Time and frequency dynamics of connectedness between green bonds, clean energy markets and carbon prices

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DISCUSSION PAPER

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Abstract

In this paper, we investigate the time and frequency dynamics of connectedness among green assets such as green bonds, clean energy markets, and carbon prices. Using daily price data, we explore return spillovers across these green financial markets by applying the novel framework on time and frequency dynamics proposed by Baruník and Krehlík (2018). This allows us to identify the direction of spillovers among our variables, and decompose the connectedness to differentiate between short-term and long-term return spillovers. Our results indicate that green bonds and carbon prices act as net receivers of shocks, but mainly in the short-term. We also observe a low level of connectedness among our clean energy markets across both low and high frequency bands, even during times of economic or political crisis. Additionally, there are periods in which connectedness between the clean energy assets is driven by the long-term. In periods of economic and political stability, carbon prices may also provide an interesting diversifying tool for short-term investors. Our results should be of interest for investors and portfolio managers who focus on green financial markets, by strengthening the notion that green financial markets can offer diversification opportunities, for both short-term and long-term investors. This paper is the first to use this framework to investigate systematic risks within green financial markets.

JEL Classification: Q40, G11, C52

Keywords: Green finance, Green Bonds, Energy Markets, Connectedness, Time-Frequency space, Systemic Risk, Portfolio Management

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1 Introduction

A key ingredient for a successful green transition is financial markets providing efficient and climate aligned capital. By facilitating the flow of capital towards climate aligned projects, the financial markets can aid in mitigating climate risk as we transition to a sustainable economy (Giglio et al., 2021). Over the years, regulators have put forth policies to facilitate this transition and discourage capital flowing towards carbon intensive investments, with the EU ETS carbon quota trading system being one of the most well-known policy instruments. However, policy regulation is not sufficient on its own. The world is depending both on public and private finance to achieve a green transition. According to Reuters, an estimated $5 trillion annually is needed until 2030 to finance a green and just transition (Thomson Reuters, 2021). A recent report from Averchenkova et al. (2020) indicates that climate finance is on an upward trajectory, albeit not as rapidly as necessary to facilitate a just transition. Therefore, giving priority to investments that are in line with climate objectives is essential.

Green bonds (GB) are fixed-income securities that are specifically designed to support environmentally friendly projects. Their main feature is their commitment to utilize the raised funds solely for financing or refinancing climate aligned projects, assets or business activities (ICMA, 2016). The first public issuance came in 2007, followed by the first corporate green bond in 2013 (Flammer, 2021). The green bond market is estimated to have grown by 49% in the five-year period prior to 2021 (WEF, 2021). Green bonds have proven especially popular as a financing tool used by banks and asset managers for clean energy and infrastructure investments (Odier, 2017). However, there are still significant gaps between the emissions of organizations' portfolios and the net-zero commitments they have declared (Bellesi and Miller, 2022). Amidst the current climate and energy crisis, it is imperative to direct capital towards projects like large scale energy and infrastructure projects that typically depend on long-term financial support (Wang and Zhi, 2016). These types of investments are also typically debt financed, meaning green bonds have the potential to play an important role in financing clean energy projects and infrastructure. This is prompting the need for thorough research in relation to the transition towards environmentally sustainable finance, and particularly green bonds (Pham and Huynh, 2020; Tang and Zhang, 2020).

Green financial assets have gained considerable popularity as sustainable investment choices. In our research, we focus on investigating three main green asset categories - green bonds (GB), clean energy stocks, and carbon prices. These assets are chosen for their relevance to environmental issues, interconnectedness, and potential financial significance. To begin with, these assets offer a clear environmental focus. Green bonds are designed to finance environmentally friendly projects, while clean energy stocks represent organizations actively engaged in producing and promoting clean energy solutions. On the other hand, carbon prices reflect the financial implications of carbon emissions and ways to mitigate them. Moreover, these assets are influenced by similar environmental factors. For instance, carbon prices, representing the cost of emitting greenhouse gases, could influence the attractiveness of green bonds and clean energy stocks. Conversely, governmental policies and the demand for renewable energy can affect both clean energy stocks and green bonds. Finally, the increasing interest of investors in aligning their portfolios with environmentally sustainable initiatives have spiked lately. Therefore, exploring these three green asset categories can provide valuable insights for investors seeking to incorporate green assets into their portfolios.

To investigate the dynamic interdependence among GB, clean energy markets and carbon quota prices, we use a novel framework by Baruník and Krehlík (2018) (BK18). This methodology is an extension of the Diebold and Yilmaz (2012) (DY12) approach and allows us to analyze the connectedness[1] among green financial assets in both the time and frequency domain. While the DY12 method analyzes the connectedness in the time domain among financial assets, the BK18 model allows us to explore the return spillovers and their direction in the time and frequency space simultaneously. Thus, with the BK18 framework we can decompose the total connectedness found by the DY12 method into various frequencies, such as high and low frequency bands[2], and determine which frequency contributes the most to the connectedness within our green financial system. Therefore, we can provide an analysis of total and directional return spillovers within our green financial market to estimate net transmitters and receivers of return spillovers among our variables[3]. Hence, by incorporating the frequency dimension we are able to estimate how return spillovers transmit among all the variables of our system for both short-term and long-term oriented financial actors.

The main reason for considering the possibility that connectedness between GB, carbon prices and clean energy markets may differ across frequencies stems from the range of economic agents involved in these markets. Market participants may operate with different time horizons due to different objectives, beliefs, risk tolerance or even access to market information (Ferrer et al., 2018). For instance, investors with short-term horizons such as hedge funds are interested

[1]The measure of system connectedness provides useful information on how much of future uncertainty of variable i is due to shocks in variables k (Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012; Baruník and Krehlík, 2018).

[2]The high frequency band corresponds to the short-term while the low frequency band corresponds to the long-term horizon.

[3]It is important to note that this paper does not aim to infer causality between the variables under examination but rather focuses on exploring the connectedness or the relationships among them.

in short-term performance and responses while long-term investors such as pension funds are mainly concerned with long-term performance, and their responses are primarily manifested in the long-run.

Consequently, we believe that incorporating the frequency domain in the dynamics of a green financial system could assist green investors - with different preferences and goals - identify investment opportunities in both the short and long-term. The BK18 method, which considers the frequency domain, is preferred in this regard. By analyzing the interactions between GB, carbon prices, and clean energy stocks over different time horizons, the BK18 method offers a deeper understanding of how the relationships between these assets may vary over time. In this way, the BK18 method could enable the identification of strategies to finance environmentally friendly projects and create economic opportunities in sectors that promote the reduction of environmental damage. This knowledge is crucial for fostering green investment practices and driving positive change towards a sustainable future.

Overall, increasing climate-aligned capital through GB, clean energy stocks, and carbon prices has the potential to drive positive change and promote sustainability in both the short and long-term. By using the BK18 method, investors can make informed decisions about incorporating green assets into their portfolios, aligning their investments with environmentally sustainable initiatives, and contributing to a more sustainable and environmentally conscious financial market.

The increasing interest in green bonds is being observed in both financial markets and academia due to their potential to finance green projects and address climate change. A substantial portion of the literature has focused on investigating what is the fundamental purpose of green bonds, their related cost of capital and the effect of certification schemes for green bonds. Significant efforts have been made to examine the existence of a premium for green bonds paid by investors, often referred to as a "greenium" (Baker et al., 2018; Hachenberg and Schiereck, 2018;Bachelet et al., 2019; Zerbib, 2019; Fatica et al., 2021; MacAskill et al., 2021; Caramichael and Rapp, 2022). As there is yet to be a consensus about the greenium (Hyun et al., 2021), issuers are focusing on transparency, often through labeling of green bonds. According to Kapraun et al. (2021) the credibility of a green label is especially important for corporate issuers. If a premium were to emerge, it is most likely in a situation where the green bond is certified by a third party (Kapraun et al., 2021). One such certifier is CICERO providing their Shades of Green assessment (CICERO, 2021) of green bonds in order to enhance transparency and credibility in the green bond market. There have also been several discussions and research efforts on the risk of using green bonds for greenwashing purposes. Flammer (2021) finds evidence that using green bonds for greenwashing purposes is too costly for firms, indicating a low risk of greenwashing being related to green bond issuance.

The BK18 framework has been widely used in exploring the connectedness among various financial assets. Ferrer et al. (2018) are among the first to exploit the BK18 framework to analyze connectedness between renewable energy stocks and oil in the time and frequency domain. In their paper, they demonstrate the recent decoupling of the alternative energy industry from the traditional energy market across frequency bands. Tiwari et al. (2018) study the volatility connectedness among stocks, sovereign bonds, CDS, and currencies. Their findings indicate that there is generally low connectedness among these assets, and that the level of connectedness varies across frequencies. Similarly, Lovcha and Perez-Laborda (2020) investigate the connectedness between the oil and gas markets, and find that the level of connectedness between these markets also varies across frequencies. Moreover, they demonstrated that the connectedness between the oil and gas markets typically occur at low frequencies, and transmitted shocks between these markets have long-lasting effects. This finding contrasts with several other studies (Ferrer et al., 2018; Jiang and Chen, 2022; Le et al., 2021) that have found that connectedness tends to occur at the high frequency band. However, Zhang and Hamori (2021) provide a more nuanced perspective, suggesting that return spillovers exhibit high frequency connectedness , whereas volatility spillovers exhibit low-frequency connectedness as showed by Lovcha and Perez-Laborda (2020). Jiang and Chen (2022) and Kang et al. (2019) both exploit the BK18 framework to analyze connectedness between oil and various assets linked to the green transition. Lastly, Kang et al. (2019) explore agricultural commodities and Jiang and Chen (2022) concentrate on new energy markets, material markets and carbon markets.

An important strand of related literature is focused on understanding and estimating the connectedness between green assets (Liu et al., 2021) and various other variables, such as different assets (Ferrer et al., 2018; Park et al., 2020; Reboredo, 2018; Reboredo et al., 2020; Alkathery and Chaudhuri, 2021; Asl et al., 2021; Le et al., 2021; Tan et al., 2021; Jiang and Chen, 2022; Tiwari et al., 2022), macroeconomic events (Naeem et al., 2020), or uncertainty measures (Pham, 2016; Haq et al., 2021; Leitao et al., 2021; Pham and Nguyen, 2022). Understanding and estimating such connectedness can help investors and portfolio managers in various areas of finance, including business cycle analysis, portfolio allocation and risk management (Baruník and Krehlík, 2018). Reboredo (2018) investigates co-movement and spillover effects between green bonds and assets such as the corporate and treasury bond market, stocks, and energy commodity markets. They find that connectedness is mainly generated in the short-term, and that green bonds display strong connectedness with corporate and treasury bonds, while the connectedness between green bonds and energy commodities is fairly weak. In 2020, Reboredo et al. (2020) corroborate these results by using the Vector Autoregression (VAR) and wavelet-based methods. However, they find that green bonds can offer important diversification benefits for energy and stock market investors, as well as low-carbon market investors due to low connectedness (Reboredo, 2018; Reboredo et al., 2020; Reboredo et al., 2022). Liu et al. (2021) focus on the interaction among green financial assets, and exploit a CoVar model to explore the dependence and risk spillovers between green bonds and clean energy markets. Their results indicate that there is significant asymmetric connectedness and risk spillovers between GB and clean energy markets, particularly in the short-term. Tiwari et al. (2022) also investigate dynamic spillover effects between green bonds and renewable energy stocks as well as carbon markets using a TVP-VAR approach. They emphasize the practical significance of connectedness estimates by demonstrating that a portfolio that minimizes connectedness reaches a higher Sharp ratio than a portfolio that minimizes correlation or variance.

Our research may have important implications for investors and governments. First, we use a novel methodology to examine the connectedness among green assets, while considering both time and frequency dynamics. In financial markets, there are diverse economic agents that may have different preferences, goals, information or risk tolerance. These agents generally operate within heterogeneous time horizons. For instance, we would expect day traders and arbitrageurs to be concerned about short-term connectedness in a financial system. Therefore, our research incorporates the time horizon through the frequency domain, and can provide further insights on diversification opportunities for green investors. Second, we put emphasis on a green financial market and the potential diversification opportunities within this kind of market, recognizing the crucial role that green finance will play in achieving a low-carbon future. Our results can provide support for investing in environmentally-friendly initiatives which can benefit not only the planet, but also create new opportunities for economic growth and development. Hence, we believe that exploring the potential diversification opportunities within green financial markets is essential for achieving a more sustainable economy.

To the best of our knowledge, this is the first study to investigate return connectedness across GB, clean energy stocks and carbon prices at both the time and frequency domain. Tiwari et al. (2022) is the most closely related study to our research, and although they include similar indices, involving carbon markets, GB and clean energy markets, our research differs in two main aspects. Firstly, we extend the data time frame used by including the post-COVID period, and secondly, we investigate connectedness, as recommended by Liu et al. (2021), by considering not only time dynamics, but also frequency dynamics.

2 Methodology

We use two different methods to investigate both time and frequency spillovers among Green Bonds, CO2 prices and clean energy markets. First, we employ the Diebold and Yilmaz (2012) methodology to explore the time dynamic connectedness between these green financial markets. Subsequently, we apply the connectedness measure introduced by Baruník and Krehlík (2018) which extends the DY12 method to the frequency domain.

Generally, financial markets can experience turbulence due to macroeconomic events that can result in financial assets illustrating high volatility, which can spillover between different markets. Diebold and Yilmaz (2012) argued that financial models which include a single-fixed parameter model could ignore significant time-dependent movements in spillovers between financial markets. Therefore, they developed a model that can examine connectedness among markets including time dynamics. Their method measures spillovers based on the generalized vector autoregressive (VAR) framework by computing its forecast error variance decomposition (FEVD), and can examine connectedness among individual or multiple financial assets such as bonds, stocks, etc. through time. More specifically, they consider a covariance stationary N-variable VAR model of order p:

$$x_t = \phi(L)x_t + \varepsilon \tag{1}$$

where x_t denotes a $n \times 1$ vector of endogenous variables, $\phi(L) = [I_N - \phi_1 L - ... - \phi_P L]$ is the N x N matrix lag-polynomial and ε_t represents a white noise with covariance matrix Σ.

The moving average representation is:

$$x_t = \Psi(L)\varepsilon_t = \sum_{i=1}^{\infty} \Psi_i \varepsilon_{t-i} + \varepsilon_t \tag{2}$$

where $\Psi(L)$ is a matrix of infinite lag polynomials that can be calculated recursively.

According to the generalized identification of Pesaran and Shin (1998) which produces variance decompositions invariant to ordering, we can calculate the generalized FEVD. The variance decompositions allow us to assess the contribution of variables into components attributable to shocks to different variables in our green finance system for a forecast horizon H. Specifically, we have:

$$\theta_{ik}(H) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} ((\Psi_h \Sigma)_{ik})^2}{\sum_{h=0}^{H} (\Psi_h \Sigma \Psi_h')_{ii}} \tag{3}$$

where Ψ_h is a $N \times N$ matrix of moving average coefficients at lag h, σ_{kk} is the k^{th} diagonal element of the Σ matrix and H is the forecast horizon. The $\theta_{jk}(H)$ denotes the contribution of the kth variable to the variance of forecast error of the variable ith, at horizon H.

In the generalized VAR framework, the row sum of the variance decomposition matrix is not necessarily equal to one. Therefore, each entry can be normalized by the row sum as:

$$\tilde{\theta}_{ik}(H) = \frac{\theta_{ik}(H)}{\sum_{k=1}^{n} \theta_{ik}(H)} \tag{4}$$

$\tilde{\theta}_{ik}(H)$ provides a measure of pairwise connectedness from k to i at horizon H. Using the variance contributions, the DY12 method allows us to compute various measures which reveal the level of connectedness among the variables in the financial system. Hence, we are able to obtain the overall connectedness of the system, the net directional spillovers of each market as well as the net pairwise spillovers among the markets.

