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Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets[☆]

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ABSTRACT

In this study, we propose a novel quantile frequency connectedness approach that enables the investigation of propagation mechanisms by virtue of quantile and frequency. This approach allows for the analysis of connectedness measures considering either different frequencies for a given quantile or different quantiles for a given frequency. We investigate dynamic integration and return transmission among a set of four well-established environmental financial indices, namely the S&P Green Bond Index, MSCI Global Environment, Dow Jones Sustainability Index World, and S&P Global Clean Energy over the period from November 28th, 2008 to January 12th, 2022. S&P Green Bond Index and S&P Global Clean Energy appear to be both short-term and long-term net receivers of shocks while MSCI Global Environment and Dow Jones Sustainability Index World are both short-term and long-term transmitters of shocks. We also find that total connectedness indices (TCIs) are heterogeneous over time and economic event dependent. Furthermore, while the time-domain TCI is rather symmetric across quantiles, this is not the case for either the short-run or the long-run TCI.

1. Introduction

The growing awareness of the significance of climate change and sustainability has raised policymakers' and investors' interest in green and environmentally friendly investments. In particular, Dutta et al. (2020) find that investors in recent years have shifted their focus towards green investments. Thus, investors now include eco-friendly firms in forming portfolios. Since their introduction by the European Investment Bank in 2007, green bonds have emerged as a catalyst for financing eco-friendly projects. Glomsrød and Wei (2018) emphasize that green bonds reduce global coal consumption, thereby increasing the component of non-fossil electricity, which is a way of further reducing global CO2 emissions. By definition, green bonds are fixed-income investments that finance environmentally friendly projects (Initiative, 2019). Reboredo and Ugolini (2020) note that green bonds under the concept of green finance have been widely adopted by governments and investors in financial markets. Subsequently, since the time of its introduction to the global financial market, the green bond market price increased from \$0.8 billion to \$257.7 billion in 2019 — with 62 countries issuing green bonds in 2019 (Initiative, 2019). Also, renewable energy investments have recently increased significantly from around 50 billion USD in 2004 to about 300 billion USD (Wilshire and Finance, 2014). Furthermore, both green bonds and green stocks have emerged as the two key environmentally friendly financial instruments among investors and are expected to play a significant role in mobilizing the expected amount of capital needed to finance the vast transformational projects earmarked for the transition of the world to a low carbon economy. On the other hand, green bond financing has emerged as the main pillar to support the global transition to clean energy and broad low-carbon economic activities (Sartzetakis, 2021). The green bond market can serve as an important bridge between capital providers, such as

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institutional investors, and sustainable assets, such as clean energy. The energy sector has begun to embrace green bonds. With the growing interest in financial markets for eco-friendly investing and growth in both size and scope, examining the magnitude of connectedness between green assets, sustainable investments and renewable energy become an important issue. This allows both market participants and the investors to detect the underlying conditions through which green financial assets and other environmentally friendly instruments can be useful for diversification purposes. This study provides fresh empirical evidence on the magnitude of interconnectedness and directional spillovers among green bonds, green stocks, sustainable investments, and clean energy stock markets under different market conditions and varying investment horizons using the robust quantile frequency approach.

Studies on the evolution of the green bond market have gained considerable attention among scholars and investment communities. Several studies focusing on the return transmission mechanism between green bond markets and global financial markets have emerged in the finance and economic literature. Some studies focus on the linkages between the green bond market and other asset classes (Broadstock et al., 2020; Tiwari et al., 2022; Reboredo, 2018; Broadstock and Cheng, 2019; Kanamura, 2020; Hammoudeh et al., 2020; Ferrer et al., 2021; Yahya et al., 2021; Broadstock et al., 2020). Other studies also examine volatility spillover effects between the green bond market and traditional assets classes (Le et al., 2021; Nguyen et al., 2021; Gao et al., 2021). Recently, an emerging strand of the literature highlights the safe haven or diversification benefits of green bond markets (Arif et al., 2021; Pham, 2021; Pham and Nguyen, 2021; Reboredo, 2018; Broadstock et al., 2020).

Interestingly, even though several studies have examined the relationship between the green bond market and conventional assets, other aspects of the green bond market remain insufficiently researched. To this end, we contribute to the emerging literature on the green bond market by examining how the green bond market relates to other eco-friendly equity markets including green stocks, clean energy, and sustainability. Specifically, we investigate how strongly interconnected the four markets are, how much one market is influencing the others, and finally which market is either a net transmitter or a net receiver of shocks. It should also be noted that, notable studies close to our paper include Pham (2021) who examines the cross-quantile dependence and frequency connectedness between the green bond and green stock markets and finds that there exists a weak relationship among these markets during normal market periods; Liu et al. (2021) who examine the association between green bond and clean energy stock markets using copulas and find a significant dependency between the green bond and clean energy market and Tiwari et al. (2022) who investigate the connectedness and the directional spillovers between the green bond, renewable energy, clean energy, and carbon price market using a time-varying parameter vector autoregressive model (TVP-VAR) and show that clean energy dominates all other markets. We argue that even though some studies exist on the relationship between green bond, clean energy, and green stocks, our paper is the first explore the relationship between the green bond market and specialized eco-friendly financial market indices including clean energy, green stocks and sustainability. Furthermore, we introduce a novel quantile frequency connectedness approach that determines the magnitude of return connectedness across the markets of interest over time under different quantiles and frequencies. In essence, this paper extends the limited literature on green bond markets by testing the impact of sustainable, environmental, and renewable energy equity markets on green bond prices and vice versa under varying market conditions using a quantile frequency connectedness model. Succinctly, in this study we address the following questions. (i) Is there increased return connectedness among green bonds, green stocks, sustainability, and clean energy markets? (ii) How does connectedness vary under both extreme and normal market conditions, as well as, across different investment horizons? This type of analysis is especially useful in identifying appropriate policies and strategies to emphasize the diversification potential of green bond markets for investors.

To address the questions above, we use price returns of the S&P Green Bond index which captures global green bond market performance; MSCI Global Environment index as a representative of global eco-friendly firms; Dow Jones Sustainable World index which reflects the performance of firms with the best sustainable investment practices and S&P Global Clean Energy index to denote performance of firms in developed and emerging economies engaged in global clean energy-related activities. Next, we employ a modified version of the quantile connectedness framework (Chatziantoniou et al., 2021b) and the frequency connectedness framework (Baruník and Křehlík, 2018) to estimate connectedness and directional spillovers between green bonds and the other three markets under extreme and normal market conditions across short-term and long-term investment horizons. The adopted estimation technique employed in this paper measures the magnitude of connectedness between the series under examination based on generalized forecast error variance decomposition of a quantile VAR model, which is further disintegrated into varying frequencies and time-scales by applying spectral representations to the forecast error variance decompositions. This approach permits us to quantify how the magnitude of connectedness and directional spillovers among the series under examination change under different time scales. To the best of our knowledge, this is the first study to provide comprehensive analysis of the relationship between the green bond market, green stocks, sustainability, and clean energy stocks under normal and extreme market conditions for different investment horizons.

A pertinent issue that requires further investigation is the possibility of increased connectedness between green bonds and eco-friendly financial instruments including green stocks, clean energy stock, and sustainable investments markets. The possibility of connectedness between the green bond market and green stocks, clean energy stocks, and sustainability can be based on the theoretical association between the bond and conventional stock markets. Following that green bond markets, green equity markets, clean energy stock, and sustainability are all sub-sectors of the overall stock and bond markets, the spillover effect across these markets can be attributed to the sources discussed above. Additionally, as green bonds, clean energy stocks, green stocks, and sustainability benefit from eco-friendly activities, connectedness can be impacted by non-financial factors including investors' pro-environmental inclinations. We make the assumption that there exist spillover effects among green bonds, green stocks, sustainability, and clean energy stocks, however, the magnitude of spillover will be asymmetric and there will be changes between extreme and normal market states and varying investment horizons.

The contribution of our paper is twofold. Our first contribution is that we propose a novel quantile frequency connectedness approach which is a modified version of the quantile connectedness approach (Chatziantoniou et al., 2021b) and the frequency connectedness approach (Baruník and Křehlík, 2018). Note that the original QVAR connectedness approach does not account for the impact among frequencies while the frequency connectedness approach is sensitive to outliers and does not account for the impact across quantiles. In our proposed model, we combine the quantiles connectedness approach with the frequency connectedness approach to account for connectedness measures across time, frequencies and quantiles. On the significance of our approach, (i) it is not only insensitive to outliers compared to the standard connectedness approach (Diebold and Yılmaz, 2012, 2014) but it also provides more in-depth connectedness information by virtue of the frequency effect (Baruník and Křehlík, 2018) under extreme markets states (Chatziantoniou et al., 2021b). Thus, this approach allows to identify time-frequency dynamics in both the left and the right tail of the distribution. According to Londono (2019) the lower (5th) and upper (95th) quantile hold a lot of information about bad and good news. (ii) our model examines the empirical importance of time-frequency sources of connectedness under extreme market states since shocks in different market states can have varied impacts on investment decisions under different investment horizons. (iii) we unveil the tail dependency structure of return spillovers among the markets under examination, which explains the tail propagation in the green bond, environmental, and sustainability markets. This is of crucial importance for both investors and policymakers. On the one hand, investors can build on the findings from this study to refine their decisions and risk measures when trading during extreme negative and positive market conditions. On the other hand, policymakers can find the insights from this study useful for effectively managing different market conditions.

