are based on a TVP–VAR connectedness approach based on generalized forecast error variance decomposition and its frequency spectral decomposition based on Baruník and Křehlík [42].

Table 4
Average long-run volatility connectedness [5-infinite trading days].

	AM	BIO	ENEF	GB	GT	HL	LGT	NR	PM	REC	REG	WTR	FROM
Advanced Materials (AM)	7.46	1.11	2.93	2.39	2.55	1.21	2.23	1.6	2	2.34	1.98	2.75	23.1
Bio/Clean Fuels (BIO)	1.25	13.01	1.96	2.36	3.27	1.2	1.19	1.67	1.31	2.03	1.69	1.99	19.91
Energy Efficiency (ENEF)	2.21	1.13	6.26	3.07	3.2	1.66	2.5	1.94	2.52	3.34	2.56	3.94	28.05
Green Building (GB)	2.02	1.45	3.37	8.01	4	1.63	2.04	1.99	2.32	3.56	2.88	3.84	29.1
Green Transportation (GT)	1.74	2.28	2.95	3.7	11.71	1.68	2.19	2.11	1.87	2.95	3.06	3.38	27.91
Healthy Living (HL)	1.61	0.92	2.48	2.56	2.71	9.29	2.04	1.51	1.82	2.22	2.26	2.76	22.88
Lighting (LGT)	1.81	0.77	2.93	2.45	2.93	1.51	7.7	1.39	2.33	2.28	2.57	2.78	23.75
Natural Resources (NR)	1.83	1.54	2.78	2.72	3.21	1.31	1.68	9.9	1.73	2.65	1.65	2.69	23.8
Pollution Mitigation (PM)	2.05	1.15	3.37	3.09	2.69	1.72	2.57	1.68	8.09	2.62	2.61	3.56	27.1
Recycling (REC)	1.86	1.17	3.6	3.46	3.3	1.47	2.06	1.81	2.19	6.62	2.62	3.86	27.39
Renewable Energy Generation (REG)	1.7	0.99	2.75	2.95	3.23	1.71	2.25	1.27	1.96	2.77	8.18	3.72	25.32
Water (WTR)	1.95	1.11	3.72	3.33	3.29	1.7	2.32	1.6	2.54	3.3	3.12	6.41	27.98
TO	20.03	13.61	32.85	32.08	34.38	16.81	23.08	18.58	22.58	30.04	27.01	35.26	306.29
Net	−3.07	−6.3	4.8	2.97	6.46	−6.07	−0.67	−5.22	−4.52	2.65	1.69	7.28	TCI = 25.52

Notes: Results are based on a TVP–VAR connectedness approach based on generalized forecast error variance decomposition and its frequency spectral decomposition based on Baruník and Křehlík [42].

transportation, lighting, pollution reduction, and renewable energy production demonstrate strong linkages with certain sectors while having weaker connections with others. This result should be considered when determining the appropriate weight for these sectors. For example, the lighting industry is more connected with energy efficiency and pollution mitigation sectors but less with others. The network of pairwise directional connectedness in Fig. 4a also clarifies the above discussion. Fig. 4b explains the status and magnitude of net pairwise directional connectedness of each sector, which confirms the previously mentioned role of each sector as either transmitter or receiver. However, it is important to note that green building and green transportation sectors transmit volatility to all sectors except the receiving from water industry.

4.2. *Total dynamic connectedness*

This study further investigates the time-varying features of total volatility connectedness among green equity sectors. Fig. 5 presents the dynamics of the total connectedness index (black-shaded area) along with its decomposition into the components of short-run (red-shaded area) and long-run connectedness (green-shaded area). The TCI varies from 49 % to 91 %, confirming the dynamic nature of connectedness

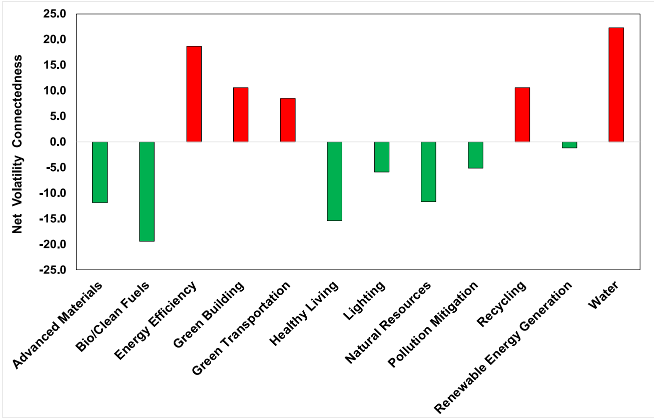

Fig. 3. The overall net contribution of green sectors. The red (green) color refers to the net status of volatility transmitters (receivers).

