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 the quantile and frequency. This approach allows to analyze different frequencies given a particular quantile or analyze different quantile connectedness measures given a certain frequency. We investigate dynamic integration and return transmission among a set of four well-established 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 September 23rd 2020. Our approach is robust and more flexible compared to the initial connectedness approach proposed by Diebold and Yilmaz (2012, 2014). S&P Green Bond Index and S&P Global Clean Energy appear to be short-term and long-term net receivers of shocks while MSCI Global Environment and Dow Jones Sustainability Index World are short-term and long-term transmitters of shocks. We also find that Total Connectedness Indices (TCIs) are heterogeneous over time and economic event dependent and that even though the time-domain TCI appears to be rather symmetric across quantiles this is not the case for short-term and long-term TCIs.

Keywords: Green bond, green equity, sustainability, clean energy, price connectedness, quantile time-frequency.

JEL codes: C32; F30; G10; Q43

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1 Introduction

The growing awareness of the significance of climate change and sustainability have raised policy markers' 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 to green investments. Thus, investors now include eco-friendly firms in forming portfolios. More specifically, 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 to transition the world to a low carbon economy. With the growing interest in financial markets for eco-friendly investment and growth in both size and scope, examining the magnitude of connectedness between green assets, sustainable investments and renewable energy becomes an important issue. This permits market participants and the investment community 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 connectedness and directional spillovers among green bond, green stocks, sustainable investments and clean energy stock markets under different market conditions and varying investment horizons using the robust quantile time frequency approach.

Studies on green bond market development have gained considerable attention among scholars and the investment community. Several studies focusing on the price connectedness between green bond markets and global financial markets have emerged in the finance and economic literature. Some studies focus on the linkages between green bond markets and other asset classes (Broadstock et al., 2020; Tiwari et al., 2021; Reboredo, 2018; Broadstock and Cheng, 2019; Kanamura, 2020; Hammoudeh et al., 2020; Ferrer et al., 2021). Other studies also examine volatility spillover effects between green bond and traditional assets classes (Le et al., 2021; Nguyen et al., 2021; Gao et al., 2021). Recently, an emerging strand of literature highlights the safe haven or diversification benefits of green bond markets (Arif et al., 2021; Pham, 2021; Pham and Nguyen, 2021; Reboredo, 2018), and the impact of policies on green bond finance for the renewable energy asset (Tolliver et al., 2020, among others). Interestingly, even though several emerging studies on the behaviour of the green bond market relative to conventional assets have been analyzed from different perspectives leading to a comprehensive emerging literature, several questions regarding the green bond market remain unanswered. For example, can the green bond market be dissociated from its nature? What factors drive both the green bond and green equity markets? Are eco-friendly firms more liquid? These and several other questions on green bond and green financial instruments are yet to be clarified. Thus, there are still many gaps inherent in the literature regarding the green bond market and the future of green investments. There is almost no empirical evidence on how this green bond market connects with other specialized markets such as the sustainable and the

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environmental equity markets. Notable studies close to this paper include Pham (2021) who examined the cross-quantile dependence and time frequency connectedness between green bond prices and green stock markets and find that there exist a weak relationship between green bond and green stock during normal market periods; Liu et al. (2021) who examined the association between green bond market and clean energy stock markets using copulas and find that a significance dependency between green bond and clean energy and Tiwari et al. (2021) who investigated the connectedness and directional spillovers between green bond and renewable energy stocks, clean energy and carbon price using a TVP-VAR model and find that clean energy dominates all other markets.

In particular, 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 time frequency model. Succinctly, the following questions are addressed in this study. (1) Is there any connectedness between the prices of green bonds, green stocks, sustainability and clean energy markets? (2) How does the connectedness vary under extreme and normal market conditions and across different investment horizons? This type of analysis is especially useful in providing appropriate policies and strategies that will enhance and strengthen the diversification potential of green bond markets to investors.

To address the questions above, we use price returns of the S&P Green Bond price index to denote global green bond market performance; MSCI Global Environment price series as a representative of global eco-friendly firms; Dow Jones Sustainable World price series to represent performance of firms with the best sustainable investment practices and S&P Global Clean Energy price 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 Baruník and Křehlík (2018) time frequency connectedness framework to estimate connectedness and directional spillovers between green bonds and other markets under extreme and normal market conditions across long-term, medium term and short term investment horizons. The adopted estimation technique used in this paper measures the magnitude of connectedness between the series under examination based on generalized forecast error variance decomposition of a vector autoregression model, which is further disintegrated into varying frequencies and time-scales by applying spectral representations to the 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. This paper to the best of our knowledge is the foremost study that provides a comprehensive analysis on the relationship between green bond market, green stocks, sustainability and clean energy stocks under normal and extreme market conditions and varying investment horizons.