Our second major contribution aside from our methodological contribution discussed above is that we provide empirical evidence on the return transmission mechanism of four major tradable environmental finance indices, namely the S&P Green Bond Index, MSCI Global Environment, Dow Jones Sustainability Index World, and S&P Global Clean Energy over the period from November 28th, 2008 to January 12th 2022. Most recent studies examine the relationship between conventional assets and emerging alternative asset classes such as green bonds, green stocks, etc. However, this study focuses entirely on green and clean energy markets.

Our results on the median connectedness dynamics reveal that the standard connectedness approach overestimates the initial effect of the COVID-19 pandemic. Additionally, we find that short-term and long-term dynamic total connectedness measures do not constantly co-move; but rather, they can also diverge and highlight different economic and financial events, as well as, their short-term and/or long-term effects. Furthermore, we found that short-term dynamics are mainly responsible for the net transmission behavior of the network of study, while over time, variables may shift their role from a net-transmitter or a net-receiver and vice versa. Our empirical results further identified the Green Bond Index as being the main net receiver of both short-term and long-term shocks, followed by Global Clean Energy. Moreover, MSCI Global Environment is the main long term net transmitter of shocks whereas the Sustainability Index World is the leading short-term net transmitter in our network. Interestingly, the total TCI is mainly driven by short-term TCI rather than long-term TCI. In more detail, the short-term TCI appears to be at least three times higher than the long-term TCI. By investigating the market risk across time and quantiles, suggestive evidence has been found that market risk is heterogeneous across time and quantiles as the dynamic total connectedness is more pronounced at the extremes. What is more, we find that the total TCI is rather symmetric, while both the short-term and long-term TCI are rather asymmetric. The short-term TCI is higher at the lower end meaning that higher connectedness is associated with negative returns while long-term TCI is higher at the upper end indicating that long-term connectedness can be associated with common positive returns and hence with long-term growth.

The outline of the paper is as follows. In Section 2 we review existing literature. In Section 3 we present the empirical methods of the study while Section 4 reports the data. We then discuss empirical findings in Section 5 and conclude the study in Section 6.

2. Literature review

The investigation of the relationship between green bonds and other eco friendly market indices, is important for both portfolio managers and policy makers. Attaining a better understanding of this relationship could in turn lead to bigger cleaner production investments and further development of green financial instruments. In recent years, a large body of the literature has studied the linkages between green bonds and various markets. In this section, we classify past studies that have inquired into the nexus between the green bond market and other financial markets into three distinct categories.

First, most recent studies focus on how the green bond market connects with conventional financial markets (see Reboredo, 2018; Park et al., 2020; Reboredo and Ugolini, 2020; Gao et al., 2021; Arif et al., 2021; Naeem et al., 2021a). Pham (2016) – being the first to study volatility behavior between the green bond market and the broader conventional bond market – confirms the existence of convergence between the green bond and conventional bond markets and further suggests diversification strategies to maximize portfolio performance. The study of Broadstock and Cheng (2019) probe further into the correlation between U.S. green and standard bonds using the DCC-GARCH model of Engle (2002) and the dynamic model averaging framework of Koop and Korobilis (2012). According to this study, several macroeconomic conditions such as daily economic activity, oil prices, and financial market volatility are factors that influence the association between U.S green bond and conventional bond markets. Ferrer et al. (2021) show that spillovers between the green bond market and several mainstream financial markets occur in the short-run. Additionally, Reboredo (2018), who uses a copula framework, finds that the green bond market offers good diversification benefits for investors in the energy market. In another related study, Reboredo and Ugolini (2020) utilize wavelet coherence transformation and multivariate VAR models to validate the dynamic correlation and network connectedness between green bonds and financial markets in a time-frequency fashion. Arif et al. (2021) find a low intergroup connectedness for conventional investments and a high intergroup connectedness for green investments. Also, Gao et al. (2021) show that risk spillovers between the green bond, foreign exchange and monetary market are not significant.

Another strand of the literature either solely focuses on the relationship between the green bond and commodity markets, or on the relationship between the green bond, commodity, and financial markets (see, Le et al., 2021; Hung, 2021; Naeem et al., 2021a). For example, Le et al. (2021) employ a non-linear Granger-causality test to bear the presence of bi-directional causality between green bond and oil prices at lower quantiles. Shahbaz et al. (2021) examine the linkages between energy markets, stock markets, and green stock returns in the wake of the Global Financial Crisis of 2008 using different quantile causality approaches. Their empirical results suggest that clean energy markets react asymmetrically to the stock and crude oil market depending on the prevailing market state. Naeem et al. (2021b) report that green bonds respond asymmetrically to different groups of commodities. Their study also supports the importance of green bonds in hedging against fluctuations in natural gas, agricultural commodities, and industrial metals and further argue that green bonds should not be used to hedge precious metals. Furthermore, Le et al. (2021) credit the importance of green bond in hedging gold, oil, silver, USD, and VIX to its shock receptive nature.

The last group of studies investigates the relationship between the green bond and other environmental markets (see, Jin et al., 2020; Hammoudeh et al., 2020; Pham, 2021; Tiwari et al., 2022). For instance, Jin et al. (2020) utilize the Diebold and Yılmaz (2012) approach and various GARCH models to analyze connectedness among different markets and to identify the most suitable market to hedge against risk in the carbon market. They find that the carbon market and the green bond market exhibit the strongest interconnectedness. Furthermore, Jin et al. (2020) offer support to previous studies by documenting that green bonds are the most suitable hedger against carbon risk, even during crisis periods. Hammoudeh et al. (2020) employ a time-varying Granger-causality technique and report that the causal flows from green bonds to other financial and environmental assets are not significant. Interestingly, the causal flow from CO2 emission allowances to green bond is significant between 2014 and 2015. More recently, other studies have also examined interdependencies between environmental and energy-related variables (e.g., Miao et al., 2019; Wang et al., 2021; Miao and Chen, 2022). Authors such as Miao et al. (2019) stress that the energy-saving and emission-reduction policies and technologies exert a decisive influence on the atmospheric environment total factor productivity (AETFP) growth. In particular, results indicate that market-motivated environmental regulation has a positive effect on AETFP growth.

From a methodological standpoint in the burgeoning literature on the dynamic interdependence between green bonds and major conventional and emerging asset classes, we observe that most of the estimation techniques employed in the past gauge the strength of connectedness and volatility transmission between green bonds and other markets by adopting GARCH based techniques (e.g., Pham, 2016), Granger causality approaches (e.g., Hammoudeh et al., 2020), wavelets (e.g., Nguyen et al., 2021), copulas (e.g. Liu et al., 2021), cross quantilogram correlation (e.g. Pham, 2021), time-domain dynamic connectedness approach Diebold and Yılmaz (2012, 2014) and their combinations (e.g., Tiwari et al., 2022; Le et al., 2021; Jin et al., 2020). Notably, most of these methods can only capture mean shocks and their transmissions disregarding the impact across the distribution of shocks. To make a further contribution to the foregoing literature, we argue that the issue requires the use of a quantile-based method. Thus, this study advances the literature on the relationship between green bond and other eco-friendly markets by adopting the QVAR model of Chatziantoniou et al. (2021b) to describe the conditional connectedness among green bonds and eco-friendly asset returns while at the same time accounting for the frequency domain (Baruník and Křehlík, 2018). The employed approach is based on the concept that the magnitude of connectedness may vary given the market state (bearish and bullish, as well as, normal market conditions) and across frequencies. In particular, our study fills a gap in the literature by being the first to provide a comprehensive analysis on the quantile frequency connectedness between green bonds and eco-friendly market indices including MSCI Global Environment Index, S&P Global Clean Energy Index, and Dow Jones Sustainability Index.