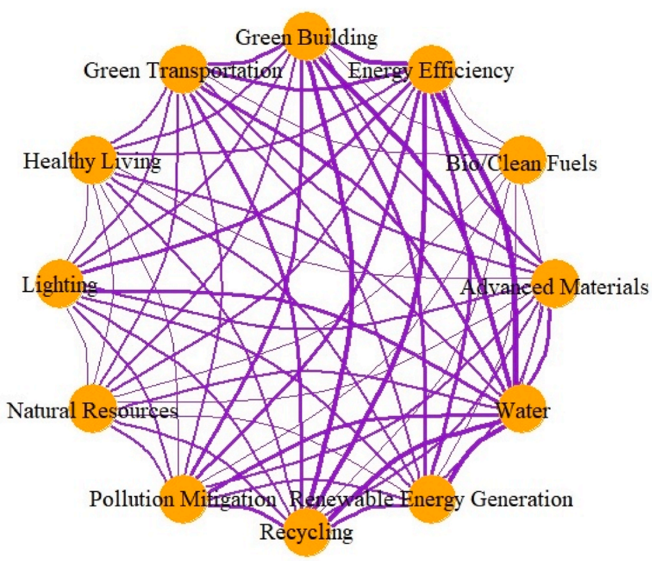

Fig. 4a. Network of total pairwise directional connectedness index. The width of a line shows the connectedness intensity.

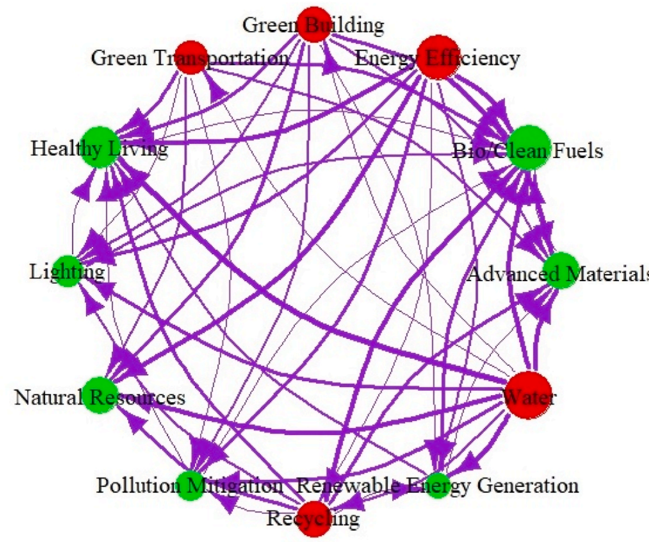

Fig. 4b. Network of net pairwise directional connectedness index. The red (green) node refers to the status of volatility transmitters (receivers) and its size represents the net connectedness effect. The arrow represents the direction of NPDC and the arrow's width shows connectedness intensity.

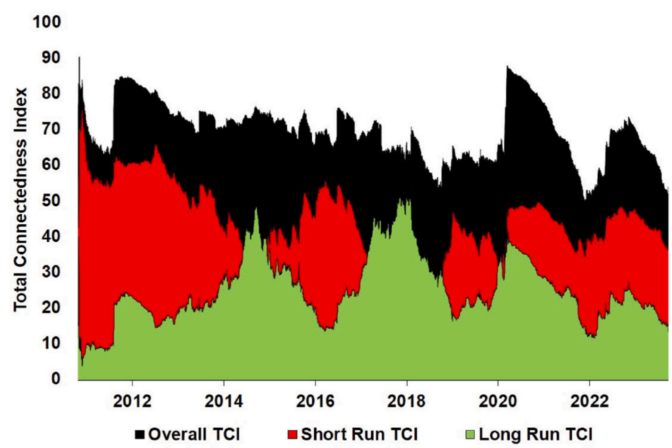

Fig. 5. Dynamic total volatility connectedness between green equity sectors in the time and frequency domain from October 2010 to September 2023.

between sectors.

At first, TCI shows a decline in connectedness from 2010 to mid-2011, which explains that the green market has started to gain stability. However, the increase in the connectedness reaching 85 % at the end of 2011 may be attributed to the peak of the European debt crisis which bounced back later by reaching an index at a lower level in June 2013. This period is characterized by the extraordinary rise in public debt in many European countries i.e., Greece, Italy, Ireland, Portugal, and Spain creating severe financial stress during the crisis period (Ferrer et al., 2021). Thereafter, the collapse in the oil market from 2014 to 2016 led to significant upward and downward movements in the connectedness index. This rise in volatility could be backed by the shifting investment trend toward sustainable energy sources, which causes the rise in prices of sectoral green equities. It is expected that the Chinese stock market turbulence in 2015–2016 also contributed to volatility swings shown by TCI. However, there is obvious stability for a short period in the sustainable market from July 2017 to February 2018 which was disturbed again by a surge in the level of connectedness in February 2018 just some days after the biggest one-day fall in Dow Jones industrial averages.