Baruník and Krehlík (2018) argued that shocks in the financial sector can affect variables at different frequencies and magnitudes. Therefore, they extended the DY12 measure to include time and frequency dynamics simultaneously. This method allows us to measure connectedness among financial markets at different frequency bands such as the short-term, medium-term and long-term. The frequency dynamics can be important for financial investors that operate in different time horizons, but also regulators that want to apply policies that can impact either individual or multiple financial markets in the short-term or long-term.

In order to incorporate the frequency aspect, Baruník and Krehlík (2018) consider the spectral representation of variance decompositions based on frequency responses instead of impulse response to shocks. Thus, they recognize a frequency response function which can be obtained as a Fourier transformation of the coefficients Ψ_h, with $i = \sqrt{(-1)}$, which can be described as:

$$\Psi(e^{-i\omega}) = \sum_{h=0}^{\infty} e^{-i\omega h} \Psi_h \tag{5}$$

where ω denotes the frequency.

Subsequently, they define the power spectrum $S_x(\omega)$ which describes how the variance of the x_t is distributed over the frequency components ω. The power spectrum is given by:

$$S_x(\omega) = \sum_{h=0}^{\infty} E(x_t x_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega h}) \Sigma \Psi(e^{i\omega h}) \tag{6}$$

Using the spectral representation, Baruník and Krehlík (2018) extract the frequency domain fractions of variance decomposition. The generalized forecast error variance decomposition at a frequency ω is:

$$\theta_{ik}(\omega) = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma)_{ik}^2}{\sum_{h=0}^{\infty} (\Psi(e^{-i\omega h})\Sigma(\Psi(e^{i\omega h}))_{ii}} \tag{7}$$

The $\theta_{ik}(\omega)$ represents the fraction of the spectrum of the ith variable at a specific frequency ω due to shocks in the kth variable. As with the DY12 method, the generalized forecast error variance decomposition can be normalized as follows:

$$\tilde{\theta}_{ik}(\omega) = \frac{\theta_{ik}(\omega)}{\sum_{h=1}^{n} \theta_{ik}(\omega)} \tag{8}$$

The $\tilde{\theta}_{ik}(\omega)$ measures pairwise connectedness from k to i at a given frequency ω. Thus, $\tilde{\theta}_{ik}(\omega)$ represents a within-frequency connectedness indicator while the DY12 measure, $\tilde{\theta}_{ik}(H)$, demonstrates pairwise connectedness at horizon H and reflects connectedness exclusively in the time domain. Consequently, the Diebold and Yilmaz (2012) method focuses on aggregate connectedness among frequencies and overlooks heterogeneous frequency responses to shocks.

In economic applications, market participants are usually concerned with short-medium-long-term connectedness rather than aggregate connectedness at a single frequency. Thus, it is important to follow the economic aspect and work with frequency bands. The incremental connectedness at a frequency band $d = (a, b)$: $a, b \in (-\pi, \pi), a < b$ is defined as:

$$\tilde{\theta}_{ik}(d) = \int_a^b \tilde{\theta}_{ik}(\omega)\, d\omega \tag{9}$$

Using the above generalized variance decomposition on frequency band d we can define various connectedness measures on the frequency domain. The overall connectedness within the frequency band d can be obtained as follows:

$$C^d = \frac{\sum_{i=1, i\neq k}^{n} \tilde{\theta}_{ik}(d)}{\sum_{ik} \tilde{\theta}_{ik}(d)} = 1 - \frac{\sum_{i=1}^{n} \tilde{\theta}_{ik}(d)}{\sum_{ik} \tilde{\theta}_{ik}(d)} \tag{10}$$

Furthermore, the BK18 method allows us to identify the direction of spillovers. For instance, the within *from* connectedness, which is the part of variance of i derived from all the other variables $i \neq k$ at the frequency band d, is given by:

$$C_{i\leftarrow \cdot}^{d} = \sum_{k=1, i\neq k}^{n} \tilde{\theta}_{ik}(d) \tag{11}$$

On the other hand, the within *to* connectedness, which is the contribution of i to all the other variables k ($i \neq k$) at the frequency band d is:

$$C_{i\rightarrow \cdot}^{d} = \sum_{k=1, i\neq k}^{n} \tilde{\theta}_{ki}(d) \tag{12}$$

By calculating the *from* and *to* connectedness we can then define the within *net* connectedness which is given by:

$$C_{i,net}^{d} = C_{i\rightarrow \cdot}^{d} - C_{i\leftarrow \cdot}^{d} \tag{13}$$

As shown by the equation the within net connectedness evaluates the difference between the variance transmitted and received by a variable. If net connectedness for a variable (for instance, i) is positive, the variable is called a net transmitter of information to the other variables in the system. On the contrary, if net connectedness is negative, the variable is called a net receiver of shocks from the rest of the variables in the system.

Except the system based connectedness measures, the BK18 method allows us to disaggregate connectedness even further and quantify pairwise relationships in our financial system. Hence, the net *pairwise* connectedness between two variables i and k can be obtained as:

$$C_{ik}^{d} = \tilde{\theta}_{ki}(d) - \tilde{\theta}_{ik}(d) \tag{14}$$

The pairwise measure enable us to recognize if a variable is a net receiver or transmitter of shocks from/to another variable in the system while considering different frequencies. In this way, we can conclude which variables are driving the spillovers in the short/long-term in our green financial system. As Tiwari et al. (2022) highlighted, it is important to investigate and understand the pairwise connectedness among green financial assets when constructing optimal portfolios. In their paper, they showed how a minimum connectedness portfolio yields a better Sharp ratio than the more typical minimum variance or minimum correlation portfolios using similar data for a green financial market. However, Tiwari et al. (2022) do not provide connectedness measures across frequencies. Thus, our chosen method extend their connectedness measures to provide insights for both long-term oriented and short-term oriented investors.

The dynamic connectedness measures have been estimated using a rolling window of 200 days and a forecast horizon (H) of 100 days. We have estimated our model with different rolling windows to confirm the robustness of our results. These robustness checks can be found in appendix B. For each rolling window we have chosen the optimal lag length of our eight variable VAR system according to the Schwarz information criterion (SIC).

In our research, we utilize two frequencies, a low and high frequency which is a common approach found in existing literature. Nevertheless, we have expanded our analysis to include a medium frequency range of 6-20 days. The results of this extended analysis can be found in Appendix B. Upon examining the findings, we observe that the medium frequency does not provide any additional information, nor does it significantly impact the main results concerning the patterns of the low and high frequencies. Hence, we can conclude that employing two frequencies in our analysis yields robust and valid results.

3 Data

3.1 Variables

Our dataset is constructed by calculated daily returns[4] for green bonds and clean energy stocks, as well as daily returns for carbon prices[5]. The dataset spans eight years, from July 30th, 2014,

[4]Following Liu et al., 2021, we calculate GB yields and Clean Energy stocks returns as follows: $[\ln(p_{it}) - \ln(p_{i,t-1})] \times 100$.

[5]As measured by the daily returns data for EU ETS quota prices.

until July 27th, 2022 and all data is based on indices, where the indices for green bonds and clean energy markets are sourced from Bloomberg while carbon quota prices are obtained from Refinitiv. To get a thorough coverage of the renewable energy sector, we include three general indices for renewable energy and two industry specific indices for wind and solar energy. In order to consider technological developments in the green transition, we include an index tracing the clean technology market. The wind and solar indices are used specifically since they represent the two renewable energy markets that attract the largest share of renewable energy investments on a global scale.

We use the S&P Green Bond index (GB) to represent the global green bond market (Reboredo, 2018; Liu et al., 2021). Bonds included in this index must be certified as "green" by The Climate Bonds Initiative (CIB, 2022). Consequently, all bonds in this index are directed at green and climate-aligned projects and investments. Further we use the S&P Global Clean Energy Index (SP_CLEAN), the Wilder Hill Clean Energy Index (ECO), and Renewable Energy Industrial Index (RENIXX) as proxies for the overall global clean energy market [6]. The S&P Clean Energy Index includes 100 companies from both developed and developing markets whose business related to clean energy. Wilder Hill Clean Energy Index is known to be the first index to track the development of the US renewable energy sector. The Renewable Energy Industrial Index reflects the 30 firms with the largest market capitalization related to the renewable energy industry, and it is the first index tracking the renewable energy sector in a global perspective. In addition our three sectoral indices are; ISE Global Wind Energy Index (ISE_WIND), MAC Global Solar Energy Stock Index (MAC_SOLAR), and finally S&P Renewable Energy and Clean Technology Index (TSX), which is similar to Liu et al. (2021). The global wind index includes active companies providing both products and services tied to the wind energy industry, while our global solar index includes companies whose core business is related to solar energy technologies and their entire value chain (raw materials and manufacturing, installation and operation, as well as financing). Our final index on renewable and clean technology tracks the performance of companies whose core business is anchored in green technologies and sustainable infrastructure projects. This range of indices has been selected to represent the clean energy, carbon, and green bond markets. Although prior studies, including those conducted by Liu et al. (2021) and Tiwari et al. (2022), have used similar data, we expand upon their research by taking into account frequency dynamics.

One potential data limitation in our study is the overlap of companies among certain indices. For example, a company operating in renewable energy infrastructure might be included in two

[6] S&P Clean Energy Index is used by Liu et al., 2021 and Tiwari et al., 2022, and Wilder Hill Clean Energy Index is also used by Liu et al. (2021) .

indices. However, it is worth noting that similar indices have been used in previous published research as demonstrated by Liu et al. (2021) and Tiwari et al. (2022). Furthermore, our chosen methodology, the BK18, can partially account for these kind of artificial spillovers by incorporating the optimal lag order into our models. This approach considers time-varying effects and can capture evolving interdependencies among those variables. Upon closer examination of the overlap between our indices and their constituents, we identified the highest overlap between RENIXX-SP_CLEAN (11.54%) and MAC_SOLAR-SP_CLEAN (14.58%). However, the remaining indices exhibit less than 10% overlap, and each index has unique weightings for the included companies and sectors. To further assess the robustness of our results, we conducted additional analyses, first excluding RENIXX, and then also excluding MAC_SOLAR. The results, available in Appendix D, confirm that even after excluding these indices, our findings and interpretations remain consistent. It is important to note that while we argue that this should not be a significant issue, we conducted these robustness analyses to further strengthen the validity of our findings.

3.2 Descriptive statistics

As a preliminary analysis, we investigate all our index return data, using GB as the main comparative return index. Each graph is scaled to show GB in relation to the other indices. Figure 1 shows all the plots with GB measured on the left-hand y-axis and the other indices measured on the right-hand axis. The graphs indicate that the clean renewable market has seen a rapid and steep increase since 2020 after the initial shock of the COVID-19 pandemic. In addition, all the market indices exhibit similar patterns with increased variability after reaching a peak in around 2021. One slight outlier is the carbon prices, which demonstrate a delayed peak and shows signs of lower variability than the rest of the renewable and clean market indices. Focusing on GB, we can observe that GB display a differing pattern compared to the other indices. Around 2016, GB experienced a peak with subsequent minor variability, followed by a substation increase from 2018 and a stabilization at a higher level. An interesting find is that even though GB were slightly affected during the early days of the pandemic, the return levels remained at a high level from mid-2020 until recently. We also notice that GB display a substantial drop since the end of 2021. This drop is likely in conjunction with rising interest rates from central banks, especially in the US and European Economic Area (EEA), after a long period with unprecedented low interest rates.

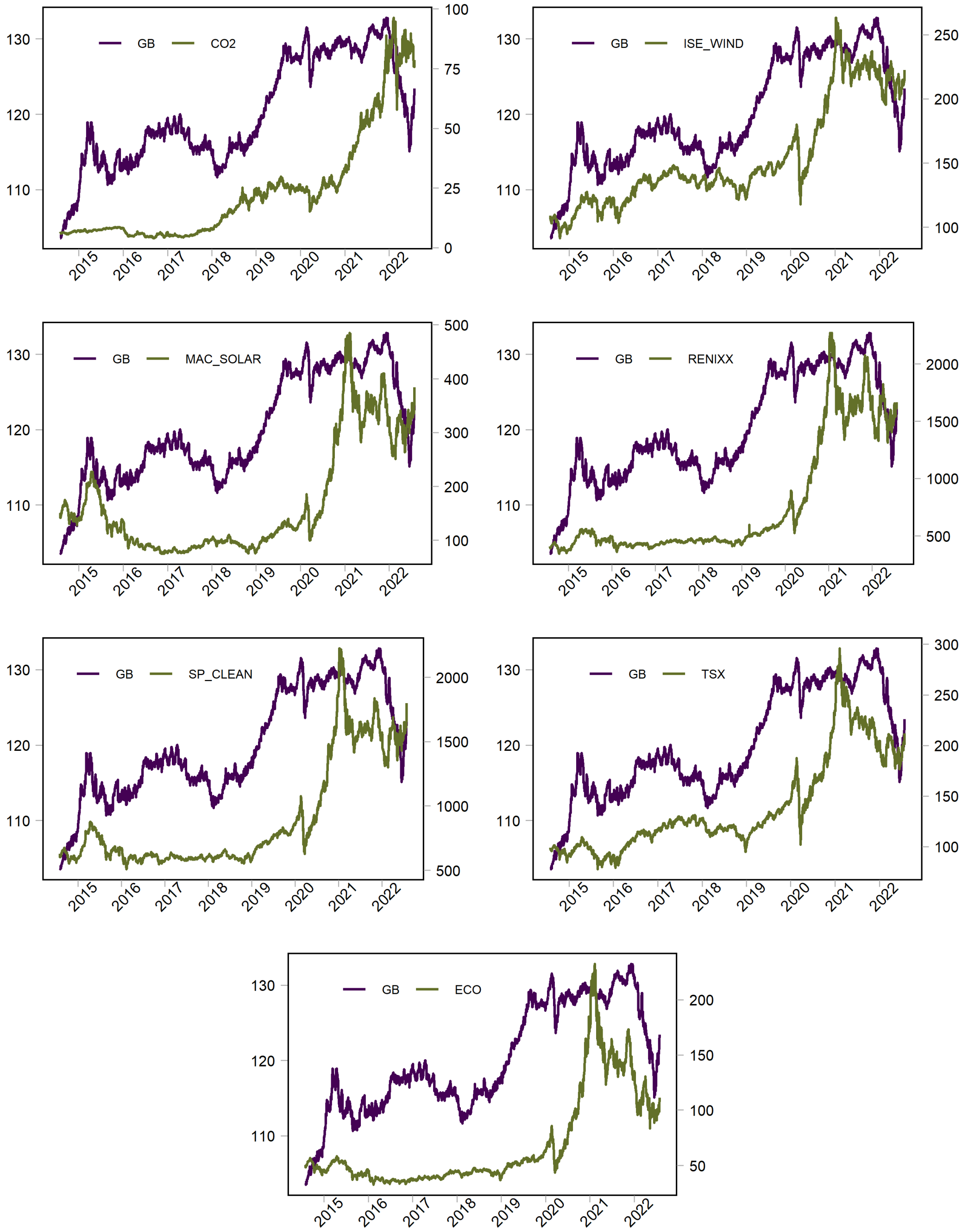

Figure 1. Scaled returns of all data series in relation to green bonds.