3. Methodology

We employ the quantile connectedness approach proposed by Chatziantoniou et al. (2021b) to examine the quantile propagation mechanism of green energy assets. It would be instructive at this point to note that the quantile frequency connectedness method employed in this study has its roots in the seminal work by Diebold and Yılmaz (2012, 2014) who introduced the method considering a generalized VAR framework that utilizes rolling-window dynamic analysis. Therefore, the concept of connectedness predicates upon the second moment of the VAR model which is the forecast error variance decomposition. Note that, forecast error variance decompositions explain how structural shocks within a network of variables affect the volatility of each variable within that network. In short, strong co-movements among the variables of the network is being reflected upon large total connectedness values. What is more, strong connectedness can be indicative of contagion among variables (i.e., captured by directional connectedness measures). Subsequently, empirical research has further developed and improved the relevant measures of connectedness by considering more advanced techniques such as time-varying parameter vector autoregressive (TVP-VAR) connectedness measures that largely overcome the constraints of the typical rolling-window dynamic analysis (Antonakakis et al., 2020a). In turn, the quantile connectedness approach is another advancement of the original approach (Chatziantoniou et al., 2021b). Quantile connectedness focuses both on extreme positive structural shocks (i.e., higher quantiles) and extreme negative structural shocks (i.e., lower quantiles) in order to assess whether strong co-movement among the variables depends on the strength of the shock (i.e., extreme quantile) and whether it requires the shock to be positive (i.e., high quantile) or negative (i.e., low quantile). Finally, frequency connectedness is also a recent advancement (Baruník and Křehlík, 2018) which classifies connectedness into high-frequency connectedness (whereby, connectedness is the result of shocks that have a short-lived impact on the variables of the network) and low-frequency connectedness (whereby, connectedness is the result of shocks that bring about structural changes within the network and leave a longer-term mark on the variables). It follows that in this study we combine all aforementioned approaches to examine the network of interest. To calculate all connectedness metrics, we first estimate a quantile vector autoregression, QVAR(p), which can be outlined as follows:

$$\boldsymbol{x}_t = \boldsymbol{\mu}_t(\tau) + \boldsymbol{\Phi}_1(\tau)\boldsymbol{x}_{t-1} + \boldsymbol{\Phi}_2(\tau)\boldsymbol{x}_{t-2} + \cdots + \boldsymbol{\Phi}_p(\tau)\boldsymbol{x}_{t-p} + \boldsymbol{u}_t(\tau) \quad (1)$$

where $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-i}$, $i = 1, \ldots, p$ are $N \times 1$ dimensional endogenous variable vectors, τ is between $[0, 1]$ and represents the quantile of interest, p stands for the lag length of the QVAR model, $\boldsymbol{\mu}(\tau)$ is an $N \times 1$ dimensional conditional mean vector, $\boldsymbol{\Phi}_j(\tau)$ is an $N \times N$ dimensional QVAR coefficient matrix, and $\boldsymbol{u}_t(\tau)$ demonstrates the $N \times 1$ dimensional error vector which has an $N \times N$ dimensional error variance–covariance matrix, $\boldsymbol{\Sigma}(\tau)$. To transform the QVAR(p) to its quantile vector moving average representation, QVMA(∞), we use Wold's theorem: $\boldsymbol{x}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j(\tau)\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \boldsymbol{\Psi}_i(\tau)\boldsymbol{u}_{t-i}$.

Subsequently, the generalized forecast error variance decomposition (GFEVD) (see, Koop et al., 1996; Pesaran and Shin, 1998) which lies at the heart of the connectedness approach is calculated.[1] The GFEVD can be interpreted as the impact a shock in series j has on series i in terms of its forecast error variance share and can be written in the following form:

$$\theta_{ij}(H) = \frac{(\boldsymbol{\Sigma}(\tau))^{-1}_{jj} \sum_{h=0}^{H} ((\boldsymbol{\Psi}_h(\tau)\boldsymbol{\Sigma}(\tau))_{ij})^2}{\sum_{h=0}^{H} (\boldsymbol{\Psi}_h(\tau)\boldsymbol{\Sigma}(\tau)\boldsymbol{\Psi}'_h(\tau))_{ii}} \quad (2)$$

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{N} \theta_{ij}(H)} \quad (3)$$

As the rows of $\tilde{\theta}_{ij}(H)$ do not sum up to one, we need to normalize them by the row sum which results in $\tilde{\theta}_{ij}$. Through the normalization, we get the following identities: $\sum_{i=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{j=1}^{N} \sum_{i=1}^{N} \tilde{\theta}_{ij}(H) = N$. Hence, each row sum is equal to unity representing how a shock in series i has influenced the series itself and all other series j.

In the next step, all connectedness measures can be computed. We start with the *(overall) net pairwise connectedness (NPDC)* which is computed as follows,

$$NPDC_{ij}(H) = \tilde{\theta}_{ij}(H) - \tilde{\theta}_{ji}(H). \quad (4)$$

If $NPDC_{ij}(H) > 0$ ($NPDC_{ij}(H) < 0$) it means that series j influences series i more (less) than vice versa. Hence, if $NPDC_{ij}(H) > 0$ series j dominates series i and vice versa.

The *(overall) total directional connectedness TO others* measures how much of a shock in series i is transmitted to all other series j:

$$TO_i(H) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}_{ji}(H) \quad (5)$$

The *(overall) total directional connectedness FROM others* measures how much series i is receiving from shocks in all other series j:

$$FROM_i(H) = \sum_{i=1, i \neq j}^{N} \tilde{\theta}_{ij}(H) \quad (6)$$

The *(overall) NET total directional connectedness* represents the difference between the *(overall) total directional connectedness TO others* and the *(overall) total directional connectedness FROM others*, which can be interpreted as the net influence series i has on the predetermined network.

$$NET_i(H) = TO_i(H) - FROM_i(H) \quad (7)$$

[1] The GFEVD is preferred over its orthogonal counterpart as the retrieved results are completely invariant of the variable ordering. Additionally, Wiesen et al. (2018) point out, that the GFEVD should be employed if no theoretical framework – which would allow to identify the error structure – is available.

If $NET_i > 0$ ($NET_i < 0$) series i influences all others j more (less) than being influenced by them. Thus, it is considered as a net transmitter (receiver) of shocks.

The *(overall) total connectedness index (TCI)* that measures the degree of network interconnectedness can be calculated by:

$$TCI(H) = N^{-1}\sum_{i=1}^{N} TO_i(H) = N^{-1}\sum_{i=1}^{N} FROM_i(H). \tag{8}$$

In other words, this measure illustrates the average impact a shock in one series has on all others. The higher the TCI value the higher is the market risk and vice versa.

So far we have focused on the connectedness assessment in the **time domain**. Analogously, we continue with the connectedness assessment in the **frequency domain**. Following the spectral decomposition method of Stiassny (1996), we can explore the connectedness relationship in the frequency domain. First, we consider the frequency response function, $\boldsymbol{\Psi}(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h}\boldsymbol{\Psi}_h$, where $i = \sqrt{-1}$ and ω denotes the frequency to continue with the spectral density of $\boldsymbol{x}_t$ at frequency ω which can be defined as a Fourier transformation of the QVMA(∞) representation:

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(\boldsymbol{x}_t\boldsymbol{x}'_{t-h})e^{-i\omega h} = \boldsymbol{\Psi}(e^{-i\omega h})\boldsymbol{\Sigma}_t\boldsymbol{\Psi}'(e^{+i\omega h}) \tag{9}$$

Notably, the frequency GFEVD is the combination of spectral density and the GFEVD. As in the time domain, we need to normalize the frequency GFEVD which can be formulated as follows,

$$\theta_{ij}(\omega) = \frac{(\boldsymbol{\Sigma}(\tau))_{jj}^{-1}\left|\sum_{h=0}^{\infty}(\boldsymbol{\Psi}(\tau)(e^{-i\omega h})\boldsymbol{\Sigma}(\tau))_{ij}\right|^2}{\sum_{h=0}^{\infty}(\boldsymbol{\Psi}(e^{-i\omega h})\boldsymbol{\Sigma}(\tau)\boldsymbol{\Psi}(\tau)(e^{i\omega h}))_{ii}} \tag{10}$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N}\theta_{ij}(\omega)} \tag{11}$$

where $\tilde{\theta}_{ij}(\omega)$ represents the portion of the spectrum of the ith series at a given frequency ω that can be attributed to a shock in the jth series. It can be interpreted as a within-frequency indicator.

To assess short-term and long-term connectedness rather than connectedness at a single frequency, we aggregate all frequencies within a specific range, $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(\omega)d\omega \tag{12}$$

From here, we can calculate exactly the same connectedness measures as in Diebold and Yılmaz (2012, 2014) which can be interpreted identically, however, in this case they refer to frequency connectedness measures that provide information about spillovers in a certain frequency ranges d:

$$NPDC_{ij}(d) = \tilde{\theta}_{ij}(d) - \tilde{\theta}_{ji}(d) \tag{13}$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{N}\tilde{\theta}_{ji}(d) \tag{14}$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N}\tilde{\theta}_{ij}(d) \tag{15}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{16}$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \tag{17}$$

In our case, we have two frequency bands illustrating short-term and long-term dynamics ranging from 1 to 5 days, $d_1 = (\pi/5, \pi)$ and from 6 to infinite days, $d_2 = (0, \pi/5]$. Thus, $NPDC_{ij}(d_1)$, $TO_i(d_1)$, $FROM_i(d_1)$, $NET_i(d_1)$, and $TCI(d_1)$ illustrate the short-term net pairwise connectedness, short-term total directional connectedness TO others, short-term total directional connectedness FROM others, short-term NET total directional connectedness, and short-term total connectedness index while $NPDC_{ij}(d_2)$, $TO_i(d_2)$, $FROM_i(d_2)$, $NET_i(d_2)$, and $TCI(d_2)$ illustrate the long-term net pairwise connectedness, long-term total directional connectedness TO others, long-term total directional connectedness FROM others, long-term NET total directional connectedness, and long-term total connectedness index.