A pertinent issue that requires further investigation is the possibility of increased connectedness between green bond and eco-friendly financial instruments including green stocks, clean energy stock and sustainable investments markets. The possibility of connectedness between green bond market and green stocks, clean energy stocks and sustainability can be based on the theoretical association between bond and conventional stock markets. Following that green bond markets, green equity markets, clean energy

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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 bond, clean energy stocks, green stocks and sustainability benefit from eco-friendly activity, the connectedness can be impacted by non-financial factors including investors' pro-environmental inclinations. We make the assumption that there exist spillover effects among green bond, green stocks, clean energy stocks and sustainability, 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. First, we propose a novel quantile frequency connectedness approach which is not only insensitive to outliers – opposed to the standard connectedness approach – but it further provides more in-depth connectedness information by the virtue of frequency and quantile. Hence, this approach allows to identify short-term and long-term dynamics both at the centre and at the extremes investigating tail dependence across variables. Second, we examine 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 September 23rd 2020. Our results reveal that the Green Bond Index and the Global Clean Energy are the main net receivers of shocks while the MSCI Global Environment and the Sustainability Index World are the major net transmitter of shocks. Short-term and long-term total dynamic connectedness, net total and net pairwise directional connectedness measures are discussed in details. That is, a careful investigation of developments in individual markets might help investors identify net transmitters of longer-term shocks and then adopt an appropriate medium/long-term strategy.

The outline of the paper is as follows. Section 2 contains the review of literature; Section 3 reports the estimation technique used; Section 4 reports the data; Section 5 illustrates the empirical discussion with Section 6 outlining the concluding remarks.

2 Literature Review

The idea of examining the relationship between green investments and other eco-friendly asset returns is central for financial risk management and policy decisions on green bonds to advance cleaner production investment and green financial instrument growth. Studies on the green bond market and its relationship with other markets have been increasing in recent terms. This is in response to calls from both the academic and practitioners press for more research to understand how well the green bond market has been able to integrate into the financial and investment system. This understanding will proffer insights into the degree of stability of the market when faced with different forms of shocks and crises. Also, the search for suitable and returns-yielding portfolios that can hedge market participants against risks has been the current movement in the investment system since the global financial crisis of 2008/2009. This has been further heightened by the outbreak of the COVID-19, in 2019. Previous studies to this effect have examined the causality, interdependence, and volatility spillovers among green bond market, financial market, and energy commodity market with respect to environmental degradation. Pham (2016) is the

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pioneer of this research, being the first to study the volatility behaviour between the green bond market and broader conventional bond market. The GARCH framework result of Pham (2016) confirms the existence of convergence between green bond and conventional markets and further suggest diversification strategies to maximize portfolio performance. The study of Broadstock and Cheng (2019) probes 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 their study, several macroeconomic conditions such as daily economic activity, oil prices, financial market volatility are factors that influence the association among U.S green bond market and conventional bonds. Ferrer et al. (2021) showed that the spillover in the world's green bond market and several mainstream financial and energy markets occurs in the short run.

In this Section, we classify past studies that have inquired into the nexus between the green bond market and other markets into three. First, some studies focus on how the green bond market connects with the financial market (see, Reboredo, 2018; Park et al., 2020; Reboredo and Ugolini, 2020; Gao et al., 2021; Arif et al., 2021; Naeem et al., 2021b). For example, Reboredo (2018) use a copula framework and find that the green bond market offers a good diversification benefit for investors in the energy stock markets. In another related study, Reboredo and Ugolini (2020) utilize wavelet coherence transformation and multivariate VAR framework to validate the dynamic correlation and network connectedness between green bonds and most of the financial series in time- and frequency-horizon. Arif et al. (2021) find a low intergroup connectedness for conventional investments, while there is a high intergroup connectedness for green investments. Also, Gao et al. (2021) disclose that the spillovers of risk between the green bond market and the foreign exchange and monetary markets are not significant. However, there is a two-way risk spillover between the green bond market and the traditional bond market.

Another strand of the literature either solely focuses on the market relationship between green bond and commodity market (see, Le et al., 2021; Hung, 2021; Naeem et al., 2021a), or the relationship between green bond, commodity and financial markets (see, Broadstock and Cheng, 2019; Le et al., 2021; Ferrer et al., 2021; Arif et al., 2021). For example, Le et al. (2021) employ a non-linear Granger-causality test to bear the presence of a bi-directional causality between green bond and oil price at lower quantiles. Shahbaz et al. (2021) examined the connections between energy markets, stock markets and green stock price returns in the wake of the 2008/2009 global financial crisis using different quantile causality approaches with results suggesting that show that clean energy markets react asymmetrically to stock markets and crude oil depending on the prevailing markets states. Naeem et al. (2021b) uncloak that green bond responds 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 some industrial metals, while they provide evidence against the hedging ability of green bonds against precious metals. Naeem et al. (2021a) credit the importance of green bond in hedging against risk in all other commodities except precious metals. Among other financial and commodity series (that is, gold, oil, silver, US dollar and VIX), Le et al. (2021) credit the importance of green bond in hedging against

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risks due to its shock's receptive nature.

The last set of studies investigates the relationship between the green bond and other environmental series (see, Jin et al., 2020; Hammoudeh et al., 2020; Pham, 2021). For instance, Jin et al. (2020) utilize the Diebold and Yılmaz (2012) approach and various GARCH models to analyze the connectedness among different markets and the most suitable market that can hedge against risk in the carbon market. Relating to the dynamic connectedness, they find that the carbon market and the green bond market have the highest connectedness. Also, they support past 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 to unveil that the causal flows from green bond to all the considered assets are not significant. However, the causal flow from CO2 emission allowances price to green bond is only significant between 2014 and 2015, while the causality from clean energy to green bond is restricted to 2019.

Although there is a wealth of studies on the green bonds and its relationship to the energy market or the financial market among others, we provide a comprehensive analysis on the relationship between green bonds and eco-friendly financial assets including green stocks, clean energy and sustainability using a battery of tests.