After some noticeable spikes in the spillover index as a result of the US–China trade war 2018–2019, COVID-19 is considered an important event that sharply increased connectedness among green equity sectors. On March 11, 2020, the declaration of COVID-19 as a global pandemic by WHO led to a dramatic rise in TCI to 89 % due to a significant drop in all green equity sector indices, just one day after the announcement. However, a gradual decline in the spillover index was noticed later, reaching 49 % in November 2021, which was its lowest since the introduction of sectoral indices. Similarly, Ferrer et al. [8] explained that the pandemic outbreak was a reason for the sudden fall in global financial markets in March 2020, which led to an increase in market volatility but swiftly declined afterward. The decline in volatility connectedness might be due to distinct government actions for the pandemic control and financial stability. In early 2022, the Russia–Ukraine conflict not only shrank the supplies of natural gas, oil, and agricultural products [84] but also created a tense environment that caused a rise in uncertainty and stress around the world, and financial markets became stressed [67]. The impact of these factors can be observed during 2022 with a noticeable upward trend in TCI (i.e., 73 %) and subsequently, a decreasing trend in risk transmission is a sign of the movement to stable market conditions. It is important to note that connectedness increases during crisis periods and reduces in calm periods.

Fig. 5 also shows that the share of short-term connectedness between green equity sectors dominates the portion of long-term connectedness in TCI throughout the period except at the end of 2014 and the start of 2018. This feature explains that the information is quickly processed among the assets included in the system [42] and shock is spread from one sector to other within short time period. This scenario underscores the importance of short-term portfolio reallocation and the possibility of diversification opportunities in the long run. Furthermore, it clarifies that these are not shocks of a permanent nature and their effects are not persistent over a long period. On the other hand, long-run connectedness shares a major portion in TCI during the period of the oil market crash in 2014 and the US–China trade war in 2018 which highlights the persistent reaction of investors towards shocks and which may become the reason for sectoral contagion and systemic risk.

4.3. Total directional volatility connectedness

To determine the dynamic role of each green sector in the connectedness network, Figs. 6–8 explain the time-varying evolution of directional connectedness TO others, FROM others, and their NET contribution. The color attribute of these figures reports the frequency distribution. Black, red, and green represent total, short-term, and long-term spillover in all figures. Red representing short-run volatility spillover is dominant throughout the sample period except in 2014 and 2017–2018 where the share of long-term transmission exceeds the short-term share. The initial period of long-run dominance was during the oil market collapse while the later period was attributed to the US decision to withdraw from the Paris Agreement, the significant drop in S&P 500, DJIA, and NASDAQ index, and the US–China trade war.

First, Fig. 6 demonstrates that volatility spillover from water and energy efficiency to other sectors is relatively larger and remains high throughout most of the sample period with moderate fluctuations. During the European debt crisis in 2012, volatility transmission to others reached a peak, however, shock transmission from bio/clean fuels, natural resources, and green building sectors to others reached its highest during the oil market crash (2014–2015). On the other hand, the volatility transmission of green transportation and renewable energy generation sectors was at its maximum level while natural resources reached the lowest level during 2018, which may be attributed to the biggest fall in DJIA, S&P 500, and NASDAQ composite indices since the last decade, the US–China trade war, and other factors. That period is considered to have a great impact on the global economies and financial markets [85,86]. The COVID-19 pandemic led to a sharp rise in spillovers to others in March 2020 and a moderate decreasing trend was noted till the end of 2021. Moreover, it is important to note that volatility spillover from the green transportation and pollution mitigation sector to others did not significantly increase during the COVID-19 episode. The Russia–Ukraine conflict might be a reason for the rising trend of volatility transmission in almost all sectors from early 2022 because this conflict gives rise to volatility across global financial markets [87].

Secondly, Fig. 7 shows the volatility received by each sector from all other sectors. The volatility received from other sectors (FROM) by each