Finally, we show the relationship between the frequency-domain measures of Baruník and Křehlík (2018) to the Diebold and Yılmaz (2012, 2014) time-domain measures:

$$NPDC_{ij}(H) = \sum_d NPDC_{ij}(d) \tag{18}$$

$$TO_i(H) = \sum_d TO_i(d) \tag{19}$$

$$FROM_i(H) = \sum_d FROM_i(d) \tag{20}$$

$$NET_i(H) = \sum_d NET_i(d) \tag{21}$$

$$TCI(H) = \sum_d TCI(d) \tag{22}$$

Intuitively speaking, the overall connectedness measures are equal to the sum of the corresponding frequency connectedness measures. Keep in mind that all those connectedness measures are based on a specific quantile, τ.[2]

4. Data

In this study, we examine the quantile frequency return connectedness between green bonds and other eco-friendly equity markets including green stocks, clean energy, and sustainability. We use daily price indices of all variables obtained from *Datastream* running from November 28th, 2008 to January 12th, 2022.

In recent times, the market for the green bond has become a global market leading to the emergence of several diverse and large issuers such as large companies, public firms, and investors around the world. To track the performance of the green bond market around the world, several indices have been created that measure the performance of the market including the S&P Green Bond Index, MSCI Green Bond Index, Solactive Green Bond Index, Dow Jones Green Bond Index, and Bank of America Merrill Lynch Green Bond Index. All these indices capture the performance of green bonds and use their own estimation techniques and criteria to select bonds from the constituents of the index. Given that all these indices exhibit similar traits and dynamics and show a near-one correlation coefficient (e.g., Reboredo, 2018), our research considers the S&P Green Bond Index as an appropriate representative of the global green bond market. Launched in 2014, the S&P Green Bond index includes green bonds which are issued by multilateral, or government, or corporate agencies globally, are denominated in multiple currencies, and have no minimum credit requirements. The bonds must be labeled "green' by Initiative (2019) and must have a maturity of at least one month from the rebalancing date. We choose the S&P green bond index as our main proxy for green bond market performance because of its extensive coverage of the global green bond market. Several studies about the green bond market rely on the S&P Green Bond Index (e.g., Le et al., 2021; Tiwari et al., 2022; Pham, 2021). Given that our green bond index represents the global green bond market, we employ several global indices to measure the financial performance of green equity markets. Because green bonds can be impacted by both non-energy and energy environmentally friendly activities, in this study we consider both energy and non-energy green equity. In particular, we use the following sectors of green equity markets: clean energy, green stocks, and sustainability.

Specifically, we use the MSCI Global Environment Price Index to represent green stocks. Regarding the definition of the MSCI Global

[2] Estimation is done using the R software program and the package `ConnectednessApproach` by Gabauer (2022).

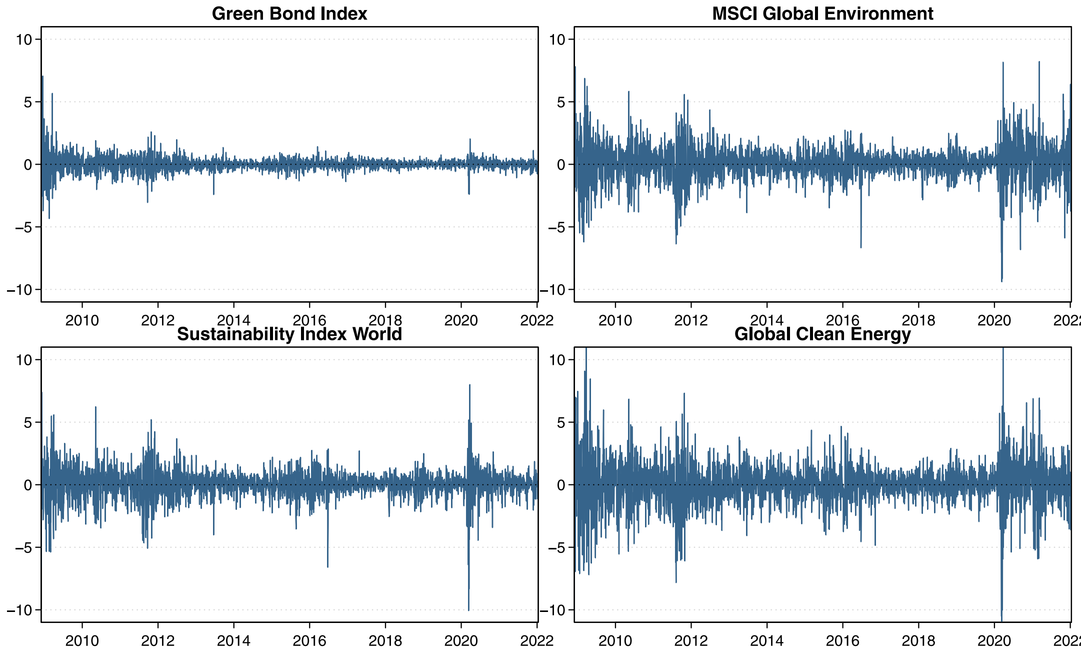

Fig. 1. Returns.

Environment Index, the index comprises securities of firms with at least 50% of revenue derived from environmentally friendly services and products. Thus, the index consists of key environmental themes, such as: Green Building, Alternative Energy, Sustainable Water, Clean Technology, or Pollution Prevention. The MSCI Global Environment Index serves as the benchmark index for market participants seeking exposure to firms whose main source of income either increases the efficient use of scarce natural resources or alleviates the effects from environmental dilapidation. We also use the Dow Jones Sustainable World Index which is the benchmark index that tracks the performance of leading firms in the field of corporate sustainability. The Dow Jones Sustainable World Index measures the global performance of firms selected in accordance with Environmental, Social, and Governance (ESG) criteria following a best-in-class approach. The Dow Jones Sustainable World Index is regarded as the benchmark index for eco-friendly investors who consider sustainability in the formation of their portfolios and provides an effective engagement platform for investors who wish to encourage companies to improve their corporate sustainability practices.

In addition, we include the S&P Global Clean Energy price index which serves as the proxy for the performance of firms engaged in clean energy-related activities in both developed and emerging economies.

As the raw series are non-stationary according to the (Elliott et al., 1996) unit-root test we are calculating the percentage changes of each series by: $x_{it} = \frac{y_{it}-y_{it-1}}{y_{it-1}}$ which are illustrated in Fig. 1. We see that all series seem to have certain volatility clusters whereas the return co-movements between MSCI Global Environment, Sustainability Index World, and Global Clean Energy appear to be more similar vis-a-vis the Green Bond Index.

Table 1 presents the summary statistics. It appears that all series have a positive mean indicating that all indices increase their prices on average. In turn, we find that the Green Bond Index has by far the smallest variance whereas the Global Clean Energy has the largest, followed by MSCI Global Environment and Sustainability Index World. Furthermore, the Green Bond Index is the only series that is significantly right-skewed while all other series are significantly left-skewed. Moreover, the empirical results reveal that all series are significantly leptokurtic and non-normally distributed. Finally, we find that all series are significantly stationary, autocorrelated and exhibit ARCH/GARCH errors. According to the non-parametric Kendall rank correlation coefficients, all returns are positively correlated. The strongest correlations occur between the MSCI Global Environmental and the Sustainability Index World, followed by the MSCI Global Environmental and Global Clean Energy while the lowest correlations occur in combination with the Green Bond Index.

5. Empirical results

In this section, we present the results of the study and discuss pertinent issues stemming from our analysis. We focus mainly on dynamic results by virtue of frequency and quantile which we obtain from an empirical framework that brings together the work by Diebold and Yılmaz (2012, 2014) and Chatziantoniou et al. (2021b). This approach allows to analyze the connectedness by various frequencies and hence can be seen as a more in-depth analysis of the time-domain connectedness approach and by quantile providing additional information regarding the tail dependencies. Thus, this framework enables us to analyze of whether the short-term and long-term connectedness changes across quantiles.

5.1. Connectedness by the virtue of frequency

5.1.1. Averaged median dynamic connectedness measures

We start by presenting average median results; that is, results that correspond to the entire sample period without considering the dynamic impact from events that occurred at specific points in time. These results are presented in Table 2. More particularly, Table 2 contains the time-domain values and the short-term as well as the long-term connectedness values in parentheses. For instance, we find that the highest own-variance share spillovers occur in the case of the Green Bond Index with 68.84%. Out of the 68.84%, 55.64% are considered as short-term own-variance spillovers while 13.20% are long-term own-variance spillovers. This means that all others account for 31.16% of the Green Bond Index forecast error variance. In detail, MSCI Global Environment, Sustainability Index World, and Global Clean Energy affect the Green Bond Index by 10.24%, 13.10%, and 7.82%, respectively. Each shock can be decomposed into short-term and long-term spillovers. In the event of the Sustainability Index World – which has the largest impact on the Green Bond Index – we find that 10.01% are caused by short-term spillovers while 3.09% originate from long-term Sustainability Index World spillovers. In total, we see that the

Table 1
Summary statistics.