3 Methodology

We employ the quantile connectedness approach proposed by Chatziantoniou et al. (2021b) to examine the quantile propagation mechanism of green energy assets. To calculate all connectedness metrics, we first estimate a quantile vector autoregression, QVAR(p), which can be outlined as follows:

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

where $\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-i}$, $i = 1, ..., p$ 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 variance-covariance matrix, $\boldsymbol{\Sigma}(\tau)$. To transform the QVAR(p) to its QVMA(∞) representation, 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 variable i in terms of its forecast

[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.

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error variance and can be written in the following form:

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

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

where $\tilde{\theta}_{ij}(H)$ denotes the contribution of the jth series to the variance of the forecast error of the ith series at horizon H. As the rows of $\tilde{\theta}_{ij}(H)$ do not sum up to one, we need to normalize them which results in $\tilde{\theta}_{ij}$. Through the normalization, we get the following identities: $\sum_{i=1}^{N}\tilde{\theta}_{ij}(H) = 1$ and $\sum_{j=1}^{N}\sum_{i=1}^{N}\tilde{\theta}_{ij}(H) = N$.

In a next step, all connectedness measures can be computed. We start with the net pairwise connectedness which is computed as follows,

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

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

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

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

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

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

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

$$NET_i(H) = TO_i(H) - FROM_i(H) \tag{7}$$

If the $NET_i > 0$ ($NET_i < 0$) 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 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 this value is the higher is the higher is the market risk and vice versa.

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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(∞):

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

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

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

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

where $\tilde{\theta}_{ij}(\omega)$ represents the portion of the spectrum of the ith variable 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 identical, however, in this case they refer to frequency connectedness measures that provide information about spillovers in a certain frequency range d:

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

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

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

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

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

All measures provide information about the specific range, however, not of the overall impact. Baruník and Křehlík (2018) suggest to weight all contribution measures of each frequency band d with respect to

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the overall system by, $\Gamma(d) = \sum_{i,j=1}^{N} \tilde{\theta}_{ij}(d)/N$.

$$
\begin{aligned}
NPD\tilde{C}_{ij}(d) =& \Gamma(d) \cdot NPDC_{ij}(d) && (18)\\
T\tilde{O}_i(d) =& \Gamma(d) \cdot TO_i(d) && (19)\\
FRO\tilde{M}_i(d) =& \Gamma(d) \cdot FROM_i(d) && (20)\\
NE\tilde{T}_i(d) =& \Gamma(d) \cdot NET_i(d) && (21)\\
TC\tilde{I}(d) =& \Gamma(d) \cdot TCI(d) && (22)
\end{aligned}
$$

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:

$$
\begin{aligned}
NPDC_{ij}(H) &= \sum_d NPDC_{ij}(d) && (23)\\
TO_i(H) &= \sum_d TO_i(d) && (24)\\
FROM_i(H) &= \sum_d FROM_i(d) && (25)\\
NET_i(H) &= \sum_d NET_i(d) && (26)\\
TCI(H) &= \sum_d TCI(d) && (27)
\end{aligned}
$$

4 Data

In this study, we examine the quantile time frequency price connectedness between green bonds, environmental and sustainability variables. We use daily price indices of all variables obtained from Datastream running from 28th November 2008 to 23rd September 2020. Specifically, we use the MSCI Global Environment Price Index. Regarding the definition of the MSCI Global Environment Index, the index constitutes securities of firms with at least 50% of revenue derived from environmentally favorable services and products. Thus, the index comprises of key environmental themes: 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 increases the efficient use of scarce natural resources or alleviates the effect of 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 DJ Sustainable World Index measure the global performance of firms selected in accordance with Environmental, Social and Governance (ESG) criteria following a best-in-class approach. The sustainability price index is regarded as the benchmark index for eco-friendly investors who consider sustainability in the formation of their portfolios and and provide an effective engagement platform for investors who wish to encourage companies to improve their corporate sustainability practices. Additionally, we include S&P Global Clean

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Energy price index which serves as the proxy for the performance of firms engaged clean energy related activities in both developed and emerging economies. Finally, we employ the S&P Green Bond Price index to denote global performance of green bond market.

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 Figure 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 more similar than with respect to the Green Bond Index.

[Insert Figure 1 around here]

Table 1 presents the summary statistics. It appears that the Green Bond Index is the only series with a positive mean while all others have negative average returns indicating that those indices have decreased in their price on average. Additionally, we find that the Green Bond Index exhibit by far the lowest variance whereas the Global Clean Energy has the largest, followed by MSCI Global Environment and Sustainability Index World. Furthermore, all series are significantly right skewed with the exception of the Green Bond Index that is significantly left skewed. Moreover, the empirical results reveal that all series are significantly non-normally and leptokurtic distributed. Finally, the findings indicate that all series are significantly 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 occur in combination with the Green Bond Index.

[Insert Table 1 around here]

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 in addition information regarding the tail dependencies. Thus, this framework enables to analyze 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.