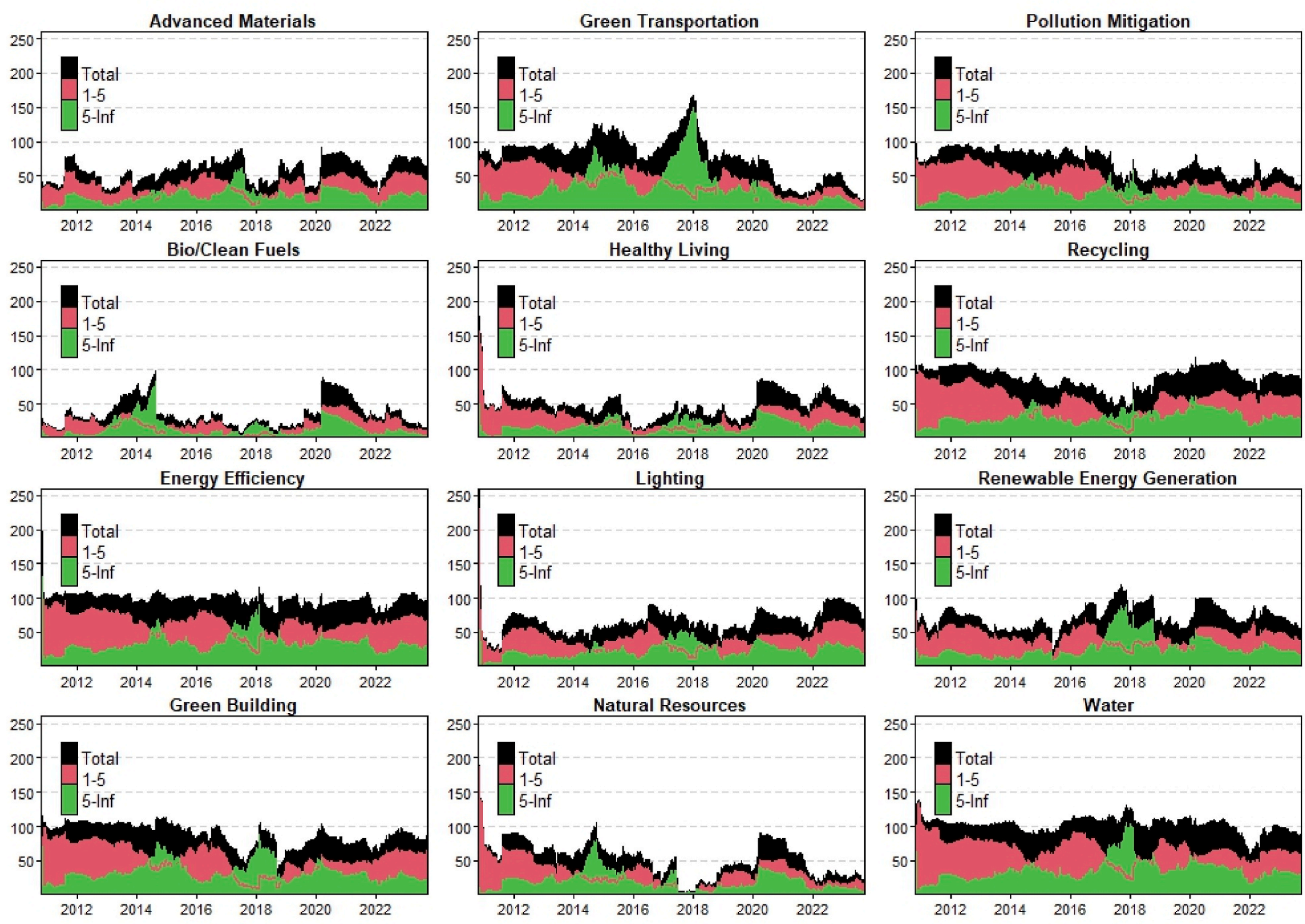

Fig. 6. Dynamic total directional volatility connectedness from one green sector to others in time and frequency domain from October 2010 to September 2023.