	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy
Mean	0.003	0.060	0.039	0.015
Variance	0.277	1.737	1.149	2.828
Skewness	0.934***	−0.287***	−0.507***	−0.172***
	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	21.499***	6.443***	9.125***	6.674***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	64089.043***	5758.674***	11600.479***	6147.058***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−2.749***	−1.969**	−2.214**	−1.903*
	(0.006)	(0.049)	(0.027)	(0.057)
$Q(20)$	52.254***	43.599***	62.107***	50.656***
	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	1121.494***	1118.390***	1545.339***	1524.724***
	(0.000)	(0.000)	(0.000)	(0.000)
Kendall's τ	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy
Green Bond Index	1.000***	0.268***	0.321***	0.225***
MSCI Global Environment	0.268***	1.000***	0.659***	0.548***
Sustainability Index World	0.321***	0.659***	1.000***	0.490***
Global Clean Energy	0.225***	0.548***	0.490***	1.000***

Notes: ***,**,* denote significance at 1%, 5% and 10% significance level; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted Portmanteau test statistics.

Table 2
Averaged dynamic connectedness table.

	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy	FROM
Green Bond Index	68.84	10.24	13.10	7.82	31.16
	(55.64, 13.20)	(7.68, 2.56)	(10.01, 3.09)	(5.82, 2.00)	(23.51, 7.65)
MSCI Global Environment	7.15	40.91	30.10	21.83	59.09
	(5.77, 1.38)	(31.82, 9.10)	(23.59, 6.52)	(16.94, 4.90)	(46.29, 12.79)
Sustainability Index World	8.96	30.61	41.68	18.75	58.32
	(7.22, 1.75)	(23.38, 7.23)	(32.69, 8.99)	(14.41, 4.35)	(45.00, 13.32)
Global Clean Energy	6.13	25.34	21.37	47.16	52.84
	(4.80, 1.32)	(19.04, 6.30)	(16.22, 5.15)	(36.19, 10.96)	(40.07, 12.77)
TO	22.24	66.18	64.58	48.41	
	(17.79, 4.45)	(50.10, 16.08)	(49.82, 14.75)	(37.16, 11.24)	TCI
NET	−8.92	7.10	6.25	−4.43	50.35
	(−5.72, −3.20)	(3.81, 3.29)	(4.82, 1.44)	(−2.91, −1.53)	(38.72, 11.63)

Notes: Results are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition. The first and second Value in parentheses () represent short- and long-term frequency connectedness measures, respectively while all other values are the corresponding time connectedness measures.

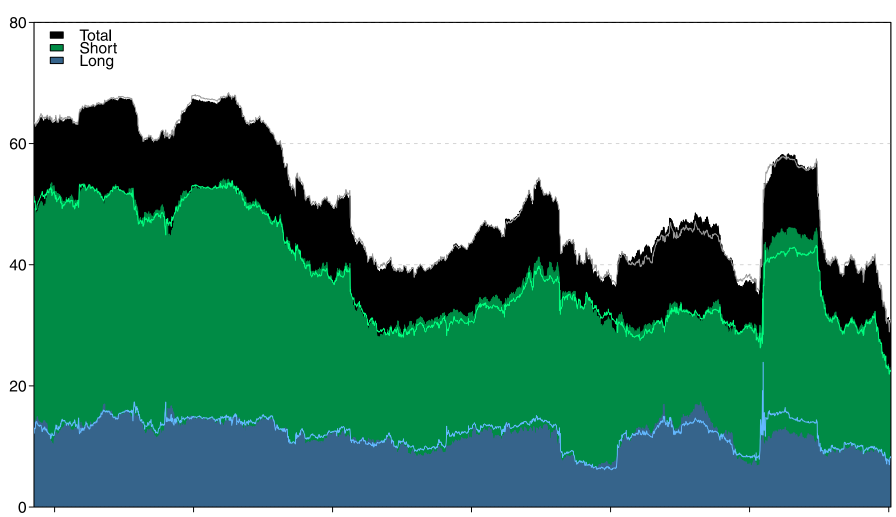

Fig. 2. Short-term, long-term and overall dynamic total connectedness.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results. The corresponding lines illustrate the results of the standard VAR time (Diebold and Yılmaz, 2012, 2014) and frequency domain connectedness approach (Baruník and Křehlík, 2018).

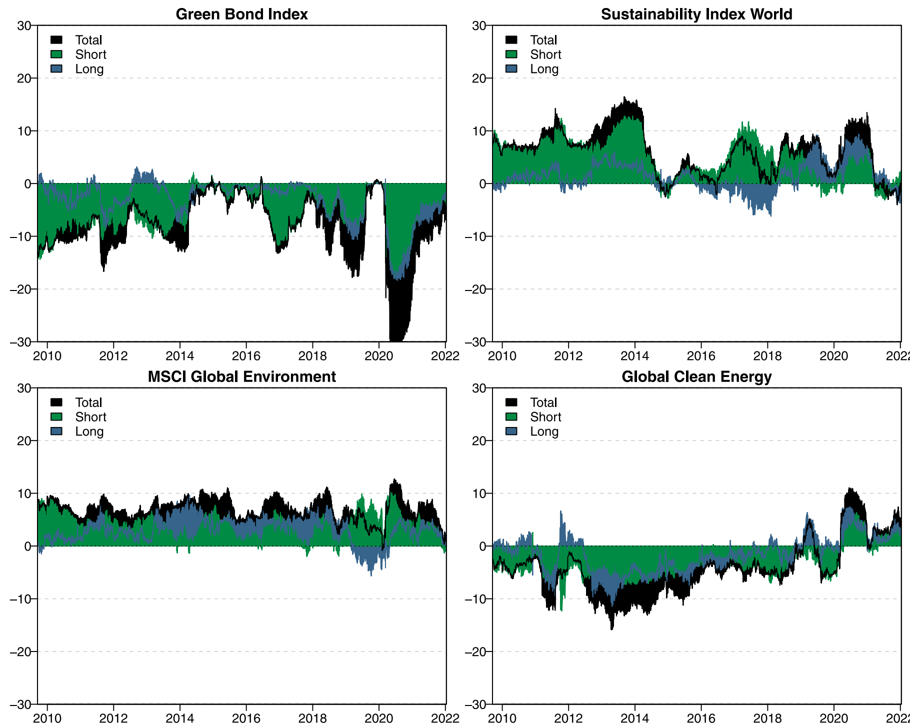

Fig. 3. Short-term, long-term and overall net total directional connectedness.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results.

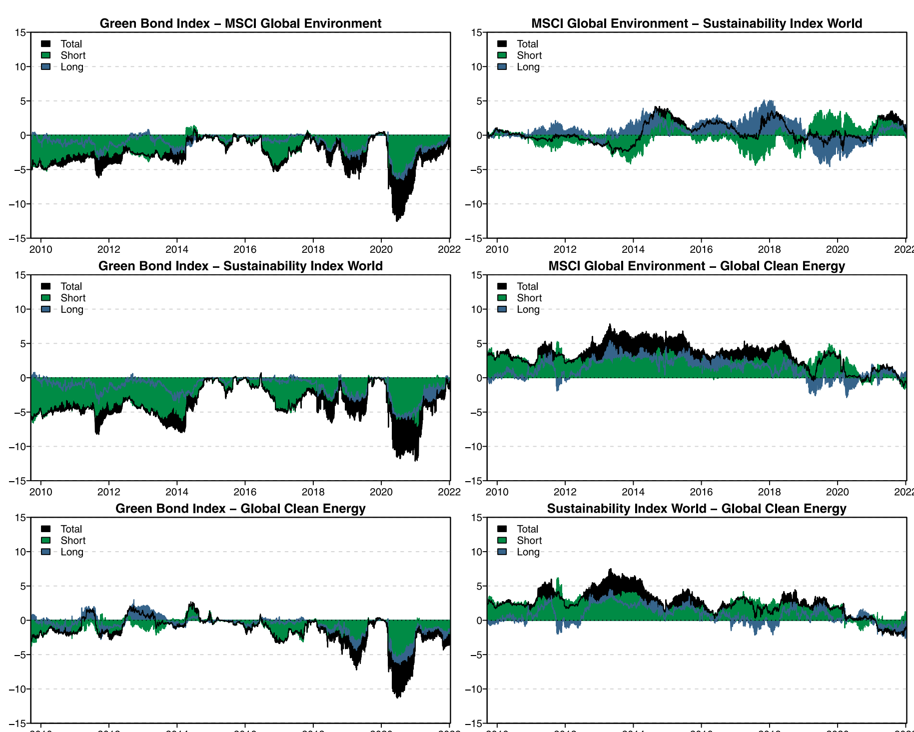

Fig. 4. Short-term, long-term and overall net pairwise directional connectedness.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area represents the time dynamic connectedness values while the green and blue areas demonstrate the long and short-term results.