Further analysis of the descriptive statistics of our variables (see Appendix A) show that all the series are significantly left skewed and the kurtosis is above 3, suggesting a leptokurtic distribution. We also use the Jarque-Bera test as well as the ADF and KPSS tests to check the normality and stationarity of our data, respectively. The results indicate non-normality and stationarity for all indices. The results are available in Table A1 in Appendix A. Additionally, GB is shown to have the lowest mean and standard deviation compared to the other indices. This verifies the smoother trend we found for GB in figure 1. It also indicates that GB display lower volatility than carbon prices and CE stocks. By contrast, carbon prices are shown to have the highest mean and standard deviation from all the other indices. Investigating the correlation between all variables, we find that the lowest correlation is found between GB, CO2 and Clean Energy stocks. This finding motivates further detailed investigation of the relationship among green bonds, carbon prices and clean energy stocks.

In conclusion, the finding that GB exhibits a distinct pattern when compared to our other indices prompts additional investigation into the relationships and connectedness within our green financial system.

4 Empirical results

The main objective of this paper is to analyze the time and frequency dynamics of connectedness among green bonds, six clean energy markets and the EU carbon market. Thus, we put emphasis on the dynamic version of the connectedness method by Barunik and Krehlik (2018). After testing several frequency bands, we have found it most useful to discuss the connectedness measures for two frequency bands. We employ the high frequency (short-term) band for movements up to five days (one working week), while the low frequency (long-term) band comprises movements from 6 to 200 days. Hence, the first frequency band represents short-term connectedness, while the second frequency band represents long-term connectedness. As a robustness check, we also estimate the connectedness, including a medium frequency. The detailed results can be found in Appendix B. For the purpose of comparison, we have included a static estimation of net pairwise directional returns for both the DY12 and BK18 methods[7]. Additionally, we have incorporated some findings from the Diebold and Yilmaz (2012) pure time-domain framework.

4.1 Total return connectedness

Figure 2 shows the overall system connectedness measured by the DY12 and BK18 methods. The DY12 results show that overall connectedness varies between approximately 40% and 80% during the investigated period. Furthermore, we notice that the two largest connectedness peaks are found around 2015-2016 and 2020. We attribute the 2020 peak to the COVID-19 outbreak, which created unprecedented challenges for society and caused significant turbulence in financial markets. During 2015-2016 both Europe and the US experienced several events leading to higher uncertainty, which is also emphasized in the Economic Policy Uncertainty index by Baker et al.

[7]This is to clearly illustrate the direction and magnitude of directional connectedness among our green assets, and can be seen in figure 5.

(2016). A major event that took place in 2015 was the Greek referendum rejecting bailout terms set forth by the EU to aid the Greek debt-crisis. In addition, towards the end of 2015 leaders from around the world gathered for the COP 21 in Paris, where tough negotiations lead to the signing of the now world-famous Paris Agreement on climate change. Subsequently, several firms and organizations have used the Paris Agreement to align their climate change mitigation and adaptation efforts. Following this event, there was the ramp up of the Brexit referendum that culminated in the UK voting to leave the EU in June 2016. Additionally, the US was experiencing a highly polarized presidential race, which resulted in the election of Donald Trump as president. Other studies have similarly observed higher connectedness between financial markets during periods of economic and political turbulence (Tiwari et al., 2018; Naeem et al., 2020; Zhang and Hamori, 2021). This indicates that financial markets experienced a peak in connectedness during the financial crisis, as uncertainty transmission was high. Additionally, it is important to point out that our green financial market is significantly exposed to US and European markets, as well as the Chinese market, due to the geographical composition in our indices.

We proceed with the decomposed total connectedness by the BK18 framework which enables us to explore the short-term and long-term connectedness in our system. Our results displayed in figure 2 suggest that periods of high connectedness are mostly driven by the high frequency band (short-term). This finding is in line with previous literature investigating different systems (Diebold and Yilmaz, 2012; Ferrer et al., 2018; Tiwari et al., 2022; Kang et al., 2019; Le et al., 2021; Zhang and Hamori, 2021; Jiang and Chen, 2022). Thus, return spillovers among the GB, CO2 and clean energy markets occur mainly in the short-term, specifically within a week. As a result, during such periods, investors in green markets may encounter difficulties in diversifying their portfolios. Albulescu et al. (2019) have shown that identifying good diversification opportunities can be challenging for investors during periods of high connectedness.

In contrast, the low frequency band (long-term) connectedness in the system only varies between 10% and 20% (see figure 2). For long-term investors interested in green finance these results indicate interesting diversification opportunities in this green financial system. The relatively low connectedness at the low frequency band (long-term) indicates that return spillovers are not substantially transmitted among the variables in the long-term, thus it will be easier for long-term investors to construct green portfolios with minimum connectedness among the assets. On the other hand, it can be difficult for short-term investors such as day traders and hedge funds to find solid diversification opportunities, as there are higher return spillovers among the variables in the short-term (high frequency band). However, it also shows that most return spillovers within the green financial system is processed quite quickly. Thus, if short-term investors have solid liquidity and strong market knowledge, there could be some diversification opportunities during less volatile periods as connectedness seems to be lower in these periods. These insights can also be useful for policy makers focusing on designing optimal and efficient climate policies for both adaptation and mitigation efforts. Policy makers, just like investors, can make decisions on different frequency bands. Climate policy makers would likely focus on adaptation policies to deal with short-term challenges but emphasize more mitigation policies to find long-term solutions to the climate crisis. Thus, understanding market spillovers at both the high frequency (short-term) and low frequency (long-term) band could be valuable for policy makers.

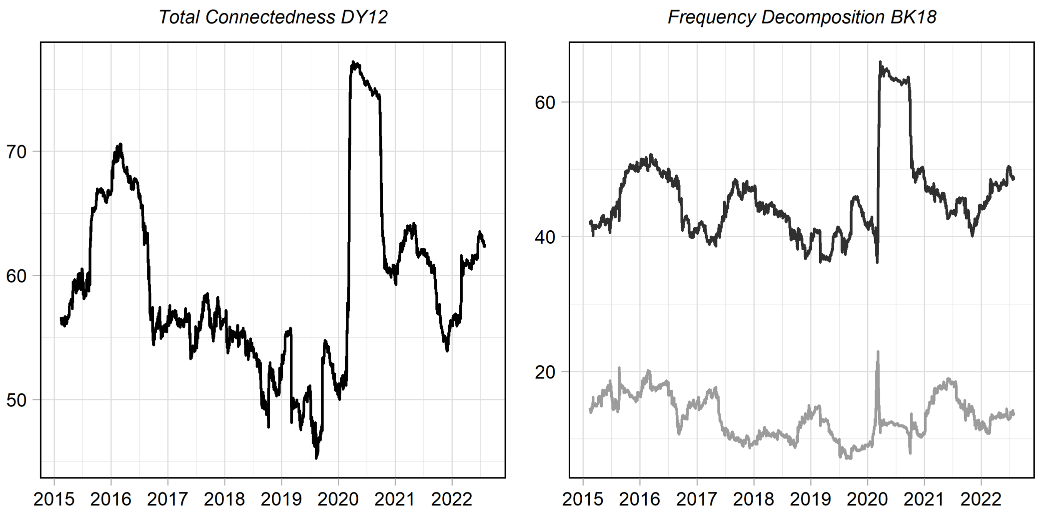

Figure 2. Total connectedness measured by DY12 framework and BK18 framework.

A noteworthy finding is that periods of severe economic events tend to be followed by periods where the connectedness in our system is driven by low frequency (long-term) transmission of shocks. In 2017 and 2021, we can observe in figure 2 a clear increase in long-term connectedness and a drop in short-term connectedness. Additionally, in the period around 2019 we can also notice that the overall connectedness is driven by the long-term rather than the short-term. In general, one could ask whether the severe economic shocks witnessed in 2015-2016 and 2020 cause investors to fear the consequences, resulting in extended periods of shock spillovers. In other words, after a severe negative shock, market participants expect that shocks in the market could have long-term impacts inducing uncertainty about the long-term stability of the market system.

Figure 2 reveals another intriguing observation - the total connectedness is not simultaneously driven by both frequencies at any particular time during the investigated period. This indicates that investors display heterogeneous responses to return shocks throughout the entire investigated period. The results clearly emphasize the importance of decomposing the system connectedness in different frequencies. In this way, we can gain a thorough understanding of the systematic risk between green financial markets, taking into account both the short-term and long-term perspectives. Therefore, we can conclude that utilizing both the DY12 and BK18 frameworks provides a more comprehensive view of the connectedness in our green financial system.

4.2 Net directional return connectedness

Figures 3 and 4 demonstrate the net directional spillovers of each variable in our system. First, figure 3 shows the DY12 results, while figure 4 shows the results from the BK18 framework. The net directional return connectedness allows us to identify net transmitters and receivers of spillovers in our green financial system. Figure 4 displays the breakdown of net return connectedness into short-term and long-term. The pink shade corresponds to the short-term component (high-frequency band), while the blue shade refers to the long-term component (low frequency band).

Figure 4 shows that the majority of the connectedness for our individual variables is driven by short-term connectedness. This finding corroborates the results in figure 2. Focusing on GB, we notice from figure 3 and figure 4 that based on both the DY12 and BK18 framework, GB is a net receiver of return spillovers from the other variables in the system. Additionally, the BK18 results reveal that GB is a net receiver of shocks in both the short-term and long-term, meaning across both frequencies. We also notice that the short-term component (high frequency) dominates the long-term (low frequency) component. Therefore, we could conclude that the short-term component drives the net directional spillover for GB. We detect a minor exception from this result in 2018, when GB acted as net transmitter of shocks in the long-term (low frequency). Some events that could be linked to this is the launch of the European Commission's sustainable finance action plan, the release of the IFC Guidance for Green Sovereign Issuers, and the issuing of the World Bank guide for public sector issuers on green bond proceeds (Richardson and Reichelt, 2018).

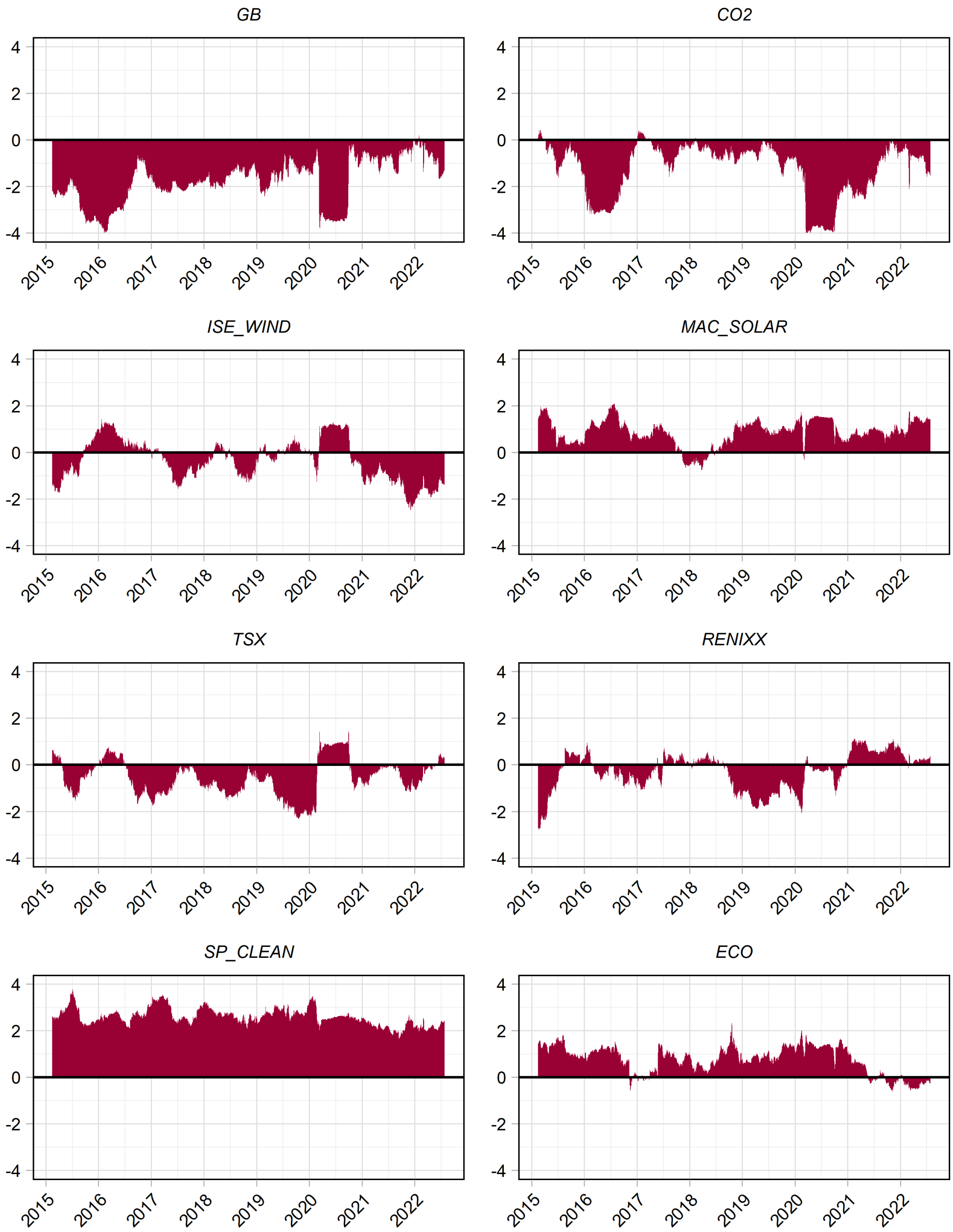

Figure 3. Net directional connectedness DY12.

In terms of market related events, it is noteworthy that in 2018 the cumulative green bond issuance reached $500bn (Richardson and Reichelt, 2018). The findings also indicate that GB is receiving fewer shocks after the COVID-19 pandemic compared to pre-pandemic. Given the increased attention towards green bonds within academia and financial markets, we could speculate whether it is possible that GB's role may shift from being a net receiver to a net transmitter of shocks in the years to come. More importantly the results show that GB exhibit relatively lower connectedness in more recent periods, indicating that GB could serve as an effective diversification instrument for investors who operate in both the short-term and long-term green financial markets.

In figures 3 and 4, we can see similar patterns for CO2 quotas as we do for GB in both the DY12 and BK18 frameworks. CO2 emerges as a net receiver of shocks across frequencies for the majority of our investigated period. Additionally, the net connectedness is mainly driven by the short-term, which is the same case as for GB. CO2 diverges from the GB pattern during times of significant political and economic uncertainty, such as Brexit and the COVID-19 pandemic. In these periods, the net directional connectedness of CO2 to the rest of the system increases to a much greater extent compared to GB. On the other hand, during times of relative political and economic stability (2017-2019), CO2 shows only minimal connectedness with the rest of our green financial system. This finding may be of interest for both short-term and long-term oriented investors, as well as for policy makers working on carbon markets like the EU ETS. Overall, it can be observed that GB and CO2 are the primary net receivers of return spillovers in both the DY12 and BK18 frameworks, which is consistent with previous literature (Le et al., 2021).

Focusing on the clean energy markets, we observe some fluctuations in the net receiving and transmitting behavior for ISE_WIND, MAC_SOLAR, TSX and RENIXX in the DY12 framework. On the contrary, ECO displays less variability than the other indices, while SP_CLEAN differs from the other variables by being a net transmitter rather than receiver of shocks. To better understand whether it is the short-term component or long-term component that drives the net directional spillovers for our clean energy assets we exploit the BK18 framework. Going into more detail regarding the clean energy variables, we can notice from figure 4 that MAC_SOLAR, SP_CLEAN, and ECO generally act as net transmitters across both frequencies during the periods around the Greek debt crisis, the signing of Paris Agreement, Brexit and COVID-19 pandemic. Thus, we can deduce that during periods of political and economic uncertainty, the net return spillovers in the green financial system are driven by the general clean energy markets as well as the solar energy industry. At the same time, we notice that the connectedness for MAC_SOLAR, and ECO is estimated to be relatively low for the whole time period. Most of the return spillover transmission is driven by SP_CLEAN, and mostly driven by the high frequency band (short-term).