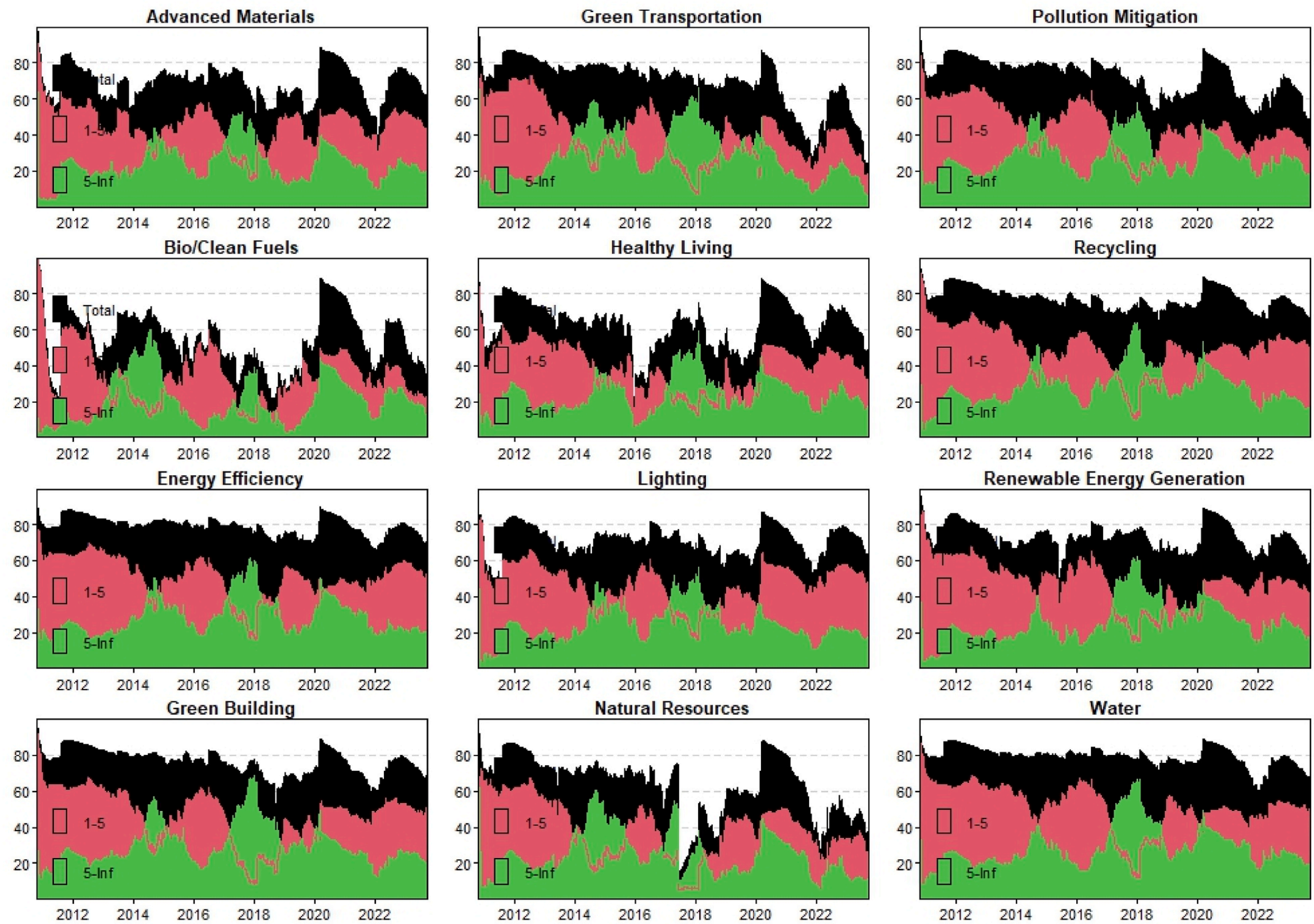

Fig. 7. Dynamic total directional volatility connectedness received by one green sector FROM others in time and frequency domain from October 2010 to September 2023.

sector showed a much smoother pattern with spillover to other sectors (TO others). This is in line with the findings regarding the connectedness among 13 financial institutions reported by Diebold and Yilmaz [41]. However, except for bio/clean fuels, healthy living and natural resources show more fluctuation during the entire sample period, which may be the reaction to different economic and financial events i.e., the European debt crisis (2012), the oil market crash (2014–2015), the US–China trade war (2018), the COVID-19 period (2020–2022) and the Russia–Ukraine conflict (2022).

Finally, the “NET” contributions in Fig. 8 show the time-varying nature of each sector’s volatility connectedness. Notably, the green transportation sector, which acted as a primary shock transmitter during the oil market crash in 2015 and the US–China trade war in 2018, propagated risks within the green equity market. The reason behind shock transmission includes the shift of funds by investors towards the traditional energy market due to low oil prices, which led to contagion effect, decreased investments and disturbance of the supply chain, and increased tariffs and trade barriers during the trade war (Bekaert et al., 2014; [88,89]). However, its function as a risk transmitter before the COVID-19 pandemic changed to that of a risk absorber after the outbreak in early 2020, facing significant volatility spillover from other sectors. The role of risk absorption following the COVID-19 pandemic has emerged because of government support packages, heightened investment, and growing awareness among investors and consumers regarding environmental issues and climate change ([90]; International Labour Organization, 2020). A similar pattern is observed in pollution mitigation industry since the end of 2017. Furthermore, recycling, lighting, renewable energy generation, and green building sectors play numerous transition roles of volatility transmitter and receiver in response to different financial and economic events, but share the same feature of shock transmission to others during the COVID-19 pandemic. Consistent with average connectedness results, water and energy efficiency sectors remained larger persistent volatility transmitters to others throughout the sample period with a slight decrease in spillover in early 2022, while advanced material, healthy living, bio/clean fuels, and natural resources sectors are net shock recipients over the whole period. Though, the magnitude of risk absorption of advanced materials gradually decreased after the pandemic was declared in March 2020 and its status moved to minimal transmitter after 2022. It is noticed that water, energy efficiency and recycling industries transmit the largest volatility shocks to other sectors. However, it is crucial to note that any policy alterations or uncertainties in the market could significantly affect the volatility of equities in green industries, given that the green market is still in its developmental phase. For instance, during a downturn or crash in the financial market, investor sentiment may amplify the spillover volatility among financial assets by selling equities [91,92], redirecting funds to safer assets [93,94], increasing the correlation between assets, which can result in a contagion effect [95] and herding behavior [96].