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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 parantheses. For instance, we find that the highest own-variance share spillovers occur in the case of the Green Bond Index with 68.37%. Out of the 68.37%, 55.72% are considered as short-term own-variance spillovers while 12.65% are long-term own-variance spillovers. This means that all others account for 31.64% 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 10.45%, 13.36% and 7.83%, 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 10.52% are caused by short-term spillovers while 2.84% originate from long-term Sustainability Index World spillovers. In total, we see that the Green Bond Index influences the market by 23.01% and is influenced by 31.64% indicating that it is a net receiver of shocks. More specifically, we see that it is a short-term and long-term net receiver of shock as the short-term net spillovers are -6.27% and long-term net spillovers are equal to -2.36%. Among the investigated series, the Green Bond Index appear to be the main net receiver of shocks followed by Global Clean Energy (-5.39%). The main net transmitter of shocks is the MSCI Global Environment (7.20%) which is also the main long-term net transmitter of shocks (4.07%). However, the Sustainability Index World which is also a strong net transmitter of shocks (6.92%) is the main short-term net transmitter (5.49%). Finally, by looking on the average TCI, we see that the short-term dynamics are more than three times larger (39.35%) than the long-term spillovers (12.01%). 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.

[INSERT TABLE 2 AROUND HERE]

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 Figure 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 lead to more accurate and reliable results. In this specific example, the standard VAR overestimated the affect of the COVID-19 pandemic. This can be seen as the extreme increase in long-term TCI gets immediately corrected afterwards. This effect is not observed in the case of QVAR frequency connectedness. All over all, we see substantially high market spillovers within environmental finance indices until 2013. In 2013, all TCIs decreased and reached a new plateau around 50% in the end of 2013 and beginning of 2014. A subsequent decline is observed until a trough of 40%

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is reached in 2015. Afterwards, 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.

[INSERT FIGURE 2 AROUND HERE]

5.1.3 Median net total directional connectedness measures

The results concerning the net transmission power of each series is of major interest in the connectedness literature. In this specific case, it brings essential information for investors and risk managers with it. 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.

In the case of 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 strengthens or weakens 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 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

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of being a net receiver of shocks. Finally, we draw our attention to the 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.

[INSERT FIGURE 3 AROUND HERE]

5.1.4 Median net pairwise directional connectedness measures

Finally, we would like to explain the bilateral dynamics in detail to understand the environmental finance index dynamics in-depth. 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. In 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 being 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 experience being 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.

[INSERT FIGURE 4 AROUND HERE]

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 Figure 5. This heatmap can be seen as a 3D illustration of the total dynamic connectedness and hence includes the information of Figure 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

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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.

[INSERT FIGURE 5 AROUND HERE]

Figure 6 shows the short-term dynamic total connectedness across time and quantiles. Notably, we find that the interconnectedness along the extremes increases, however, decreases at the very end. Furthermore, a slight asymmetry among the time-varying quantile connectedness occur 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 occure - crises periods - is higher than during periods of positive returns - technological improvements.

[INSERT FIGURE 6 AROUND HERE]

Figure 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 appear to be related to long-term market growth. During the COVID-19 pandemic many countries spend money on sustainable and green energy projects which might be reflected in Figure 7 as well.

[INSERT FIGURE 7 AROUND HERE]

Finally, we have a look at the average TCI values across quantiles shown in Figure 8. We would get the TCI values of Table 2 if we look at the intersections of the three curves with 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.

[INSERT FIGURE 8 AROUND HERE]

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6 Concluding remarks

This study proposes a novel econometric framework; namely, the quantile frequency connectedness approach that allows to analyze the network transmission mechanism by the virtue of frequency and quantile. The quantile connectedness component leads to more accurate results as it is outlier insensitive (see, Chatziantoniou et al., 2021b) opposed 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 to examine heterogeneous effects across frequencies.

With this novel approach, we have 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 September 23rd 2020.

Our results on the median connectedness dynamics have revealed that the standard connectedness approach overestimated the intial effect of the COVID-19 pandemic. Additionally, we have seen that short-term and long-term dynamic total connectedness measures do not co-move constantly, they can also diverge in their movement and highlight different economic and financial events and their impact on the short-term and/or long-term effect. Furthermore, we found 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 receiver of shocks. Our empirical results have identified the Green Bond Index as the main net receiver of short-term as well as long-term shocks, followed by Global Clean Energy. Moreover, MSCI Global Environment has been detected as the main net transmitter of shocks and long-term net transmitter whereas Sustainabily Index World has been 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 has been at least three times higher than the long-term TCI.

By investigating the market risk over time and quantiles, suggestive evidence have been found that market risk is heterogeneous over time and across quantiles as the dynamic total connectedness is more pronounced at the extremes. What is more, we find that the total TCI is rather symmetric, 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 assumed 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 long-term growth.

Future research could focus on the quantile connectedness across stock market volatilities to identify whether low (high) volatility clusters in one series is associated with low (high) volatility clusters in another series. In addition, net total directional and net pairwise directional connectedness measures could be investigated over time and quantiles (Chatziantoniou et al., 2021b).