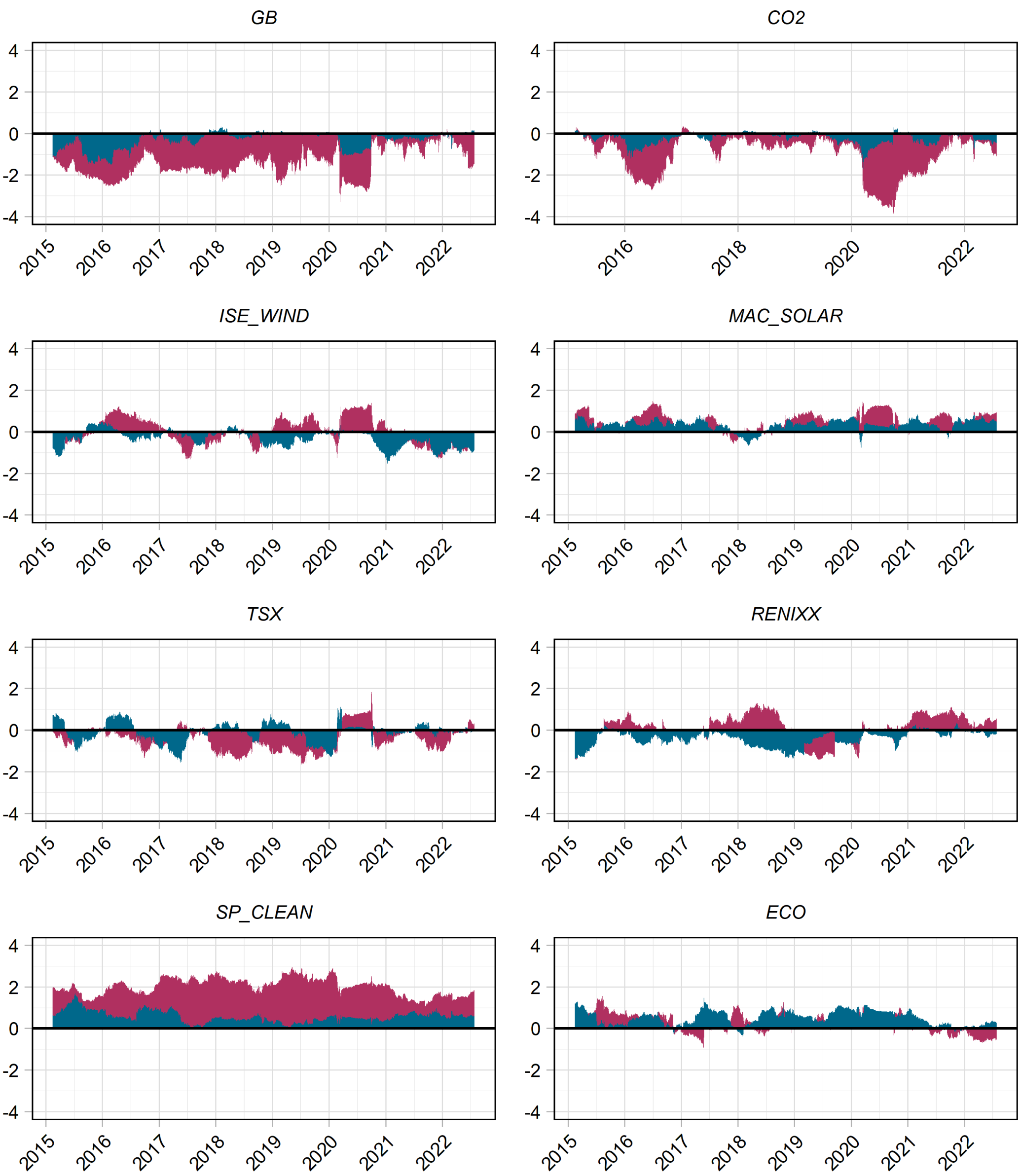

Figure 4. Net directional connectedness BK18.

A particularly interesting finding from the decomposed frequencies is that even though both SP_CLEAN and ECO emerge as net transmitters in the system, their connectedness to the system is driven by different frequencies and their connectedness displays different magnitudes. The net directional connectedness for SP_CLEAN is influenced by the high frequency band (short-term), whereas the connectedness for ECO seems to be mainly driven by the low frequency band (long-term). However, since the outbreak of the war in Ukraine and significant monetary policy tightening, especially from the Federal reserve system (FED), it seems that it is the short-term net spillovers that drive the net directional spillovers from ECO to our green finance system. This finding becomes clear when investigating both figures 3 and 4. From figure 3 ECO emerges as a net receiver of spillovers after mid-2021, and in figure 4 it is clear that it is the short-term (high frequency) spillover that dominates the long-term (low frequency) spillover.

In figure 4, we also observe that the net directional connectedness for ISE_WIND and RENIXX is not dominated by one frequency but is equally affected by both frequencies in different time periods. For the case of ISE_WIND, which represents the wind energy market, the results demonstrate that the return transmission during the macroeconomic events of 2016 and during COVID-19 was mainly driven by the high frequency band, indicating that shocks are transmitted rapidly through the system. However, both during the time of the signing of the Paris Agreement and post-COVID-19 ISE_WIND seems to act as a net receiver of return spillover in our green financial system. On the other hand, RENIXX follows a different pattern than ISE_WIND, being a net transmitter of spillovers driven by the short-term in the post-COVID period while it appears to be a net receiver during the macroeconomic events of 2015-2016 switching between short-term and long-term connectedness. Lastly, TSX emerges as the most volatile variable switching multiple times between being a net transmitter and receiver of return spillovers at different frequencies.

Overall, our results suggest that GB, CO2, and clean energy markets react differently to market events and that return connectedeness varies depending on the frequency, especially among clean energy markets. Moreover, we observe that the connectedness of most clean energy markets remains considerably low throughout the entire analyzed period, as opposed to the high connectedness exhibited by SP_CLEAN and GB, as well as CO2 during times of economic and political instability. Consequently, our analysis suggests that SP_CLEAN is the primary net spillover transmitter within our green financial system, while GB serves as the primary receiver of return spillovers. Overall, the results provide interesting insights for investors that are seeking opportunities to explore green financial markets and identify potential diversification strategies for their portfolios.

4.3 Pairwise directional return connectedness

In this section, we shift our focus to the pairwise directional return spillovers to shed some light on the key transmitters and receivers of shocks in a bi-variate setting. First, we will provide an overview of the net receivers and transmitters between the variables in the system by presenting the static pairwise results from both the DY12 and BK18 frameworks. The results are shown in the network graph in figure 5. For comparison purposes, we have also included the DY12 results. Additionally, we have focused on the pairwise connectedness between GB and CO2 since we are particularly interested in the relationship of these two markets with the clean energy market. Nevertheless, we have provided a brief commentary of the results for the clean energy variables. The dynamic DY12 pairwise results and the clean energy pairwise results can be found in Appendix C.

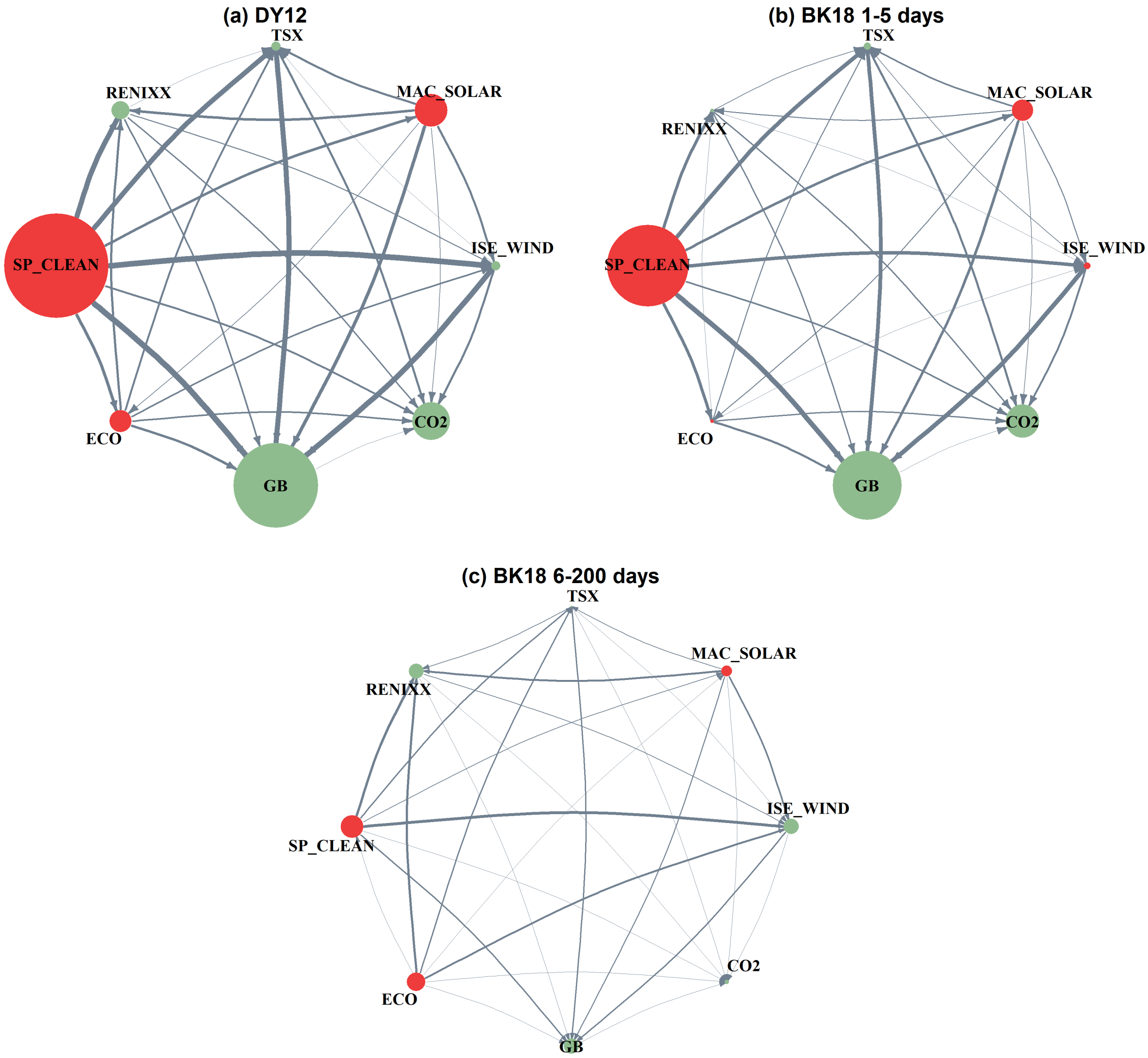

Figure 5. Net pairwise directional connectedness measured using both the DY12 and BK18 framework. *Note*: The size of the nodes is proportional to the magnitude of each variable as transmitter/receiver of return connectedness to/from each one of the remaining variables in our green financial system. Additionally, the color of the node indicates whether a variable is a net transmitter/receiver of connectedness to/from all the other variables. In this figure net transmitters are colored red and net receivers are colored green. Finally, the thickness of the line arrows reflects the strength of the connectedness between a pair of variables, which means that thicker edges represent stronger net pairwise connectedness.

From figure 5 we see that GB emerges as the largest net receiver of return shocks in our green financial system, followed by CO2. The only pairwise relationship where GB is a net transmitter of return spillovers is between GB and CO2, but the net transmission is marginal, which is made clear by the significantly weak line going between GB and CO2. Furthermore, from part (b) in figure 5, we observe that the magnitude of shocks received by GB is primarily in the high frequency band, corresponding to 1-5 days. Three variables stand out as the strongest transmitters of return spillovers to GB, namely SP_CLEAN, TSX and ISE_WIND, with SP_CLEAN having the most significant effect. Again, we observe that this relationship is predominantly driven by the high frequency band, suggesting that the return spillovers are rapidly processed, within a single work week. There is some evidence of long-term (low-frequency) connectedness that arises during periods of turbulence, such as the Greek debt crisis, Brexit and COVID-19.

The analysis of CO2 reveals that it is the second largest net receiver, both in the high and low frequency bands. However, the magnitude of the connectedness is rather weak and almost negligible in the long-term, as indicated by part (c) in figure 5 and figure 7 (also figure C.2 in Appendix C). In figure 7, we observe that this generated marginal connectedness is mostly driven by the short-term (high frequency), especially during the Brexit and COVID-19 pandemic. In addition, except for a few exceptions, there is barely any long-term connectedness during the investigated period. Generally, during times of political and economic instability, CO2 tends to be more strongly connected with the clean energy markets and GB market at the high frequency band. Overall, it appears that CO2 is quite decoupled from the other variables in our green financial system. Furthermore, some may argue that certain investors regard CO2 as a commodity that can be used as a financial speculative instrument, much like the financialization of crude oil (Ferrer et al., 2018). Thus, certain investors may own "brown" stocks associated with polluting industries such as steel companies, while simultaneously purchasing carbon quotas to offset the perceived adverse impact of owning these stocks. The use of carbon quotas as a speculative instrument could be the reason for the lack of connectedness between CO2 and clean energy markets, similar to what has been observed for conventional and renewable energy markets (Ferrer et al., 2018; Asl et al., 2021).

When investigating the pairwise directional connectedness of our clean energy market variables we come across several interesting findings. First, in our static model in figure 5, SP_CLEAN displays relatively strong transmission of return spillovers to GB, ISE_WIND, RENIXX and TSX. However, we notice a relatively weaker connectedness between SP_CLEAN and MAC_-SOLAR, as well as SP_CLEAN and ECO. Focusing on the dynamic model, results indicate that SP_CLEAN is the main driver of return spillovers in our green financial system, both in the DY12 framework and the BK18 framework. Moreover, most of the pairwise connectedness between SP_CLEAN and the rest of the variables in the system is generated in the short-term (high frequency band). This finding also corroborates the net directional results in figure 4, where SP_CLEAN is showed to generate most connectedness at the short-term (high frequency band).

Figure 6. Net directional pairwise connectedness between green bonds and the green financial system measured at high and low frequency.

A noteworthy finding is that although the ISE_WIND seems to be a net receiver of return spillovers in the dynamic DY12 framework, in the BK18 frequency framework it emerges as a net transmitter in the short-term, and switches to a net receiver in the long-term. These insights into the wind energy market in the context of our green financial market may also be of interest for various investors and policy makers, as wind energy is a popular investment option for investors interested in renewable energy. Overall, the wind industry exhibits rather low connectedness to the other green financial markets, rendering it an attractive diversification opportunity. Yet, it may be beneficial for short-term green investors to be aware of the potential spillover from the general clean energy market represented by SP_CLEAN, and the potential spillovers from ISE_WIND to GB, and from ISE_WIND to CO2 especially during highly turbulent times.