Various investment strategies are provided to investors and practitioners by exploring the dynamic interconnections among green sectors. First, it is observed that the relationships between green sector equities

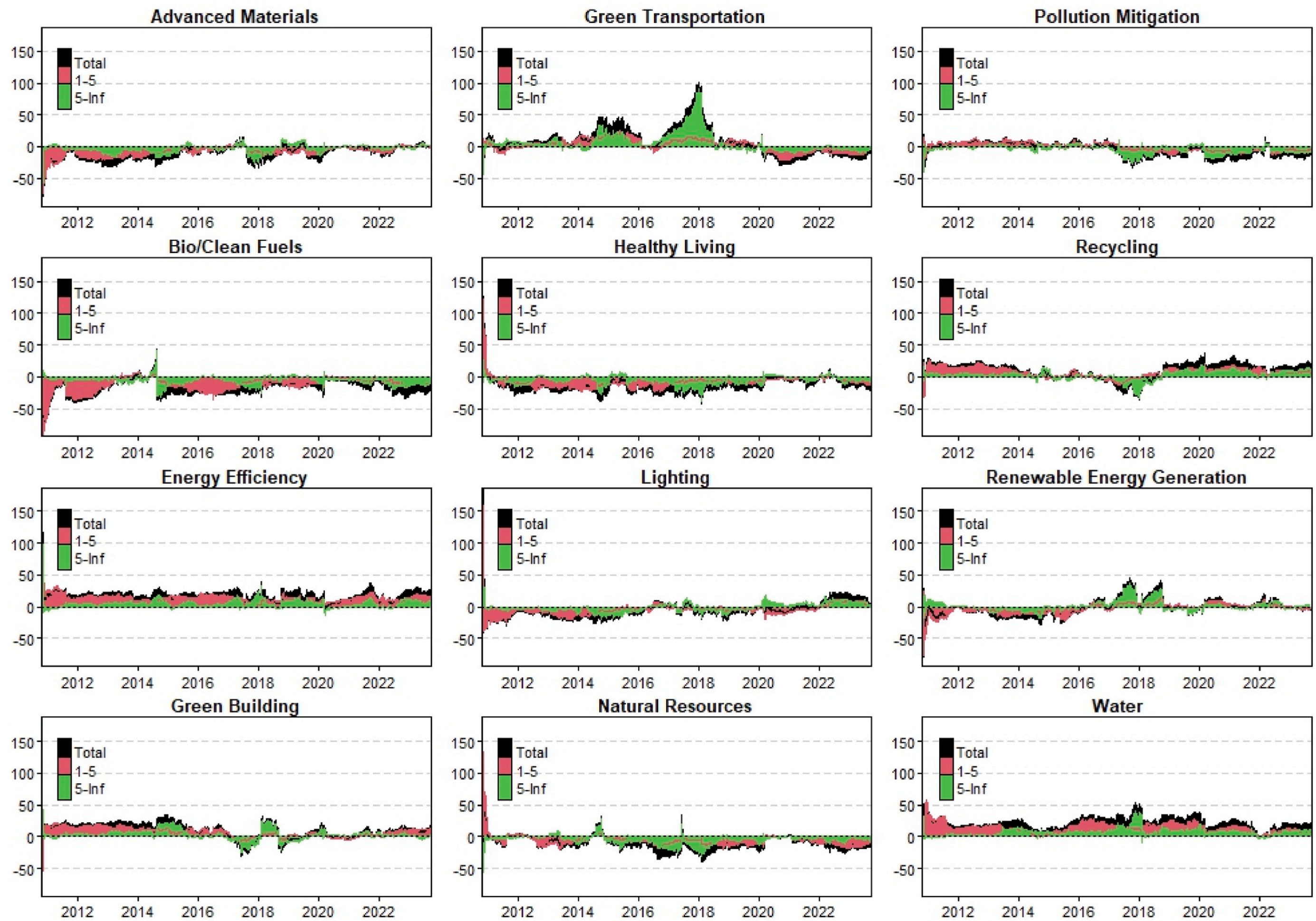

Fig. 8. Dynamic net total volatility directional connectedness of green sectors in time and frequency domain from October 2010 to September 2023.

fluctuate over time and frequencies, creating opportunities for diversification. Investors could consider incorporating a mix of growth sector equities to construct a well-diversified portfolio during stable market conditions (July 2017 to early 2018. This mix could include water management, energy efficiency, recycling, green building, less correlated sectors like biofuels and natural resources, and moderately connected industries such as advanced materials and pollution mitigation sectors to create a well-diversified portfolio.