Green Bond Index influences the market by 22.24% and is influenced by 31.16% indicating that it is a net receiver of shocks (−8.92%). More specifically, we see that it is a short-term and long-term net receiver of shock as the short-term net spillovers are −5.72% and long-term

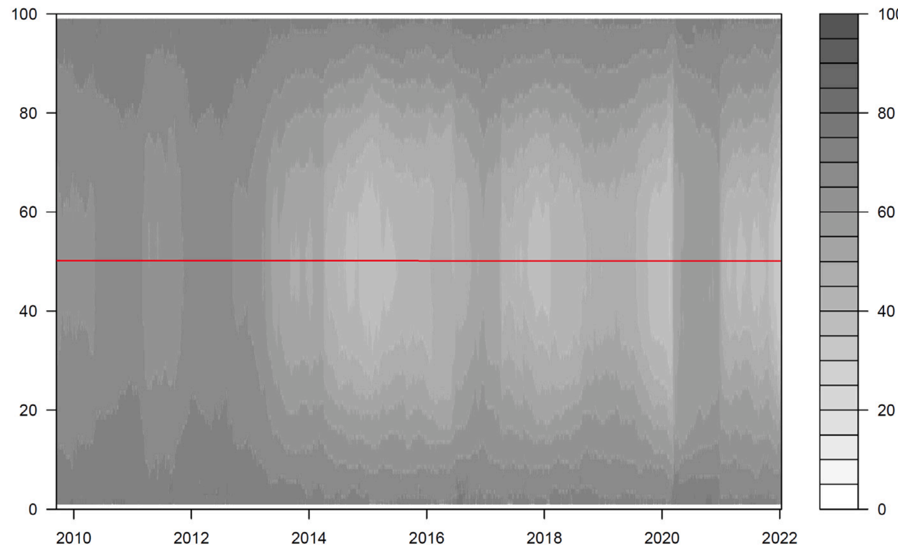

Fig. 5. Overall dynamic total connectedness over time and quantiles.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition.

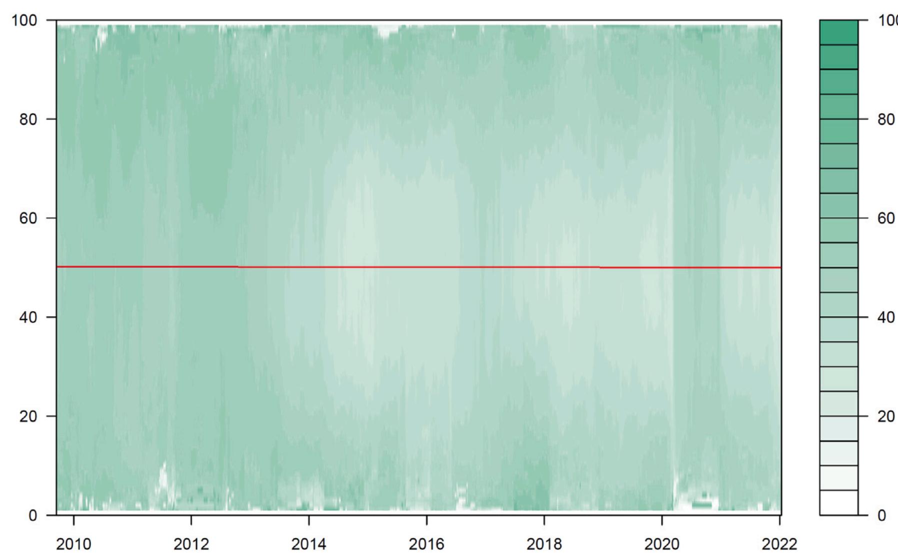

Fig. 6. Short-term dynamic total connectedness over time and quantiles.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition.

net spillovers are equal to −3.20%. Among the investigated series, the Green Bond Index appears to be the main net receiver of shocks followed by Global Clean Energy (−4.43%). The emergence of green bonds as net receivers of shocks in the entire system is not surprising since green bond financing has emerged as the main pillar supporting the global transition to clean energy and broad low-carbon economic activities (Sartzetakis, 2021). Also, following that income from green bonds is used to embark on eco-friendly projects, the green bond market is likely to receive shocks from firms that use funds from the green bonds market for their environmentally friendly projects. The main net transmitter of shocks is the MSCI Global Environment (7.10%) which is also the main long-term net transmitter of shocks (3.81%). However, the Sustainability Index World which is also a strong net transmitter of shocks (6.25%) is the main short-term net transmitter (4.82%). Finally, by looking on the average TCI, we see that the short-term dynamics are more than three times larger (38.72%) than the long-term spillovers (11.63%). As those values only demonstrate the average connectedness measures which might mask time-specific and time-varying effects, we continue by focusing on the dynamic connectedness plots.

5.1.2. Median dynamic total connectedness

Now, we continue with interpreting the median short-term, long-term, and total dynamic connectedness.Those series are illustrated in Fig. 2 and compared with the frequency connectedness results retrieved from the Baruník and Křehlík (2018) approach. As we can see, both approaches lead to similar results throughout the sample period except for the period after 2020 marked by the COVID-19 pandemic. This is caused by the fact that the standard VAR model is based on OLS regressions which are sensitive to outliers which is not the case for quantile regressions. Hence, whenever we observe large differences between the two approaches it is mainly caused by the inability of VARs to deal with outliers. Thus, the QVAR connectedness approach leads to more accurate and reliable results. In this specific example, the standard VAR overestimated the effect of the COVID-19 pandemic. This can be seen as the extreme increase in long-term TCI gets immediately corrected afterward. This effect is not observed in the case of QVAR frequency connectedness. All overall, we see substantially high market spillovers within environmental finance indices until 2013. In

2013, all TCIs decreased and reached a new plateau of around 50% at the end of 2013 and the beginning of 2014. A subsequent decline is observed until a trough of 40%is reached in 2015. Afterward, we see that market risk increased until a peak – in all three TCIs – is reached in 2017. The subsequent sudden drop led to the lowest long-term TCI value throughout the period of investigation while this is not the case for the short-term and total TCI. Even though both declined until 2018, the long-term TCI rather stayed constant until its increase in spring 2018 which also affects the total TCI but has not affected the short-term TCI at all. The highest long-term TCI value is reached in 2019 whereas during those times we see that short-term TCI has decreased. Thus, short-term and long-term dynamics are important to be considered separately. Just analyzing the total TCI, would mask from where the movements originated. This is especially important when looking at the beginning of the COVID-19 pandemic. The frequency analysis reveals that the increase in the total TCI is mainly driven by the short-term dynamics, not by the long-term dynamics. This is important for investors and risk managers as a substantial change in the long-term TCI usually illustrates that the whole market structure is changed severely (see, Chatziantoniou et al., 2021a). This analysis does not only reveal that the standard VAR and QVAR frequency connectedness measures behave similarly and hence can be used as alternatives, it further highlights the superiority of the QVAR approach in the event of outliers, and the importance of decomposing the total TCI into short-term and long-term TCI to improve the explainability of the total TCI's movements. Additionally, it should be stressed that similar dynamics of the overall TCI are illustrated in Tiwari et al. (2022) employing a TVP-VAR (Antonakakis et al., 2020a) and a LASSO-VAR connectedness approach (Gabauer et al., 2020). The additional information regarding the short-run and long-run TCI dynamics reveal that the overall TCI dynamics have been mainly driven by short-run dynamics which are more volatile than long-run dynamics.[3]

5.1.3. Median net total directional connectedness measures

The results concerning the net transmission power of each series are of major interest in the connectedness literature. In this specific case, it brings with it essential information for both investors and risk managers. By decomposing the net total directional connectedness into short-term and long-term dynamics, we have found that long-term dynamics are solely responsible for each of the four series of being a net transmitter or receiver of shocks while the short-term net transmission mechanism draws a very clear picture.

These findings are given in Fig. 3. Please note that positive values correspond to net transmitters of shocks into the system while negative values to net receivers of shocks. Dynamic analysis implies that the variables of the network may shift roles across time. Note also that black shaded area results correspond to total connectedness, while green-shaded and blue-shaded results break down the analysis into short and long-run connectedness results, respectively. In the case of the green Bond Index, we observe that throughout the period of time the short-term dynamics point to the fact that it is a net receiver of shock, just temporarily and always caused by the long-term dynamics the series becomes a net transmitter of shocks. Hence, the long-term dynamics either strengthen or weaken the net transmission power of a series whereas the short-term dynamics are rather constant over time; either being a net transmitter or receiver of shocks. This information is of major interest for financial advisors and investors as the short-term characteristic of being a transmitter of the receiver is not changing, however, providing information about the series influence on the network or the network's influence on the series and hence its investment risk. Continuing with MSCI Global Environment shows that this series is a short-term net transmitter of shocks throughout the period of time while this is also true for the long-term dynamics except for the period between 2019 and 2020 where it has been a long-term net receiver of shocks. A similar picture is shown when looking at the Sustainability Index World. Throughout the sample period, this series has been a short-term net transmitter of shocks while long-term dynamics are less regular. Between 2014 and 2019, the series has experienced a phase of being a net receiver of shocks. Finally, we draw our attention to Global Clean Energy which is a long-term and short-term receiver of shocks. This series is the only one that has shown a change in the short-term net transmission mechanism. At apparently became a net receiver of shocks after the beginning of the COVID-19 pandemic.