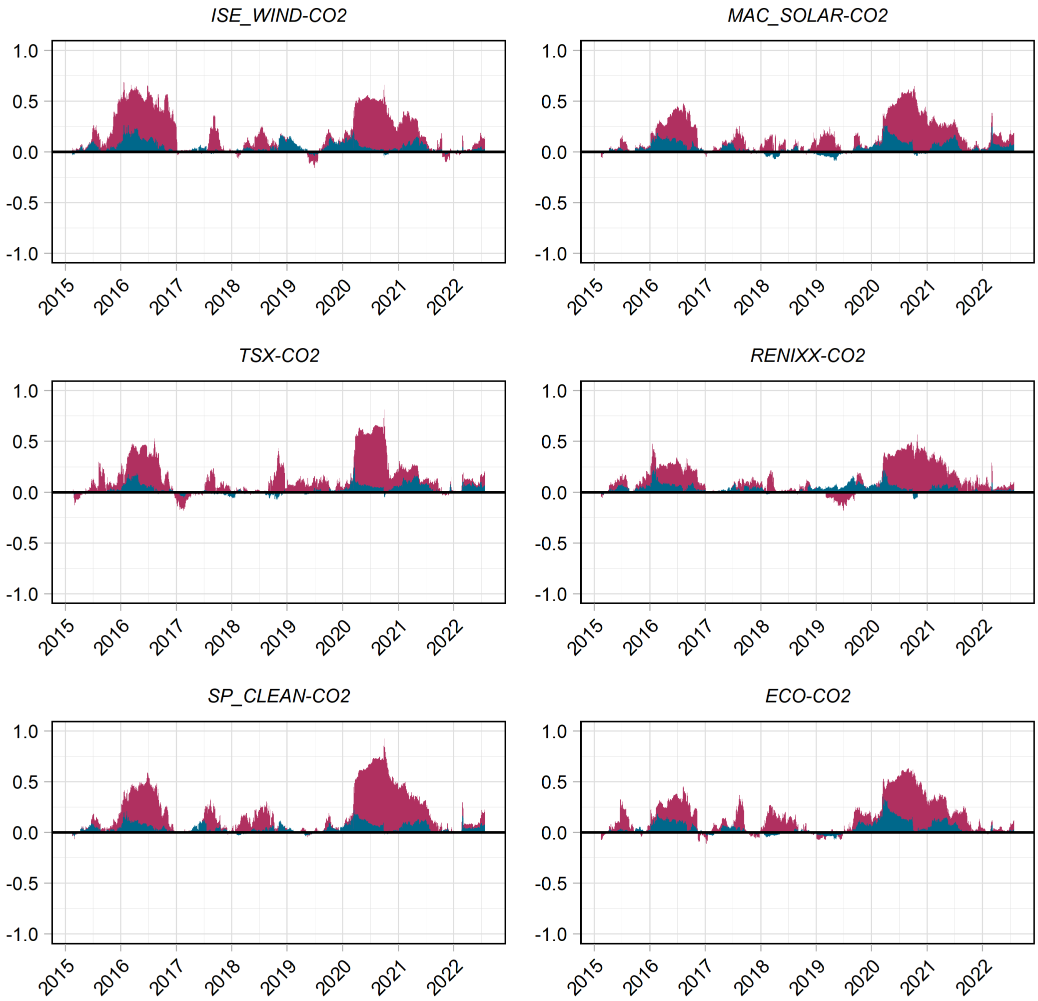

Figure 7. Net directional pairwise connectedness between carbon market returns and the clean energy markets at high and low frequency.

Another interesting result associated with the clean energy markets is that ECO, which is identified as a net receiver at both frequency bands is mainly influenced by the long-term component. Additionally, as depicted in figure 5, ECO is the only variable that increases in magnitude at the long-term (6-200 days). A potential answer to this result may be that ECO could be constructed from stocks that tend to be more have investors who scrutinize information more thoroughly after a shock, resulting in a larger spillover magnitude in the long-term (low frequency band). We notice that the pairwise directional spillover between ECO and GB, and ECO and CO2 is rather low and mostly driven by the short-term in figures 6 and figure 7, indicating that most of the low frequency (long-term) return spillover transmission occurs between ECO and other clean energy markets. This can also be seen in figure 5 part (c), where the return spillover from ECO at the low frequency band is transmitted mainly to RENIXX, ISE_WIND and TSX.

5 Discussion

Our results show that connectedness in the green financial system is both time and frequency dependent. In line with previous studies (Diebold and Yilmaz, 2009; Albulescu et al., 2019; Naeem et al., 2020), we find that periods of political and economic uncertainty tend to increase connectedness between the assets under examination.

An interesting finding is that periods of severe economic events tend to be followed by periods where the connectedness in our system is driven by long-term (low frequency) transmission of shocks. This prompt us to question whether investors fear the aftermath and the uncertainty surrounding the resolution of these severe economic shocks. Thus, new information is examined with greater scrutiny, which translates into shock spillovers being transmitted over longer periods. Following a serious shock, market participants anticipate that disruptions in the market may have lasting impacts, including uncertainty about the long-term stability of the market. Such a finding can be of great interest for both investors and policy makers in planning and portfolio management.

Following the COVID-19 pandemic, from early 2020 until today, the total return connectedness has continued to remain at higher levels than those observed before the pandemic. This connectedness is likely linked to the energy crisis in Europe, the war in Ukraine and tightening monetary policies across Europe and the US. Nevertheless, the relatively low connectedness between our green assets indicates prospects for diversification in the long-run, as well as among specific assets in the short-term. Numerous financial market leaders suggest investing in climate-aligned assets, which as demonstrated, can be advantageous for investors. Among the most famous is BlackRock CEO Larry Fink, emphasizing the importance of aligning the financial markets and climate efforts in his letters to CEOs in 2021 and 2022. Moreover, the World Bank has faced increasing pressure to tackle climate change[8], and to quickly ramp up efforts to allocate more money to finance climate initiatives.

Overall, our results show that the system connectedness is mainly created at the high frequency band. Consequently, most of the return spillovers between our green assets are transmitted through the system within a week. Thus, investors in climate finance can find it easier to construct a diversified green portfolio in the long-run than in the short-run. One may assume

[8] Article from Financial Times (2023).

that this finding might stimulate or attract a long-term perspective towards green investments rather than prompting short-term speculation. This is particularly crucial for a successful green transition and can motivate policy makers to design policies that encourage investors with long-term investment preferences to invest in the green financial market. Simultaneously, the world is lagging in terms of financing the green transition. Therefore, we can argue that it is also essential to motivate short-term investors to secure a rapid influx of capital. Policy makers can enhance the attractiveness of the green financial market for short-term investors by designing policies that target reducing the short-term connectedness.

GB and CO2 are estimated as net receivers of shocks, with most of the return spillovers occurring at the high frequency (short-term) band. Furthermore, since 2021, there has been a significant decrease in net connectedness across the different frequency bands for GB. The fact that GB and CO2 are net receivers implies that they are not key determinants of the performance of clean energy and clean technology stocks. Consequently, we can assume that GB, CO2 prices and clean energy stocks can be utilized by investors for portfolio diversification. Importantly, both GB and CO2 exhibit relatively low connectedness at the low frequency band. Thus, these assets could provide an interesting avenue for long-term investors who focus on green financial markets. Our findings can encourage long-term investors such as pension funds and sovereign funds to consider creating fully climate-aligned portfolios.

Our findings indicate a low level of connectedness of CO2 prices with the other green assets in our system during periods of stability. The level of connectedness, however, increases significantly during highly turbulent periods, specifically in 2016 and 2020. CO2 quotas can be perceived as a commodity used as a speculative instrument by certain investors, such as short-term traders and hedge funds, similar to the financialization of crude oil discussed by Ferrer et al. (2018). For instance, some investors may purchase carbon quotas as a potential hedge against climate risk in their portfolios when owning "brown" stocks. This may affect the lack of connectedness between CO2 and the clean energy market, similar to the documented decoupling of traditional and new renewable energy markets (Ferrer et al., 2018; Asl et al., 2021). Consequently, CO2 has the potential to act as an interesting diversification tool for portfolios that include clean energy stocks and/or green bonds.

Our findings also suggest that SP_CLEAN is a main driver of the high frequency return spillovers, while the connectedness associated with the other clean energy markets is relatively low across both frequencies. There are prolonged periods where the net connectedness of the clean energy assets is primarily driven by the low frequency (the long-term). Upon analyzing the pairwise connectedness results, it becomes apparent that the primary contributor to long-term connectedness is the transmission of spillovers among the various clean energy indices, rather than the relationship between GB-CO2 and clean energy markets[9] Therefore, the clean energy assets could be used as diversification tools for short-term portfolios. This finding could be valuable for short-term investors, including day traders and hedge funds, who are seeking diversification opportunities within the green financial markets.

6 Conclusion

In recent years, the world has witnessed a significant surge in the awareness and need for finance that aligns with climate goals. This trend can be attributed to the need for green transition investment in response to the pressing challenge of climate change. Green bonds and carbon markets along with clean energy markets can be seen as the most important financial building blocks for a successful green transition in line with the Paris Agreement, the EU Green Deal and other global and regional climate initiatives.

This paper investigates the time and frequency dynamics of connectedness among green bonds, carbon prices, and clean energy markets, using the novel connectedness framework by Baruník and Krehlík (2018), regarded as an extension to the spillover index approach by Diebold and Yilmaz (2012). The BK18 framework allows us to explore the connectedness between our chosen green assets in both the time and frequency domain simultaneously. Therefore, we can decompose the total and directional connectedness, found by the DY12 framework, to different frequencies and discover short and long-term connectedness between our chosen assets. The BK18 connectedness results can facilitate portfolio diversification for investors operating in different time horizons, eventually increasing funding for environmentally friendly projects. This can cultivate positive change towards a sustainable future and assist into achieving the global sustainability goals. We selected two frequency bands that represent the short-term and long-term horizon. The high frequency band comprising 1-5 days (equivalent to a working week) represents a short-term horizon, while the low frequency band of 6-200 days refers to a long-term horizon[10].

Our empirical results provide insights into the green financial market, where SP_CLEAN generally transmits return spillovers, while GB and carbon prices act as net receivers, and the other clean energy markets display a rather low net connectedness. We find that generally, high frequency band (short-term) return spillovers dominate low frequency band (long-term)

[9]In the preceding paragraph, we noted that connectedness is mainly driven by the short-term spillovers among GB-CO2, and clean energy markets.

[10]While we have also used three frequency bands (see Appendix B), the medium-term horizon has not yielded significant insights. Furthermore, aligning our frequency bands with those used in previous studies has made it easier to compare our results with the existing literature.

spillovers in magnitude. This means that, as per today, the green financial market benefits the long-term investors who operate at the low frequency band, even more in turbulent periods, as most return spillover connectedness is found in the short-term. Thus, it appears that generally the green financial market is quite efficient in rapidly processing information, resulting in shock transmissions mainly occurring within one working week. Moreover, discovering rather low connectedness in the long-term implies that these markets appear to be primarily driven by their own fundamentals and the overall economic standing. Our analysis also reveals that several of our clean energy indices exhibit low connectedness, even at at the high frequency band (short-term). This finding may interest short-term investors and incentivize increased capital in these markets.

Our results regarding CO2 quota prices reveal low connectedness with the rest of the system during periods of stability, with a notable increase only during highly uncertain political and economic periods. CO2 prices display an increased connectedness during the Brexit crisis and the COVID-19 pandemic, while for the remainder of the time period, CO2 appears to be weakly connected both with green bonds and clean energy markets. This finding may present opportunities for short-term investors who wish to diversify their green portfolio by including CO2 as a potential option. However, short-term investors should be aware of considerable return spillovers during extremely turbulent periods, which can make portfolio diversification more difficult, or less reliable. Overall, our results provide evidence of diversification prospects in green financial markets. This underscores the potential for investors to take advantage of these prospects and further promote the green financial transition.

Concerning policy makers, we would suggest that they pursue policy mixes that encourage greater investments from long-term investors, while also providing incentives for short-term investors to facilitate essential short-term climate capital. Policies can also enhance the attractiveness of the green financial market for short-term investors by designing policies that target reducing the short-term connectedness, especially aimed at GB. Moreover, providing insights into the connectedness between various clean energy markets in both the short-term and long-term could aid in designing and revising policies for an efficient and fair green transition.

An interesting next step for researchers and investors would be to compare minimum connectedness portfolios created at different frequencies to investigate short-term and long-term hedging opportunities in line with Tiwari et al. (2022). Lastly, it would be interesting to explore the possibilities of estimating which return spillovers are positive or negative in nature. These are important future research agendas, not accomplished using the DY12 and BK18 frameworks.

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A Appendix

Table A1. Summary Statistics and Tests.

	GB	CO2	ISE_WIND	MAC_SOLAR	TSX	RENIXX	SP_CLEAN	ECO
Mean	0.006	0.088	0.024	0.032	0.026	0.048	0.036	0.027
Std. Dev.	0.269	2.413	0.954	1.805	1.235	1.538	1.31	1.882
Min	-2.403	-19.453	-11.708	-14.854	-14.617	-16.343	-12.507	-16.952
Max	1.447	16.191	9.835	11.264	10.834	17.246	10.979	13.338
Skewness	-0.441	-0.433	-0.88	-0.534	-1.266	-0.174	-0.586	-0.498
Kurtosis	6.399	7.855	18.192	7.78	22.414	15.751	13.398	8.867
Jarque-Bera	5075.7^{***}	7597.7^{***}	40642^{***}	7502.9^{***}	61902^{***}	30198^{***}	22007^{***}	9686.7^{***}
ADF	-13.621^{***}	-14.309^{***}	-13.72^{***}	-13.188^{***}	-12.969^{***}	-13.323^{***}	-12.525^{***}	-12.974^{***}
KPSS	0.074	0.06	0.032	0.06	0.043	0.068	0.047	0.088
Observations	2920	2920	2920	2920	2920	2920	2920	2920

Notes: i) *, ** and ***, respectively denote rejection of the null hypothesis at 1%, 5% and 10% significance levels. ii) ADF: Augmented Dickey-Fuller, KPSS: Kwiatkowski-Phillips-Schmidt-Shin

B Appendix

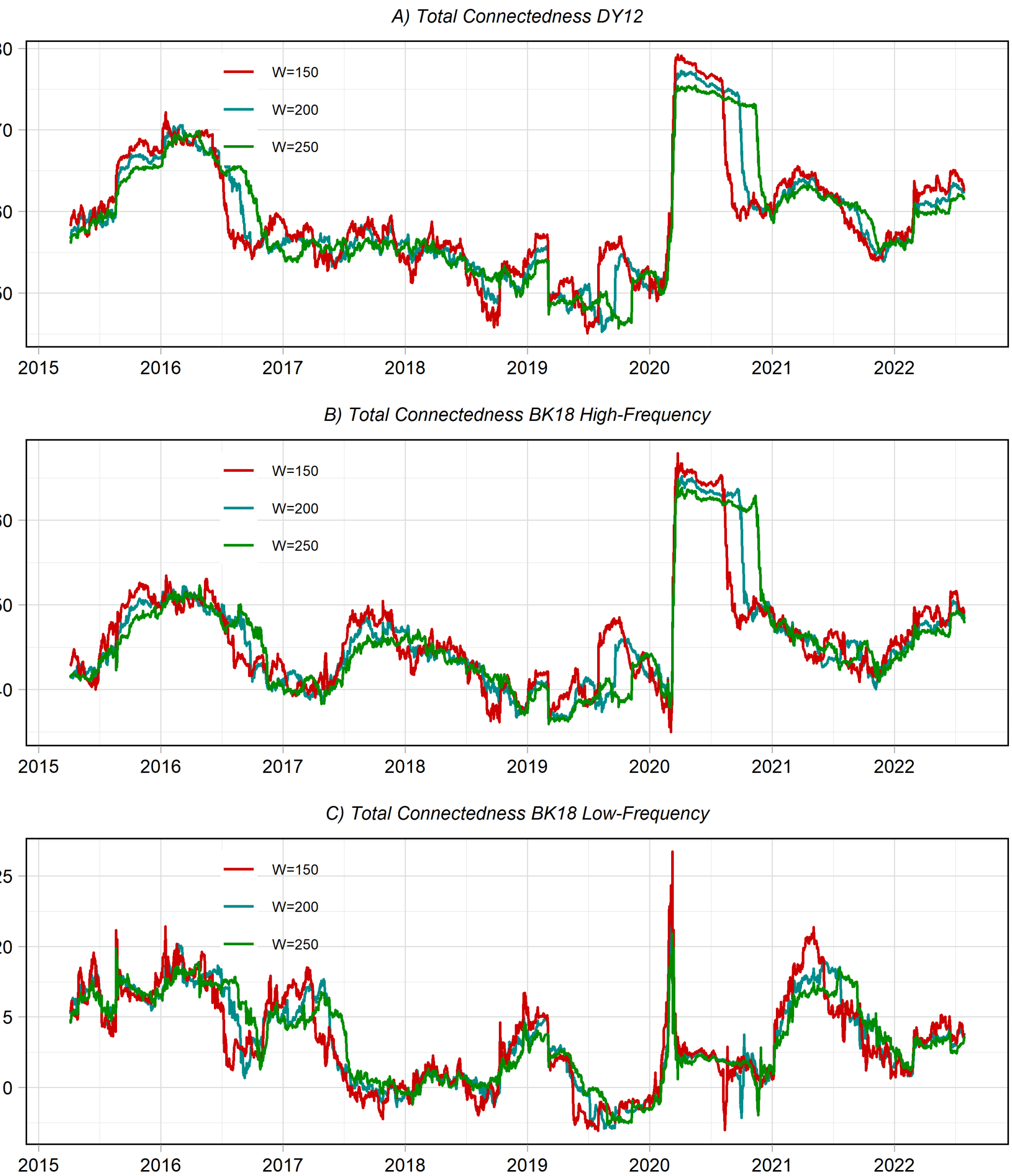

Figure B.1. Robustness check using different rolling window sizes (150, 200 and 250 days). *Notes*: i) The rolling window of 200 days represents our main results in the paper, ii) This figure displays the overall time-varying connectedness of DY12 and the time-frequency connectedness of BK18 for two frequency bands (low and high).