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Table 1: Summary Statistics

	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy
Mean	-0.001	-0.03	-0.02	0.018
Variance	0.282	1.551	1.181	2.651
Skewness	-0.787***	0.840***	0.821***	0.743***
	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	17.608***	9.132***	10.518***	8.999***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	40145.634***	11075.234***	14557.442***	10686.062***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-2.159**	-1.443	-1.661*	-1.282
	(0.031)	(0.149)	(0.097)	(0.200)
$Q(10)$	18.375***	37.092***	28.482***	25.388***
	(0.001)	(0.000)	(0.000)	(0.000)
$Q^2(10)$	702.705***	717.954***	953.533***	1012.476***
	(0.000)	(0.000)	(0.000)	(0.000)
	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy
Green Bond Index	1.000	0.287	0.331	0.231
MSCI Global Environment	0.287	1.000	0.706	0.554
Sustainability Index World	0.331	0.706	1.000	0.512
Global Clean Energy	0.231	0.554	0.512	1.000

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Table 2: Averaged Dynamic Connectedness Table

	Green Bond Index	MSCI Global Environment	Sustainability Index World	Global Clean Energy	FROM
Green Bond Index	68.37	10.45	13.36	7.83	31.64
	(55.72, 12.65)	(8.03,2.42)	(10.52, 2.84)	(5.94, 1.89)	(24.29, 7.15)
MSCI Global Environment	7.40	39.73	31.63	21.25	60.26
	(5.94, 1.46)	(30.57, 9.16)	(24.58, 7.05)	(16.36, 4.89)	(46.87, 13.39)
Sustainability Index World	9.29	31.97	39.82	18.92	60.18
	(7.43, 1.86)	(24.23, 7.74)	(30.86, 8.96)	(14.40, 4.52)	(46.06, 14.12)
Global Clean Energy	6.34	25.04	22.04	46.61	53.39
	(4.86, 1.47)	(18.68, 6.36)	(16.48, 5.56)	(35.60, 11.01)	(39.99, 13.40)
TO	23.01	67.46	67.00	48.00	
	(18.22, 4.79)	(50.94, 16.52)	(51.55, 15.45)	(36.70, 11.30)	TCI
NET	-8.63	7.20	6.82	-5.39	51.36
	(-6.27, -2.36)	(4.07, 3.13)	(5.49, 1.33)	(-3.29, -2.10)	(39.35, 12.01)

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 parantheses () represent short- and long-term frequency connectedness measures, respectively while all other values are the corresponding time connectedness measures.

Figure 1: Returns

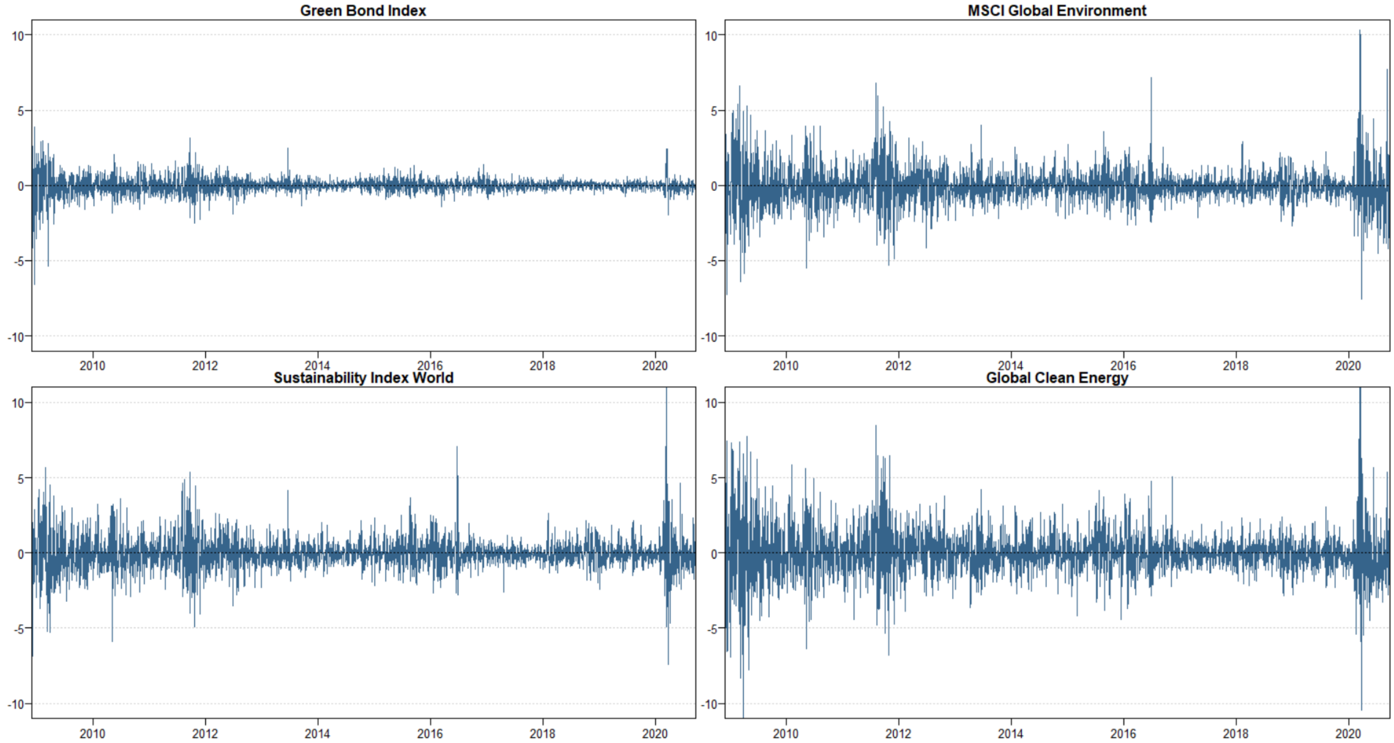
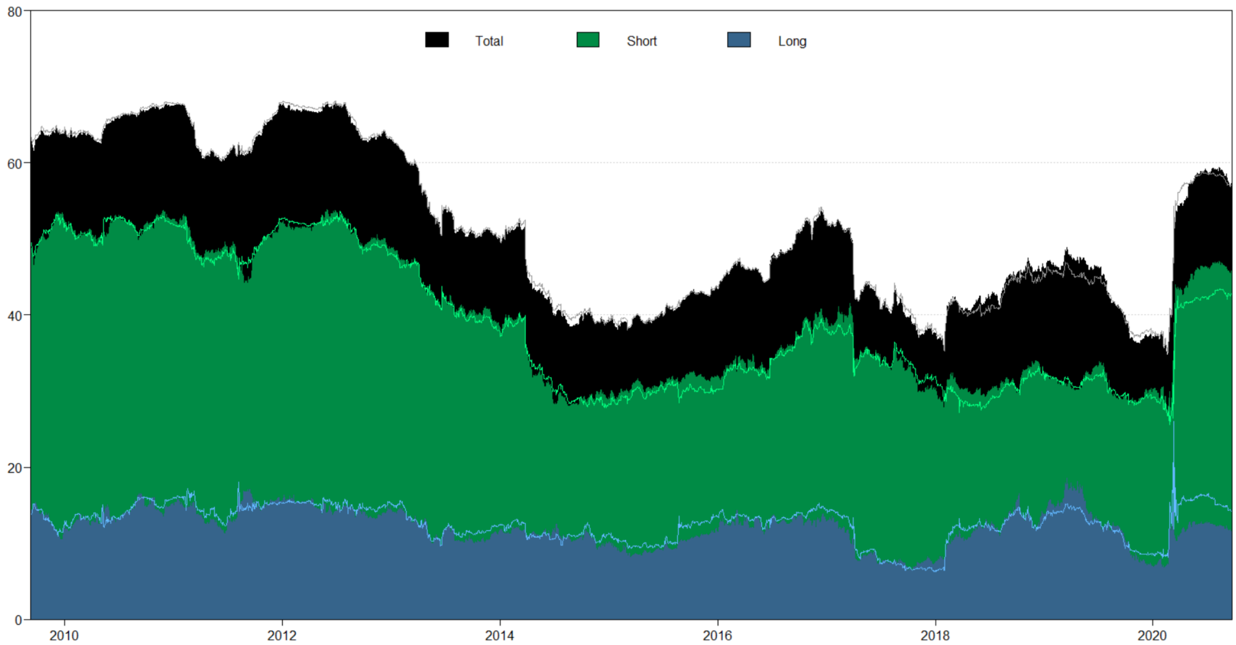