Second, the sense of connectedness surged during the crisis, as noted by Aloui and Hkiri [97] and illustrated in Fig. 5, emphasizing the necessity for thoroughly comprehending the evolving inter-sector relationships throughout crisis episodes to lessen exposure to market risks. For instance, Figs. 6–8 depict how the connectedness traits of sectors fluctuated during the COVID-19 crisis, which is essential to consider for making optimal portfolio selections. For example, investors might construct their portfolios by selecting from sectors that consistently exhibit shock transmission to others, such as energy efficiency and water, demonstrating their resilience and strength in the face of a crisis. Additionally, sectors related to green building, healthy living, and natural resources also emerge as viable candidates due to their net volatility connectedness values being close to zero, indicating their capacity for resilience during crises. Furthermore, incorporating a notable portion of safe-haven assets, such as gold and bonds, is advisable during crises to mitigate portfolio risk, as highlighted by Akhtaruzzaman et al. [98], Flavin et al. [99], and Gürgün and Ünalmış [100].

Third, the dynamic interconnectedness in the frequency domain also necessitates carefully selecting green equities according to the evolving patterns of connectedness among them. According to Mensi et al. [101], the relationships between assets in the short run (or long run) provide opportunities for diversification in the long term (or short term). For example, volatility interconnectedness among nearly all green sector equities predominantly occurs in the short term throughout the entire sample, except for the long-term volatility interconnectedness that emerged in late 2014 during the oil market crash and around 2018 due to the US–China trade conflict and other significant events. In situations where short-run connectedness is present, strategies such as pair trading [102] and derivatives can be employed; while including multiple asset classes and factor diversification can be utilized when long run connectedness is observed.

5. Conclusions

The green equity market is fast-growing due to greater interest among investors and policymakers. This may be through a change in investors' beliefs and norms associated with environmental awareness or planned behavioral change due to international treaties (i.e., Paris Agreement) or intergovernmental aspirational goals (i.e., SDGs). However, this environment-friendly attitude among investors and policymakers requires understanding of the connectedness and volatility spillovers of the green equity market to achieve portfolio diversification, reduce overall market risk, and design targeted industrial development plans (Chirila, 2022). Therefore, this study empirically investigates time-varying volatility spillovers between equities of 12 green sectors by applying a novel TVP–VAR frequency approach from October 2010 to

September 2023.

The results of average connectedness indicated that water, energy efficiency, green building and recycling are largest transmitters of volatility shocks to others and considered as systemically important sectors. In contrast, bio/clean fuels, healthy living, advanced materials and natural resources are significant risk absorber sectors. Total dynamic connectedness analysis confirms the time-varying nature of volatility connectedness and is mainly concentrated in the short run except for long-run dominance during the oil market crash in 2014 and in 2017–2018 which may be due to the US–China trade war and other notable events. Furthermore, volatility spillover is seen to intensify during a crisis period more specifically during COVID-19, confirming the contagion phenomena. However, a dynamic directional analysis explains that each sector reacts differently during different episodes of crisis.

The findings of this study offer valuable practical insights for investors, portfolio managers, and policymakers. The static and pairwise network connectedness analysis provides a general understanding of inter-sectoral connectedness. This information is crucial for investors and practitioners to diversify their portfolios and manage associated risks effectively. For instance, investors should not combine closely connected sectors in a portfolio [103], such as water, energy efficiency, recycling, and green building sectors. The equities of these sectors can be combined with less connected industries such as bio/clean fuels, advanced materials, natural resources, and healthy living. Additionally, green transportation, lighting, pollution mitigation, and renewable energy generation industries show strong connections with some sectors while weak connections with others, which must be considered when assigning optimal weight to these sectors. Second, connectedness among assets intensifies during crisis when the diversification of portfolios becomes more important [104,105]. Therefore, dynamic volatility connectedness analysis is helpful for sustainable investors to readjust their portfolios during trubulent times by observing the connectedness pattern between green sectors and equities. For example, during the COVID-19 pandemic in 2020, investors could choose stable sectors that displayed consistent patterns of volatility transmission and demonstrated resilience, such as the energy efficiency and water sectors, alongside industries with minimal shock transmission, like green building, healthy living, and natural resources. Additionally, assets with safe haven properties, such as gold and bonds, can be included in a portfolio to hedge against risk during a crisis. Investors should also watch the performance of systematically important sectors for timely portfolio rebalance to reduce systemic risk exposure because any shock originating from these sectors is transmitted to other industries in the system [34]. The dynamic connectedness analysis within the frequency domain indicates that short-term volatility connectedness exists among nearly all green sectors, necessitating adopting short-term investment strategies for portfolio management.