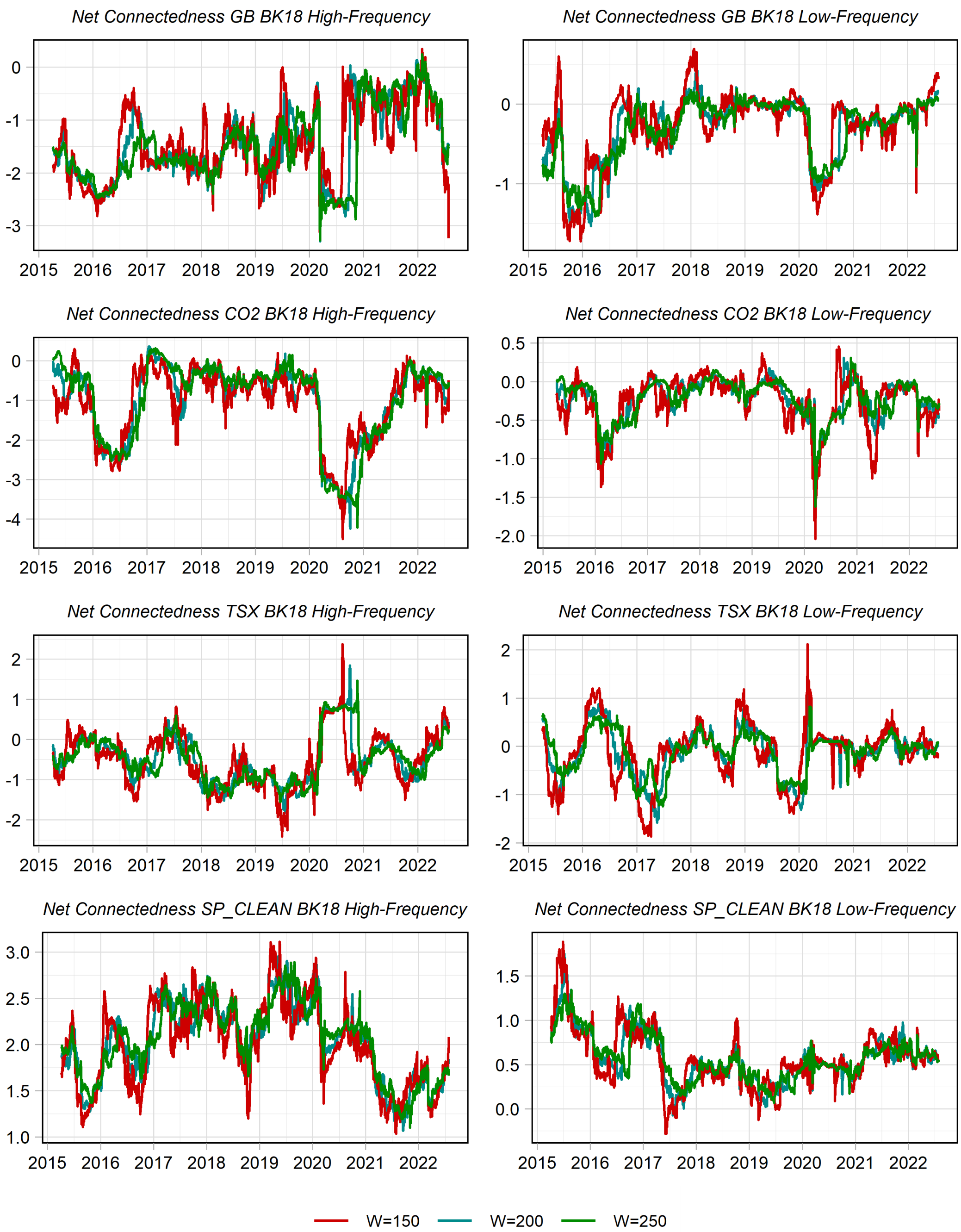

Figure B.2. Robustness check using different rolling window sizes (150, 200 and 250 days). *Notes*: i) The rolling window of 200 days represents our main results in the paper, ii) This figure displays the net time-frequency connectedness of BK18 for two frequency bands (low and high). For simplicity, we split the indices in two graphs.

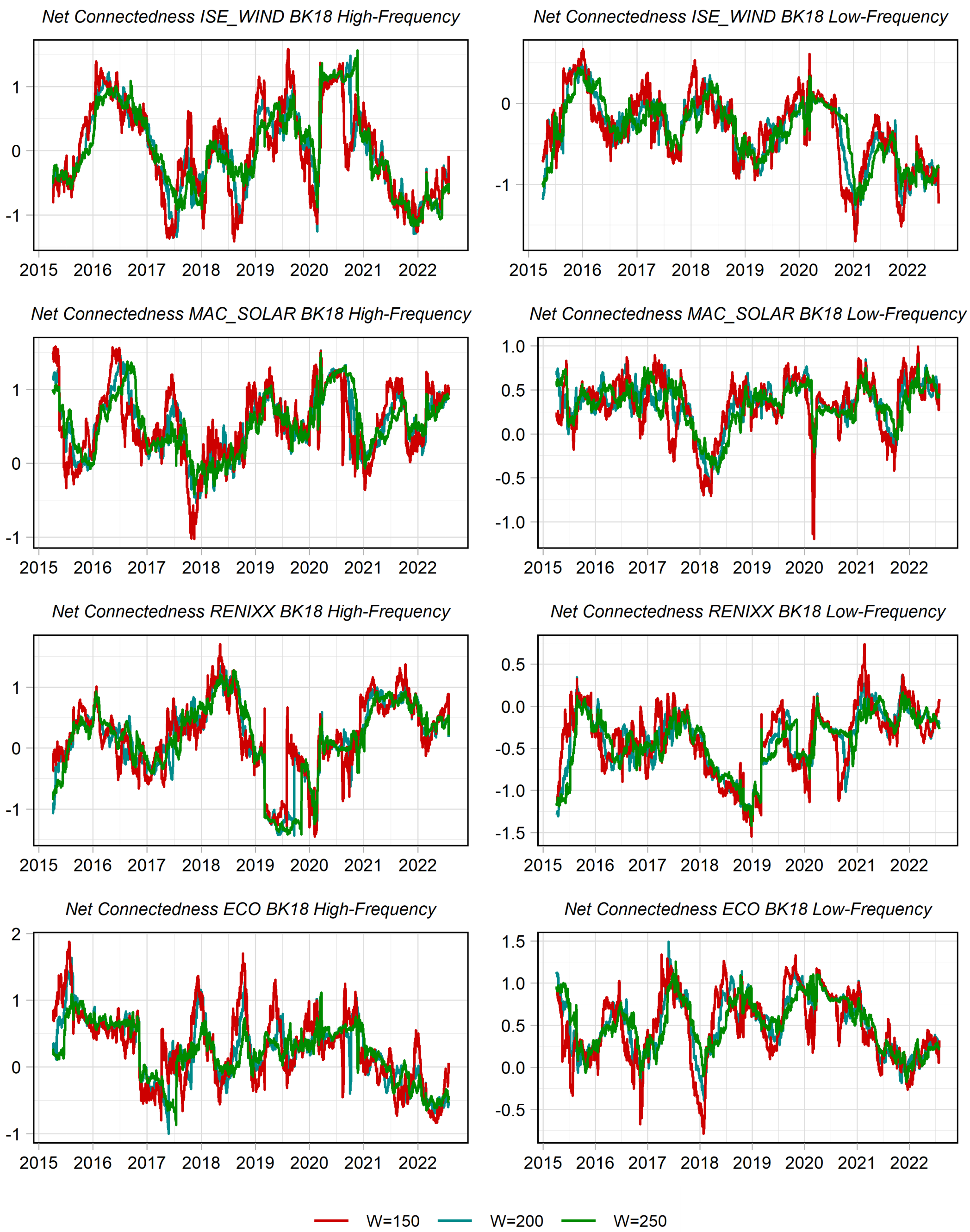

Figure B.3. Robustness check using different rolling window sizes (150, 200 and 250 days). *Notes*: i) The rolling window of 200 days represents our main results in the paper, ii) This figure displays the net time-frequency connectedness of BK18 for two frequency bands (low and high). For simplicity, we split the indices in two graphs.

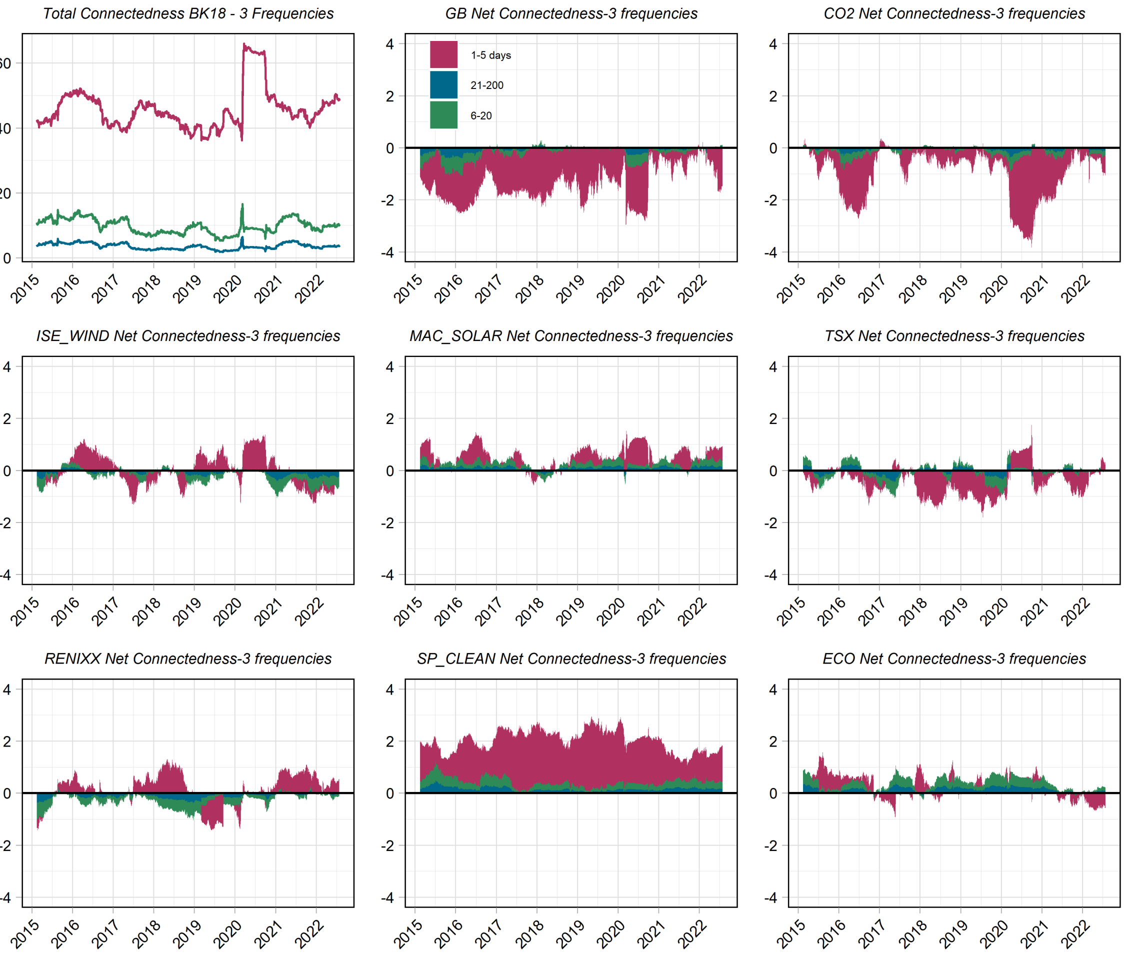

Figure B.4. Robustness check using three frequency bands. *Note*: i) This figure displays the total connectedness of our system, but also the net connectedness for each index in three frequencies.

C Appendix

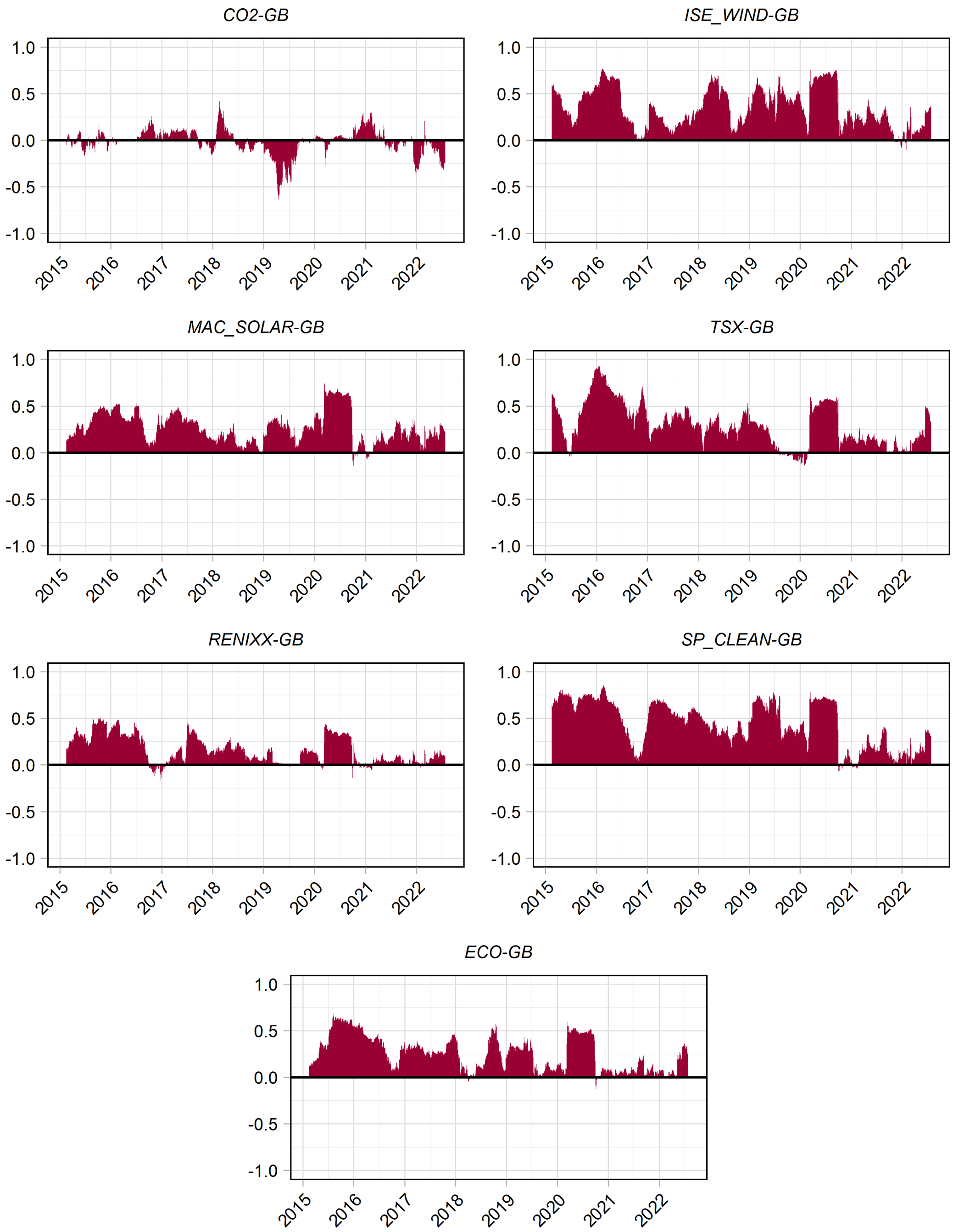

Figure C.1. Net directional pairwise connectedness between green bonds and the green financial measured by the DY12.