Figure 2: Dynamic total connectedness



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 and frequency domain connectedness approach.

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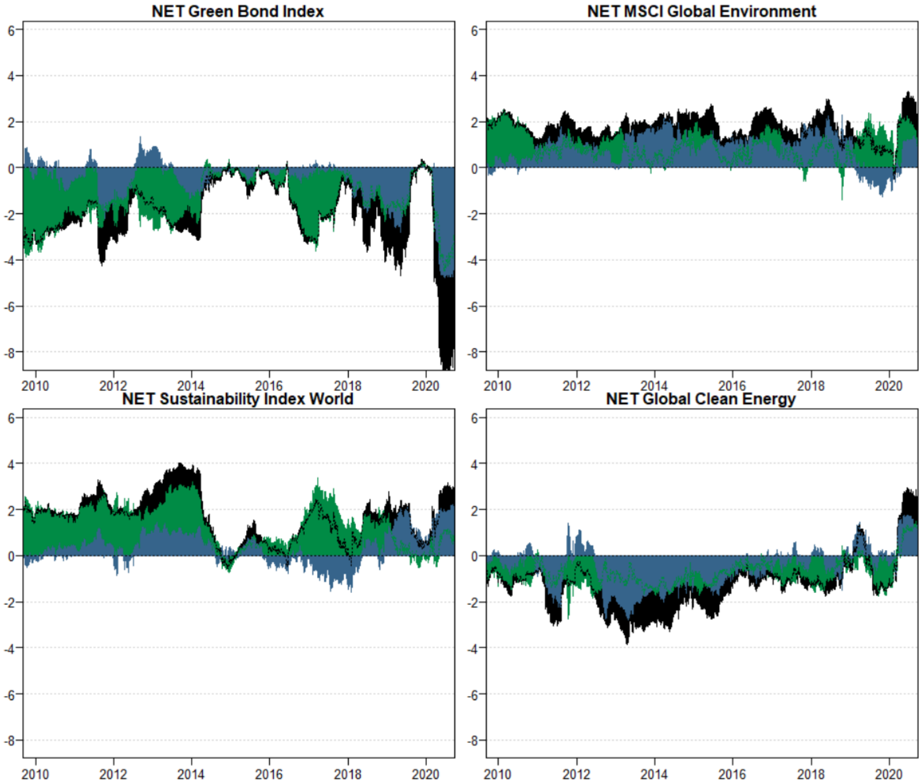
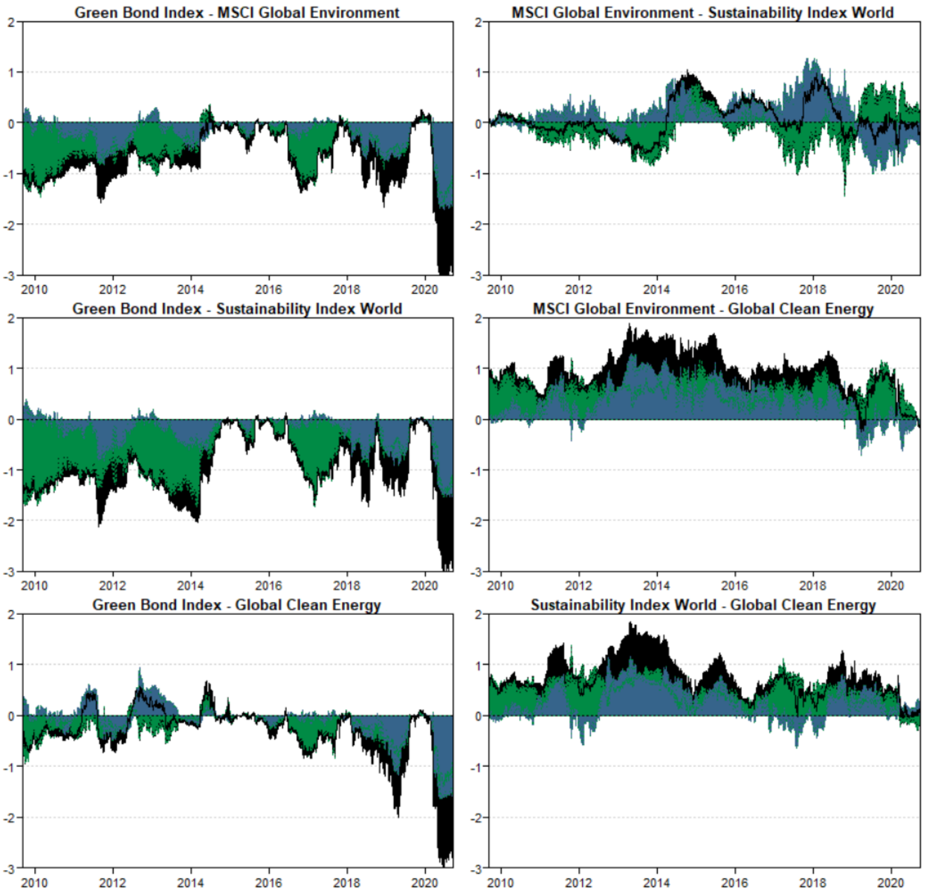
Figure 3: Dynamic net total directional connectedness