5.1.4. Median net pairwise directional connectedness measures

Finally, we would like to explain the bilateral dynamics in detail in order to understand the environmental finance index dynamics in depth. Results are illustrated in Fig. 4. As was the case with directional connectedness results, positive values correspond to net transmitters while negative values to net receivers of shocks. In turn, the green-shaded area corresponds to short-run connectedness dynamics while the blue shaded area corresponds to longer-term connectedness dynamics. Pairwise connectedness analysis offers the opportunity to consider pairs of variables and investigate the evolution of the interrelation with the passing of time. When it comes to relations with the Green Bond Index, we clearly see that all other series are almost constantly on the dominating end of the propagation mechanism. At almost every point in time, the short-term net pairwise connectedness highlights the domination of the Green Bond Index. This indicates that even though this index obtains the lowest correlations with all others and hence is the most independent one from a simultaneous dependence perspective, its value is heavily driven by shocks in all other series. This in turn means that a shock in one of the other series will cause a net change in the Green Bond Index while this is not the case vice versa. Moreover, we see that Global Clean Energy is constantly dominated by MSCI Global Environment and Sustainability Index World. In both cases, this series of experiences is dominated constantly when it comes to short-term dynamics. Additionally, it is also in most periods of time, a long-term net receiver of shocks, however, its power increased in the end of the sample period. Finally, we focus on the linkage between MSCI Global Environment and Sustainability Index World — which represent highly correlated series. Notably, we find that this is the only relation that changes in the short-term as well as in the long-term net transmission position. Also the aggregated net total directional connectedness switches its sign multiple times. In more detail, we see that the Sustainability Index World is mainly dominating in the short-term as only during the period from mid-2014 until 2016 and after 2019 it has been dominated while on the other side MSCI Global Environment is rather a long-term net pairwise transmitter of shocks as it almost dominated the Sustainability Index World until 2019, when it became a net pairwise receiver of shocks.[4]

5.2. Connectedness by the virtue of quantile

In this subsection, we shift our focus to on the market risk by quantiles. Hence, this point of view is more general than the previous one, as we previously fixed the quantile — median. To provide an overview of the quantile frequency connectedness benefits, we pay attention to the time-varying market interconnectedness conditional on the investigated quantile as shown in Fig. 5. This heatmap can be seen as a 3D illustration of the total dynamic connectedness and

[3] For robustness purposes, we have used the Wilder Hill Clean Energy Index and the iShares Global Clean Energy Index as alternatives to the MSCI Global Environment Index and re-estimated the median dynamic total connectedness. Fig. A.1 illustrates that the total connectedness indices are qualitatively similar and hence demonstrate that our results are robust.

[4] In order to quantify the differences between the pre- and post-COVID-19 period, the associated averaged connectedness measures are illustrated in Tables A.1 and A.2, respectively.

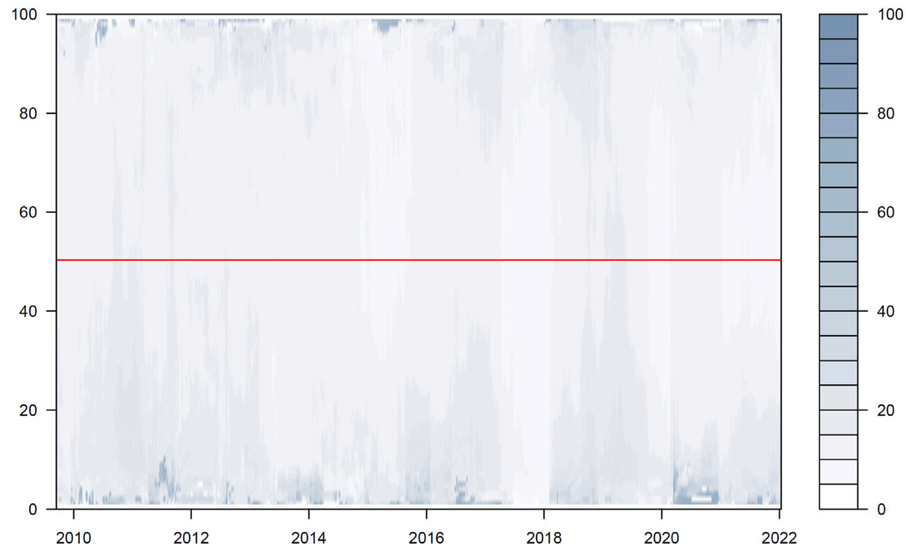

Fig. 7. Long-term dynamic total connectedness over time and quantiles.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition.

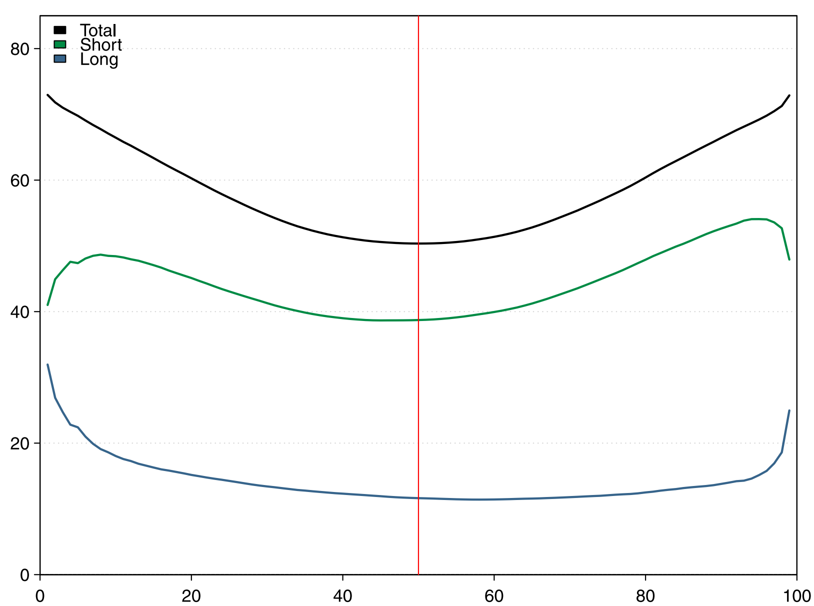

Fig. 8. Averaged short-term, long-term and overall dynamic total connectedness over quantiles.
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition.

hence includes the information of Fig. 2 - cut through along the red line. In addition, to the information concerning the median dynamic total connectedness, we can further extract information regarding the connectedness behavior at the tails. We further find that the market interconnectedness is higher at the extremes — lowest and highest quantiles, along the horizontal axis. This observation is in line with the results of Chatziantoniou et al. (2021b). Shades along the vertical axis reflect periods of higher uncertainty across quantiles which might mark in general economic and financial crisis. In our case, we can clearly identify the COVID-19 pandemic that started in 2020. Furthermore, we identify higher market risk from the beginning of our sample period until the beginning of 2014, when the market interconnectedness dropped significantly across all quantiles. Interestingly, the connectedness appears to be rather symmetric around the mean of the y-axis indicating that spillovers between highly positive returns and spillovers between highly negative returns behave similarly.

Fig. 6 shows the short-term dynamic total connectedness across time and quantiles. Notably,we find that the interconnectedness along with the extremes increases, however, decreases at the very end. Furthermore, a slight asymmetry among the time-varying quantile connectedness occurs as it appears that the short-term spillovers are higher on the lower end than on the upper end. This would indicate that market risk or market uncertainty during periods when negative returns occur – crises periods – is higher than during periods of positive returns — technological improvements.

Fig. 7 draws another interesting picture. It seems as if long-term total connectedness is higher during periods of positive returns than negative returns. Intuitively, this makes a lot of sense as common positive stock returns occur during prosperous periods or periods that are marked with many technological changes. Hence, long-term connectedness appears to be related to long-term market growth. During

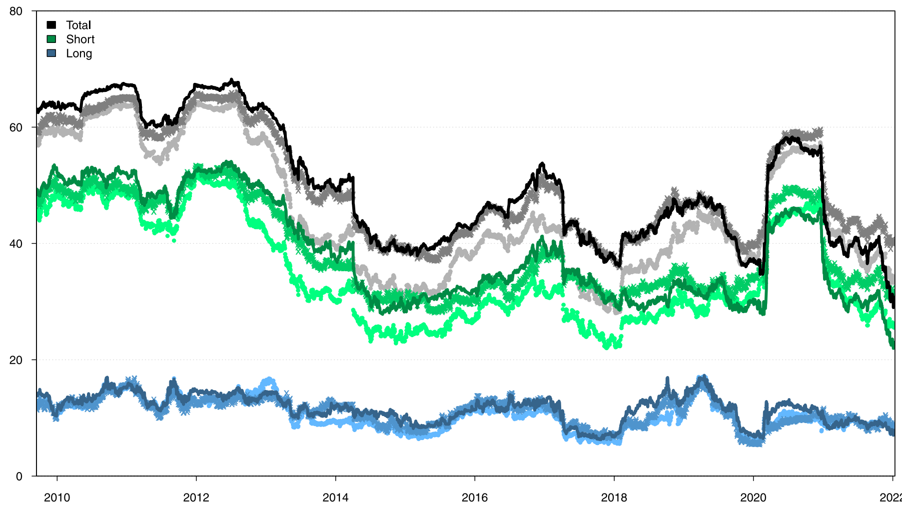

Fig. A.1. Short-term, long-term and overall dynamic total connectedness.
Notes: Robustness results by exchanging MSCI Global Environment with either Wilder Hill Clean Energy Index or iShares Global Clean Energy Index. Lines represent results based upon MSCI Global Environment, points the Wilder Hill Clean Energy Index and crosses the iShares Global Clean Energy Index. All results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition.