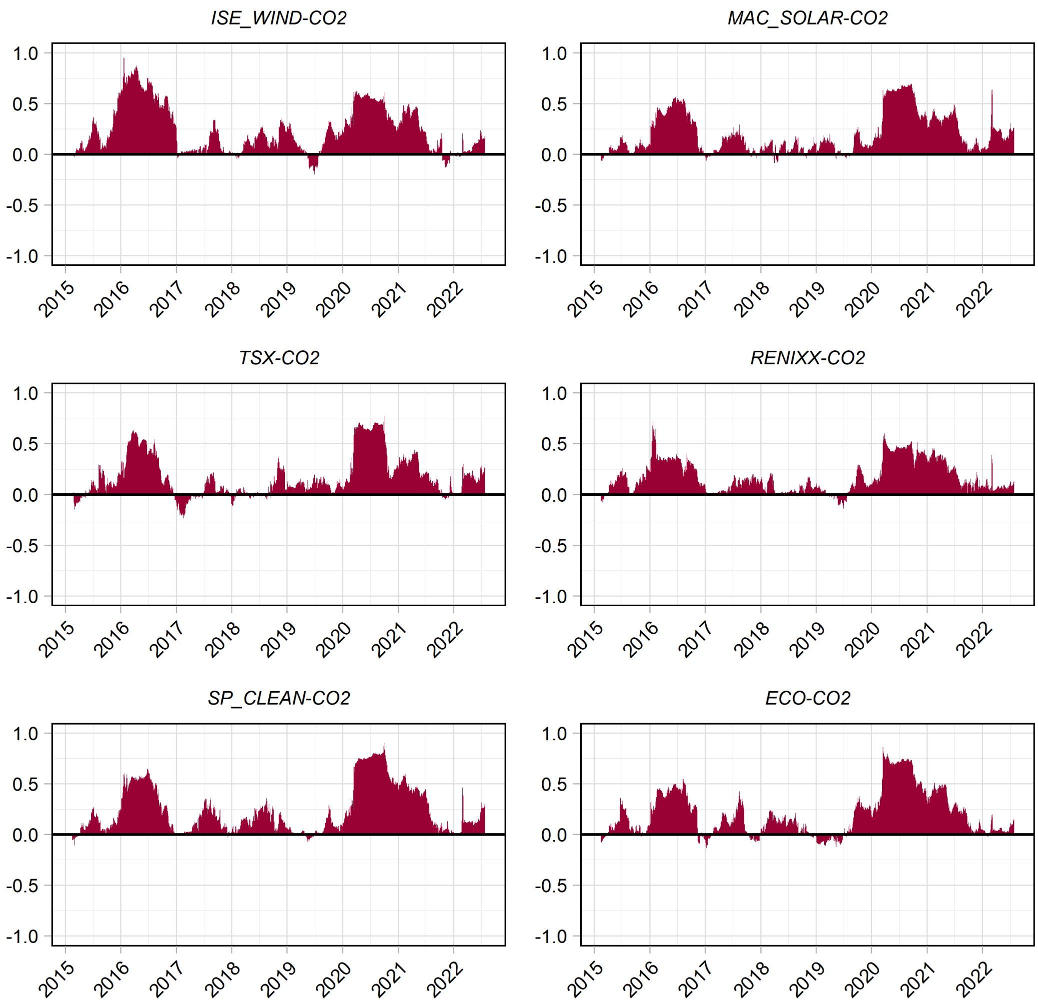

Figure C.2. Net directional pairwise connectedness between CO2 and the green financial measured by the DY12.

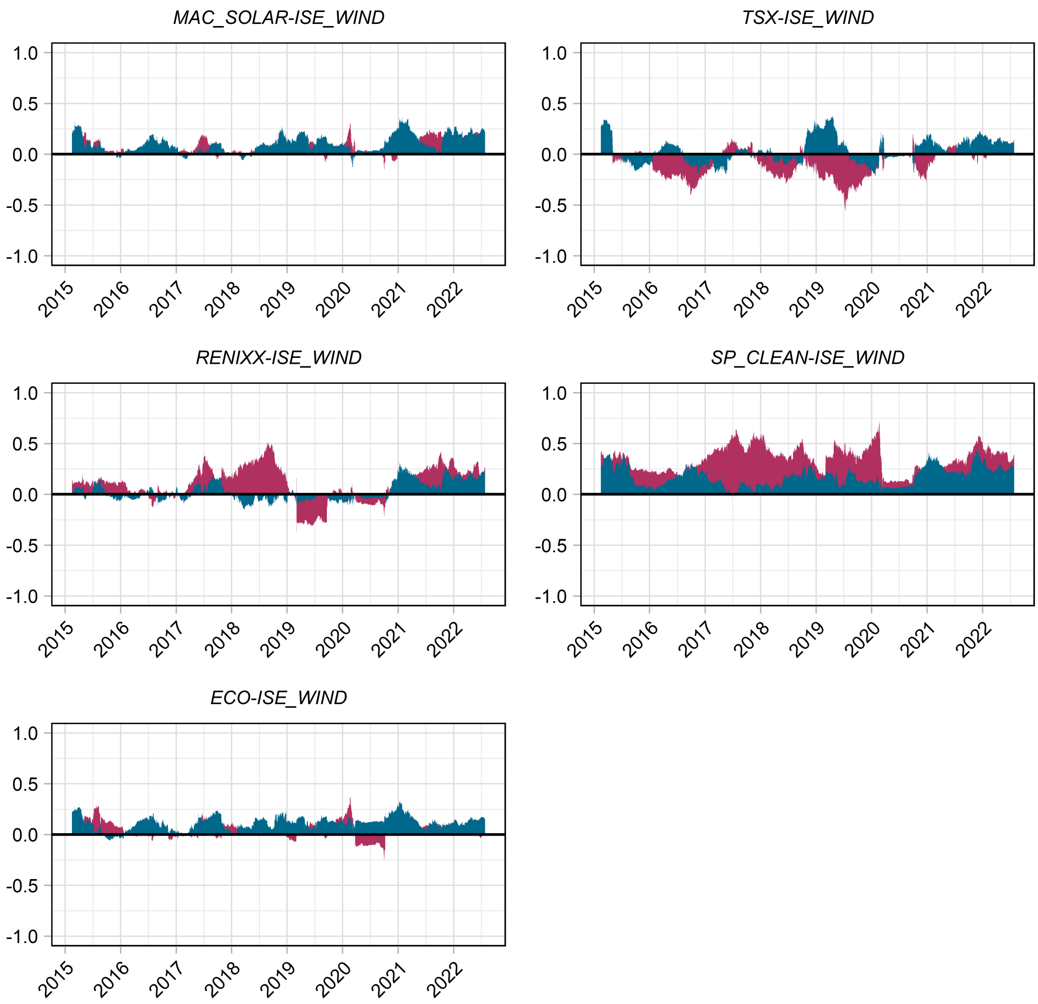

Figure C.3. Net directional pairwise connectedness between ISE_WIND and other clean energy markets using the BK18 framework.

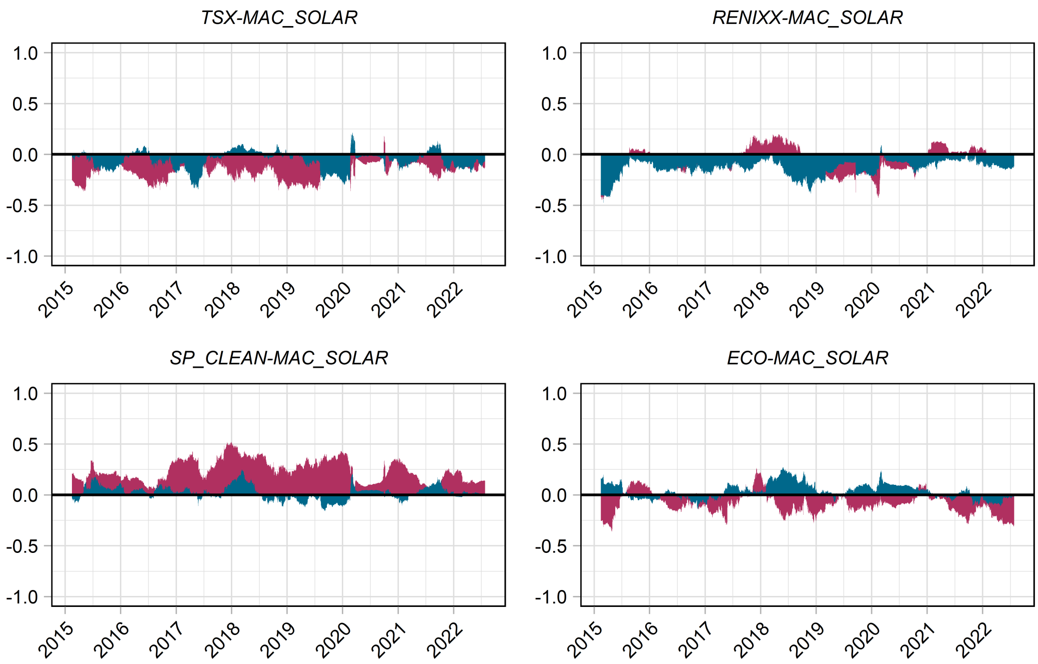

Figure C.4. Net directional pairwise connectedness between MAC_SOLAR and other clean energy markets using the BK18 framework.

Figure C.5. Net directional pairwise connectedness between TSX and other clean energy markets using the BK18 framework.

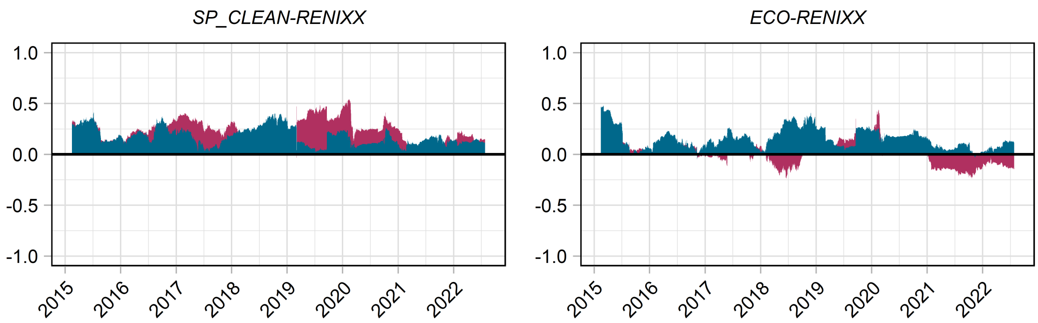

Figure C.6. Net directional pairwise connectedness between RENIXX and other clean energy markets using the BK18 framework.

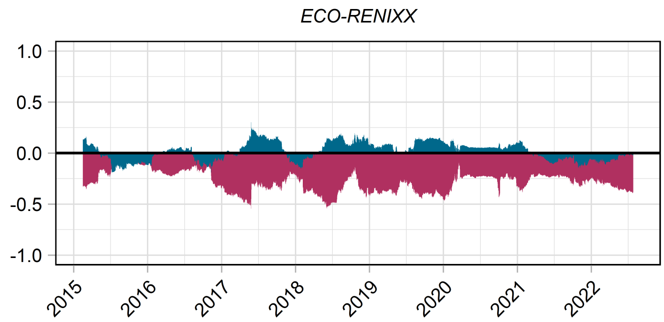

Figure C.7. Net directional pairwise connectedness between ECO and RENIXX using the BK18 framework.

D Appendix

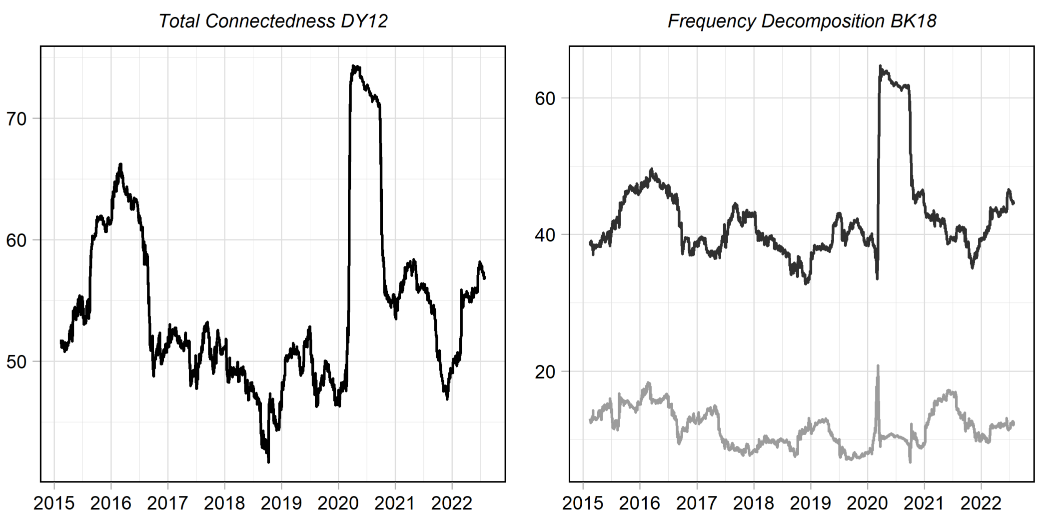

Figure D.1. Total connectedness measured by DY12 framework and BK18 framework without RENIXX.