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.

Figure 4: Dynamic 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.

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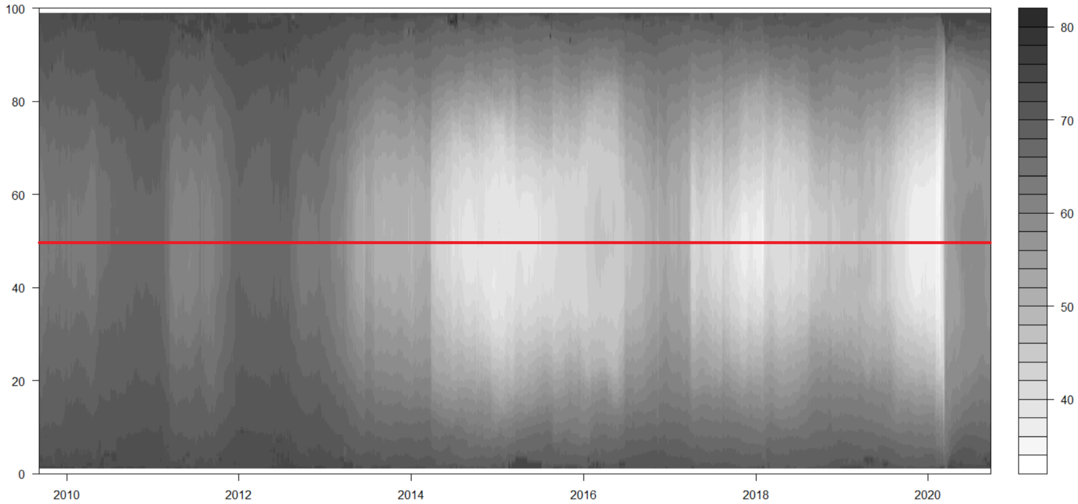
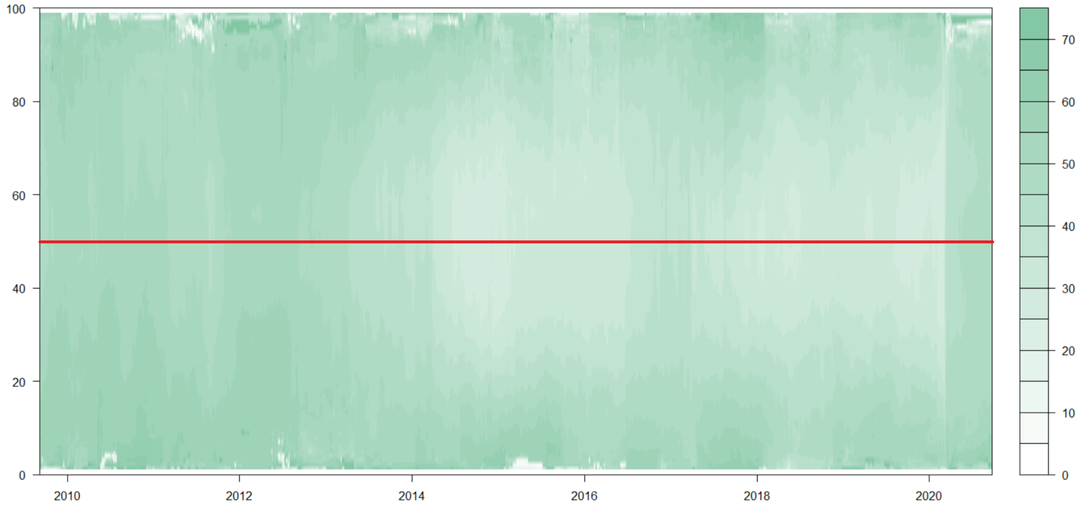
Figure 5: Dynamic total connectedness over quantiles