For policymakers and market regulators, understanding the role of each sector in volatility spillover and market instability can be beneficial for ensuring the smooth operation of the green equity market. Policymakers should carefully monitor the performance of systematically important sectors (namely water, energy efficiency, green building, and recycling) to minimize the risk contagion and market breakdown, as an increase in volatility spillover in these sectors can act as an early warning indicator of financial distress [34]. During a crisis, policymakers must focus on stabilizing these sectors to mitigate systemic risk, as these industries transmit shocks to other economic sectors. Furthermore, targeted industrial development strategies and support initiatives, such as tax breaks and low-interest loans, can be offered to industries that can absorb risks to help them avoid liquidity crises during tough times. For instance, during the COVID-19 pandemic, the green transportation and pollution mitigation sectors transitioned from risk transmitters to risk absorbers, necessitating specific assistance from regulatory bodies. Additionally, short-term volatility spillover may lead to transient uncertainty in the green market, which should be effectively managed by implementing appropriate strategies to promote market stability.

The current study can be extended further based on the aforementioned grounds. First, connectedness and volatility spillover from conventional sectors (e.g., energy, technology, materials, industrials, among others) to green sectors can be investigated because shocks may be transmitted from traditional to sustainable markets ([63,106]; J. [107]). Second, future studies could focus on identifying the green sector(s) that may act as a potential source of risk propagation during different crisis events by segmenting the sample and utilizing advanced methods such as Bayesian Networks. Third, for a more nuanced analysis of the impact of asymmetric shocks on portfolio performance robustness, future research could employ the Nonlinear Autoregressive Distributed Lag (NARDL) model. Finally, various climate and economic policy uncertainties as well as volatilities in oil and financial markets may have significant impact on the volatilities of green sectors. Therefore, future research may be carried out to explore the factors that serve as determinants of volatility spillover in the green equity market. Finally, environmentally conscious investors may be interested in information regarding the integration of green equity sectors with other sustainable assets to find more diversification opportunities.

CRediT authorship contribution statement

Nasir Nadeem: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Imran Abbas Jadoon:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Faheem Aslam:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paulo Ferreira:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Paulo Ferreira acknowledges the financial support of Fundação para a Ciência e a Tecnologia (Grant UIDB/05064/2020).

Appendix 1

NASDAQ OMX Notation	Sector	Number of companies	Details
GRNAM	NASDAQ OMX Advanced Materials	7	This sector tracks the performance of companies producing material that supports renewable technologies or decreases dependence on petroleum-based products.

(continued on next page)

(*continued*)

NASDAQ OMX Notation	Sector	Number of companies	Details
GRNBIO	NASDAQ OMX Bio/Clean Fuels	8	Includes companies that produce fuel from plant-based raw material for transportation which replaced petroleum-based fuel.
GRNENEF	NASDAQ OMX Energy Efficiency Index	43	Includes companies that increase energy efficiency and has four subsector companies i.e., Energy Management, Energy Storage, Smart Grid and Green IT.
GRNGB	NASDAQ OMX Green Building	27	These companies deal with the construction of buildings with advanced designs for efficiency gains in water and energy consumption.
GRNHL	NASDAQ OMX Healthy Living	11	Producing personal care, food and other related products by using natural, benign, and certified ingredients through sustainable agricultural practices.
GRNLIGHT	NASDAQ OMX Lighting	7	These companies manufacture advanced lighting technologies that increase energy efficiency such as LEDs and compact fluorescents.
GRNNR	NASDAQ OMX Natural Resources	4	Includes companies that deal with forestry, agriculture, and other natural product manufacturing industries by using sustainable methods e.g., Forest Stewardship Certified Forestry and certified organic agriculture.
GRNPOL	NASDAQ OMX Pollution Mitigation	6	Includes companies producing goods and services that help reduce pollution from traditional plants, factories, and industries.
GRNREC	NASDAQ OMX Recycling	24	Includes companies that help to reduce the waste stream and extend the useful life of parts from precious metal products, and reuse, recover and recycle them for use in next-generation products.
GRNREG	NASDAQ OMX Renewable Energy Generation	89	Includes companies that produce energy using renewable sources such as fuel cells, waves, wind, solar and geothermal. This sector has four sub-sectors.
GRNTRN	NASDAQ OMX Green Transportation	39	Includes companies focusing on energy efficiency and reducing pollution arising from trains, automobiles, and other means of transport.
GRNWATER	NASDAQ OMX Water	64	Includes companies that purify and conserve water for industries, businesses and homes.

Data availability

Data will be made available on request.

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