Table A.1
Averaged dynamic connectedness table (pre-COVID-19 period).

	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy	FROM
Green Bond Index	68.50	10.42	13.43	7.64	31.50
	(56.04,12.46)	(8.06,2.36)	(10.56,2.88)	(5.90,1.75)	(24.51,6.98)
MSCI Global Environment	7.76	39.63	31.77	20.85	60.37
	(6.26,1.50)	(30.60,9.02)	(24.86,6.91)	(16.10,4.75)	(47.22,13.16)
Sustainability Index World	9.68	32.18	39.73	18.40	60.27
	(7.76,1.92)	(24.34,7.85)	(30.73,9.00)	(13.89,4.52)	(45.98,14.29)
Global Clean Energy	6.56	24.93	21.62	46.89	53.11
	(5.07,1.49)	(18.51,6.41)	(16.09,5.54)	(35.75,11.14)	(39.67,13.44)
TO	24.00	67.53	66.83	46.89	
	(19.08,4.91)	(50.91,16.62)	(51.51,15.32)	(35.88,11.02)	TCI
NET	−7.50	7.15	6.56	−6.21	51.31
	(−5.43,−2.07)	(3.69,3.46)	(5.53,1.03)	(−3.79,−2.42)	(39.34,11.97)

Notes: Results are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition. The first and second Value in parentheses () represent short- and long-term frequency connectedness measures, respectively while all other values are the corresponding time connectedness measures.

the COVID-19 pandemic, many countries spend money on sustainable and green energy projects which might be reflected in Fig. 7 as well.

Finally, we have a look at the average TCI values across quantiles shown in Fig. 8. We would get the TCI values of Table 2 if we look at the intersections of the three curves with a vertical line at the middle of the x-axis. Interestingly, we find that the average total TCI across quantiles is symmetric around the x-axis while this is not the case for short-term and long-term TCI. As described above, the short-term TCI is higher at the lower end – during periods of negative returns – while the long-term TCI is higher at the upper end — during periods of positive returns. This finding is essential for investors and risk managers as it carries information concerning the short-term and long-term market risk spillovers and hence investment opportunity and risk with it.

6. Concluding remarks

This study proposed a novel econometric framework; namely, the quantile frequency connectedness approach that allows the analysis of the network transmission mechanism by virtue of frequency and quantile. We argued that, the quantile connectedness component leads to more accurate results as it is outlier insensitive (see, Chatziantoniou et al., 2021b) compared to the standard connectedness approach in the spirit of Diebold and Yılmaz (2012, 2014). By adding the frequency connectedness component of Baruník and Křehlík (2018) to this framework, researchers can decompose the time-domain connectedness measures into different frequencies in order to examine heterogeneous effects across frequencies.

With this novel approach, we investigated the return transmission mechanism among four environmental finance indices, namely, the S&P Green Bond Index, MSCI Global Environment, Dow Jones Sustainability Index World, and S&P Global Clean Energy over the period from November 28th, 2008 to January 12th, 2022.

Our results on the median connectedness dynamics revealed that the standard connectedness approach overestimates the initial effect of the COVID-19 pandemic. Additionally, we showed that short-term and long-term dynamic total connectedness measures do not always move in the same direction, but they can also diverge thereby highlighting different economic and financial events and their corresponding impact in the short-run and/or long-run. Furthermore, we find that short-term dynamics are mainly responsible for the net transmission behavior of the investigated network while the long-term aspect might change the aggregated classification of being a net transmitter or net receiver of shocks. Our empirical results identify the Green Bond Index as being the main net receiver of short-term as well as long-term shocks, followed by Global Clean Energy. Moreover, MSCI Global Environment acted

Table A.2
Averaged dynamic connectedness table (COVID-19 period).

	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy	FROM
Green Bond Index	70.66	9.27	11.36	8.70	29.34
	(53.70,16.96)	(5.73,3.54)	(7.20,4.16)	(5.43,3.27)	(18.36,10.98)
MSCI Global Environment	4.05	47.47	21.68	26.81	52.54
	(3.28,0.77)	(37.99,9.48)	(17.15,4.54)	(21.18,5.63)	(41.61,10.93)
Sustainability Index World	5.29	22.64	51.55	20.52	48.45
	(4.46,0.84)	(18.56,4.08)	(42.61,8.93)	(17.05,3.48)	(40.06,8.39)
Global Clean Energy	3.94	27.43	20.10	48.53	51.47
	(3.45,0.49)	(21.72,5.71)	(16.92,3.18)	(38.46,10.06)	(42.09,9.39)
TO	13.29	59.34	53.15	56.03	
	(11.19,2.10)	(46.00,13.34)	(41.27,11.88)	(43.65,12.38)	TCI
NET	−16.05	6.80	4.69	4.56	45.45
	(−7.17,−8.88)	(4.40,2.41)	(1.21,3.48)	(1.57,2.99)	(35.53,9.92)

Notes: Results are based on a 200-days rolling-window QVAR model with lag length of order 1 (BIC) and a 100-step-ahead generalized forecast error variance decomposition. The first and second Value in parentheses () represent short- and long-term frequency connectedness measures, respectively while all other values are the corresponding time connectedness measures.

as the main net transmitter of shocks in the long-run whereas the Sustainability Index World was the leading short-term net transmitter in our network. Interestingly, the total TCI was mainly driven by short-term TCI rather than long-term TCI. By investigating market risk across time and quantiles, evidence was found that market risk was heterogeneous over time and across quantiles considering that dynamic total connectedness was more pronounced at the extremes. What is more, we found that the total TCI to be rather symmetric, and both the short-term and long-term TCI to be rather asymmetric. The short-term TCI was higher at the lower end.

Our findings have important implications for investors and policymakers. As far as policymakers are concerned, evidence suggests that it is crucial for green finance policymakers to pay significant attention to the dynamic changes of spillovers among the markets examined in this study. In particular, it is essential for policymakers to understand clearly the patterns of return spillovers, particularly during extreme market conditions. Thus, there is the need for policymakers to intervene by enacting policies and strategies that will ensure the smooth recovery of the market after extreme positive or negative market states. Given that evidence showed that MSCI Global Environment is a net transmitter of shocks, policies aimed at developing the green finance markets should consider the significant impact of eco-friendly assets on introducing policies to drive green finance investments. What is more, given that green bond and clean energy stocks are marginally connected and with both assets emerging as net receivers of shocks, policymakers should consider these markets independently in their policy formulation strategies.

With regard to investors, given that Green Bonds appear to emerge as receivers of shocks from other eco-friendly assets, it seems that green bonds facilitated diversification in portfolios that include stocks that focus mainly on green investments. Also, investors need to ensure that they pay close attention to the dynamics of the net directional spillovers between the markets under examination by distinguishing net contributors from net receivers of shocks. The findings of the study may also serve as a guideline for portfolio investors in their trading strategy formulations. For institutional and private investors, our results also have a major impact. In retrospect, policymakers can use our findings to encourage businesses to be sustainable which in effect will help reduce pollution and climate change. Portfolio managers on the other hand, may be encouraged to add more of the constituents of the MSCI Global Environment Index to their portfolio risk management strategies.

Even though our research has practical and theoretical implications, there are a number of topics that might be examined in future research. First, future studies may investigate the impact of climate change and investment sentiments on the return transmission across eco-friendly assets. Second, another possible direction for future research might be the consideration of uncertainty factors on eco-friendly assets such as economic policy uncertainty, climate change, social network uncertainty or other uncertainty measures. Third, future studies may use diverse methods to identify the relationship among eco-friendly assets. Given that the literature on green finance and sustainable investment is still emerging, future research could address the presence of cyclical patterns and volatility persistence in eco-friendly assets by employing fractional integration approaches (Gil-Alana et al., 2020; Abakah et al., 2021) as well as Markov-switching copulas (Tiwari et al., 2022; Abakah et al., 2021). Finally, another pathway could be to evaluate the diversification properties of green financial products from the perspective of portfolio and risk management (Antonakakis et al., 2020b; Broadstock et al., 2020).

CRediT authorship contribution statement

Ioannis Chatziantoniou: Conceptualization, Formal analysis, Writing – original draft. **Emmanuel Joel Aikins Abakah:** Conceptualization, Writing – original draft. **David Gabauer:** Conceptualization, Data curation, Methodology, Software, Visualization. **Aviral Kumar Tiwari:** Conceptualization, Writing – original draft.

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.

Appendix

See Tables A.1 and A.2.

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