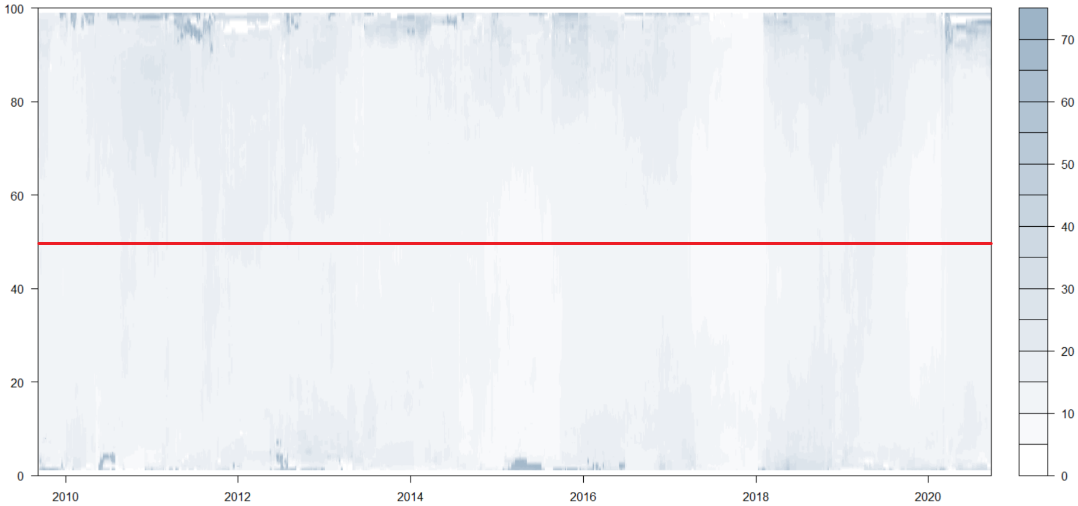
Notes: Results are based on a QVAR model with a 200 days rolling-window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition.

Figure 6: Dynamic short-term 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.

Figure 7: Dynamic long-term 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.

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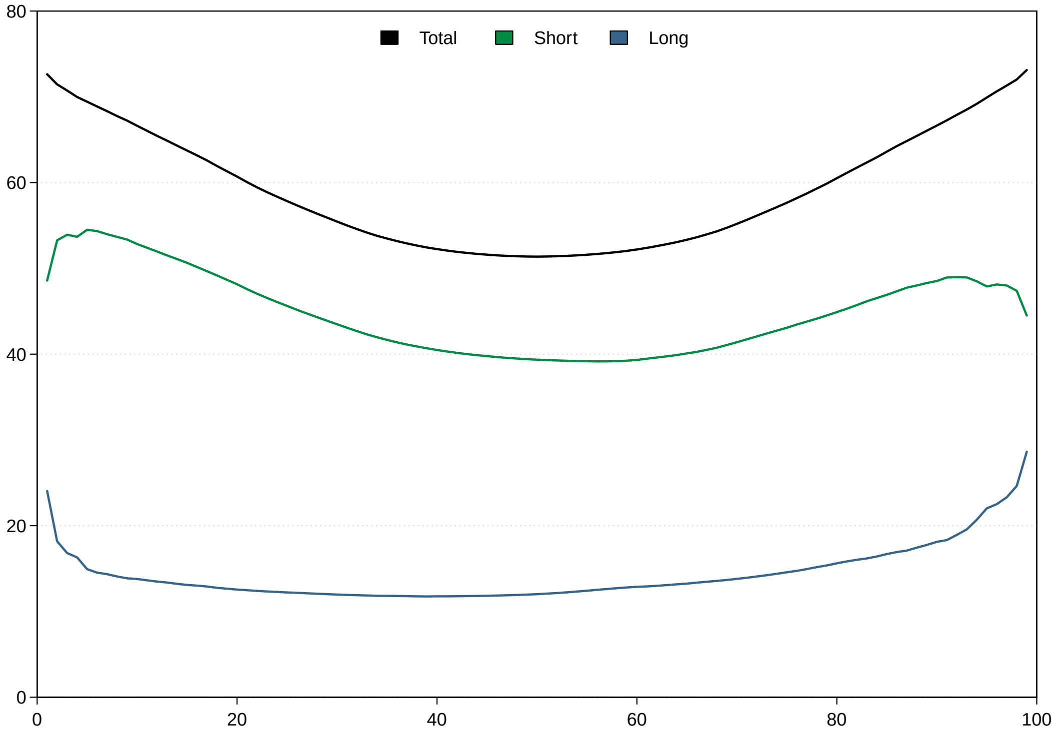
Figure 8: Averaged total dynamic connectedness over quantiles



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.

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