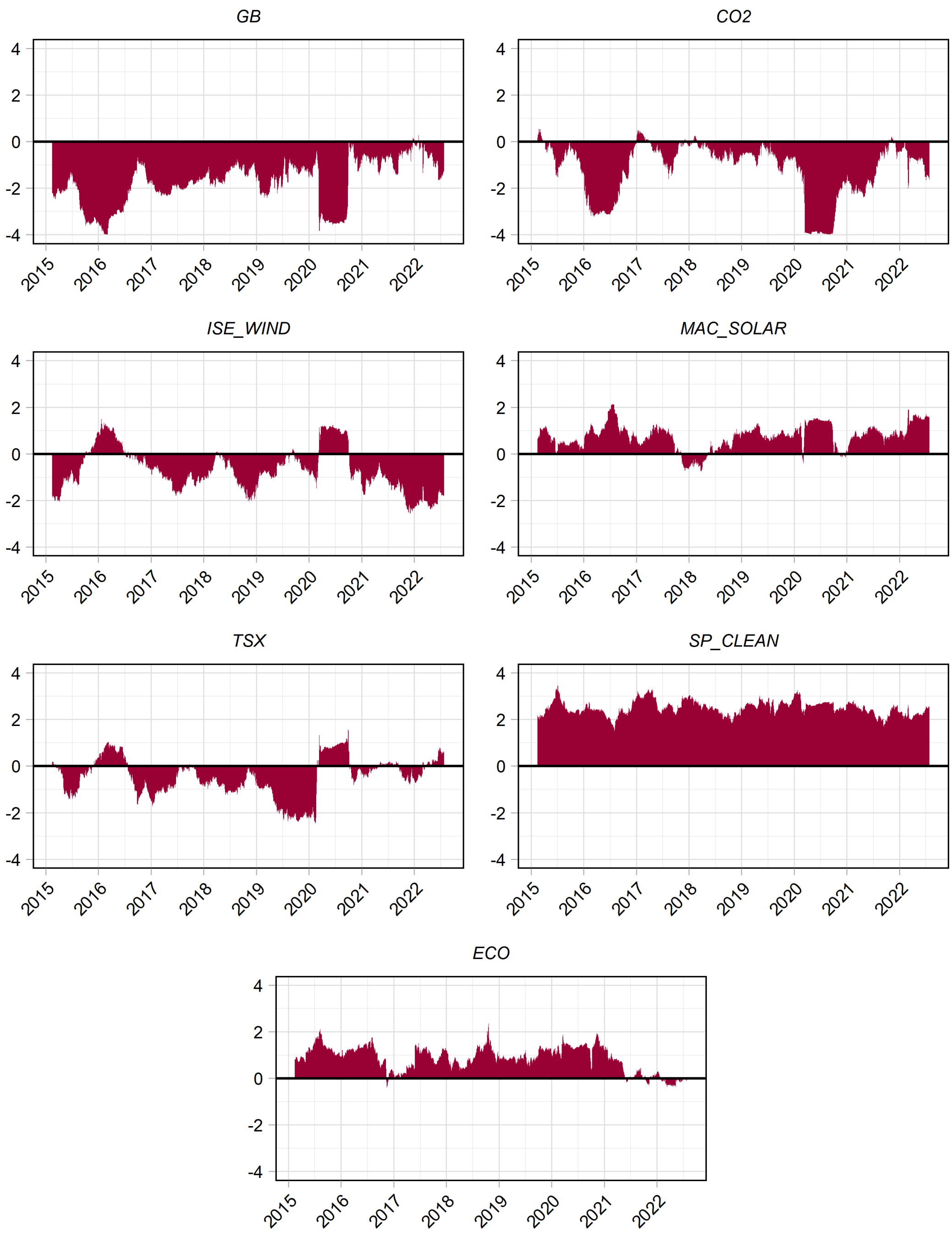

Figure D.2. Net directional connectedness DY12 without RENIXX.

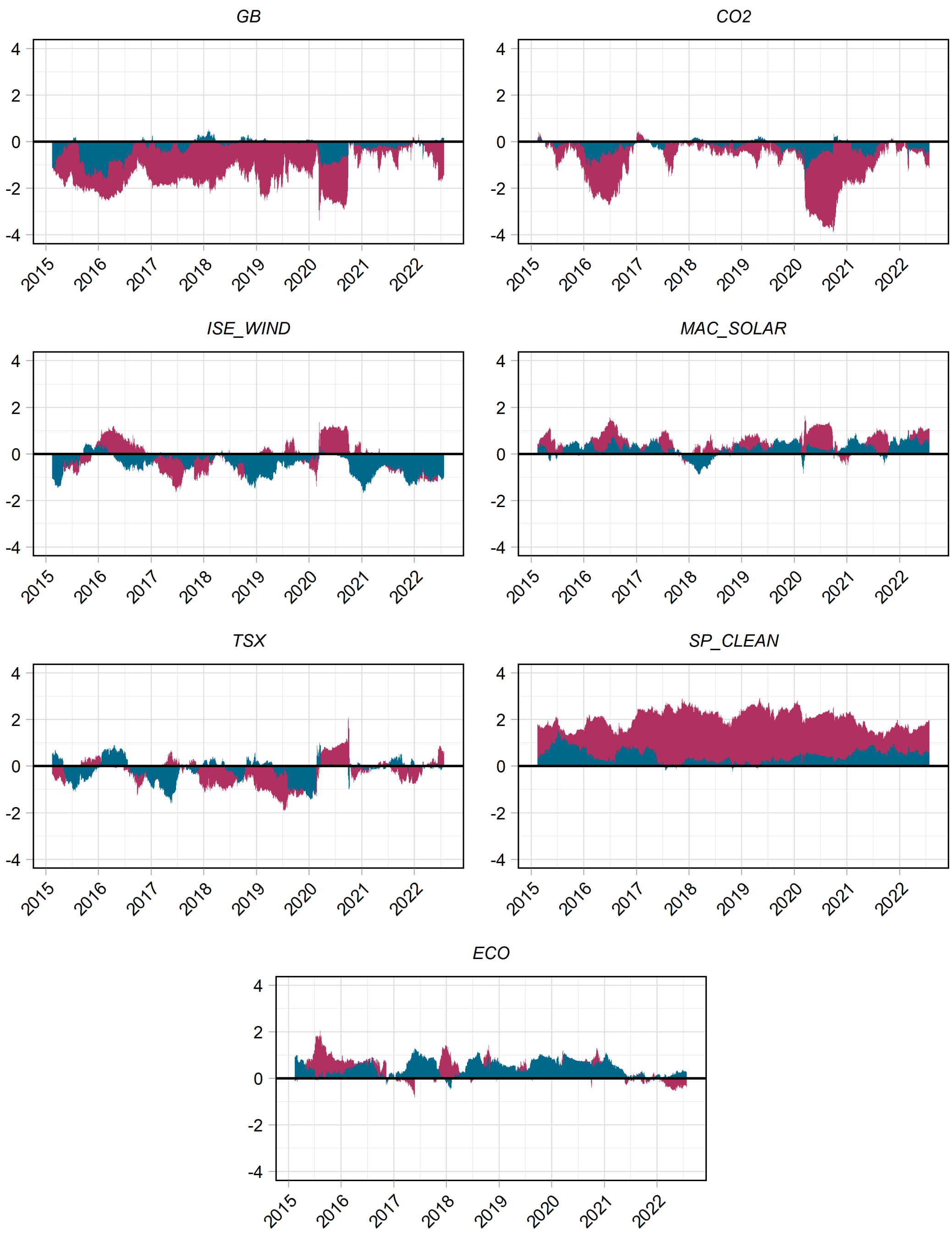

Figure D.3. Net directional connectedness BK18 without RENIXX.

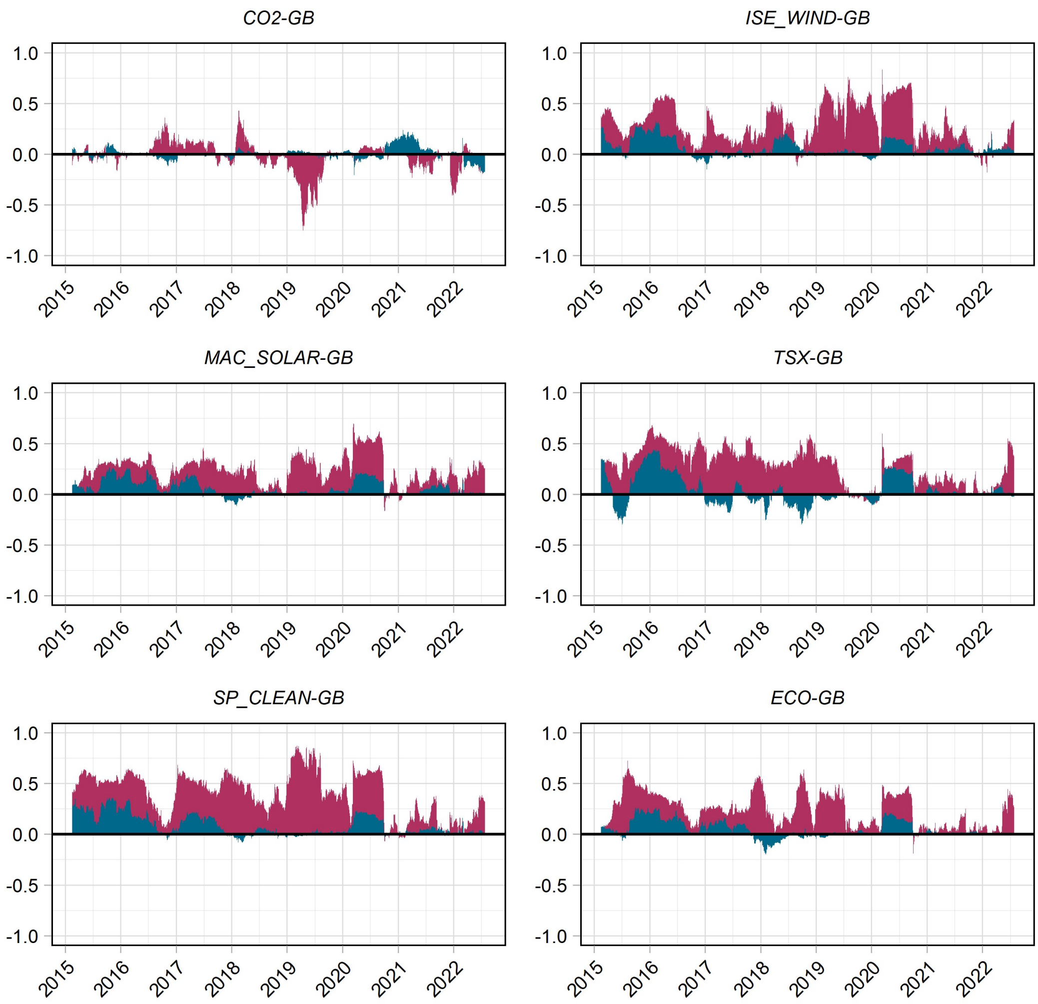

Figure D.4. Net directional pairwise connectedness between green bonds and the green financial system without RENIXX.

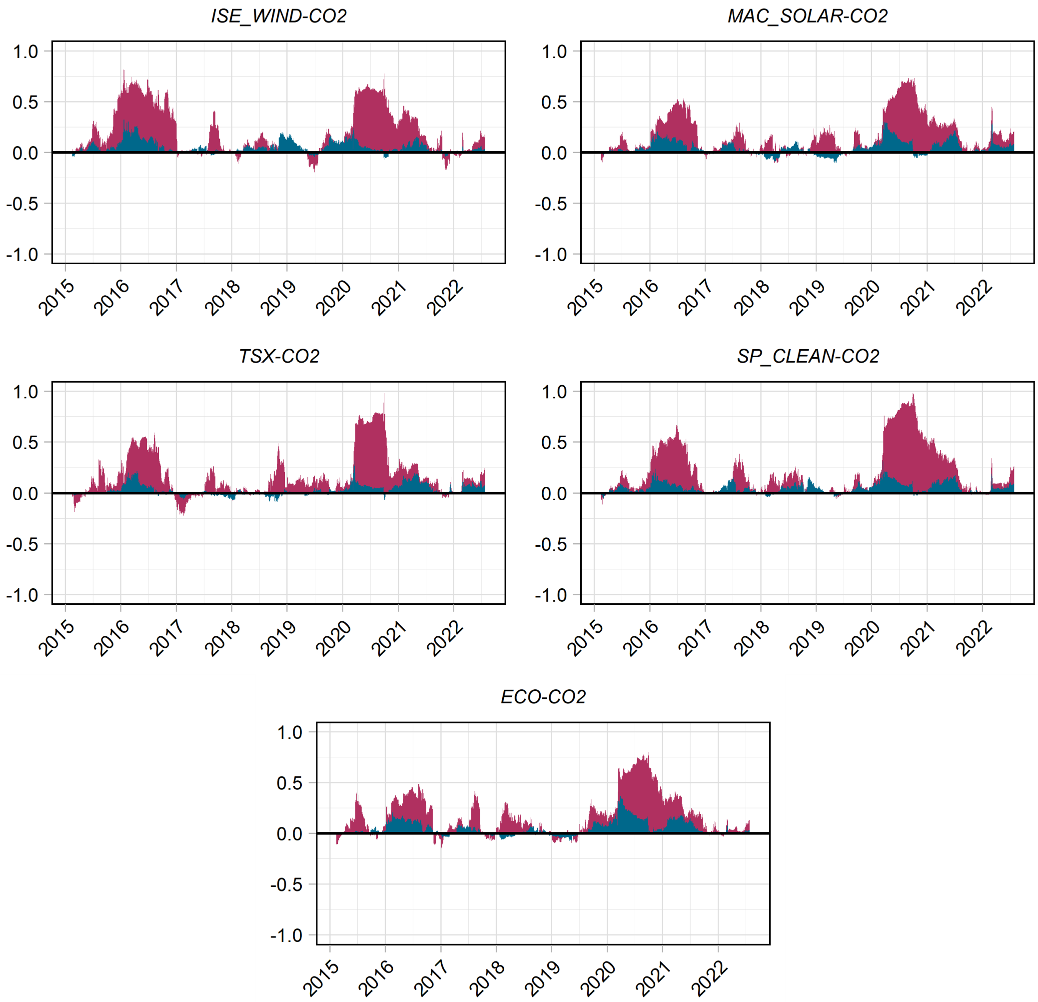

Figure D.5. Net directional pairwise connectedness between carbon market returns and the green financial system without RENIXX.

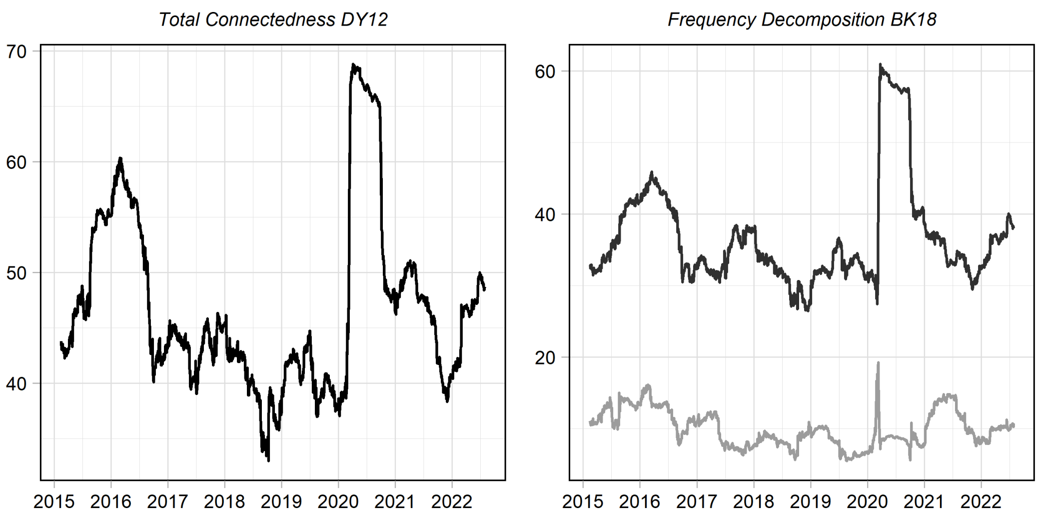

Figure D.6. Total connectedness measured by DY12 framework and BK18 framework without RENIXX and MAC_SOLAR.

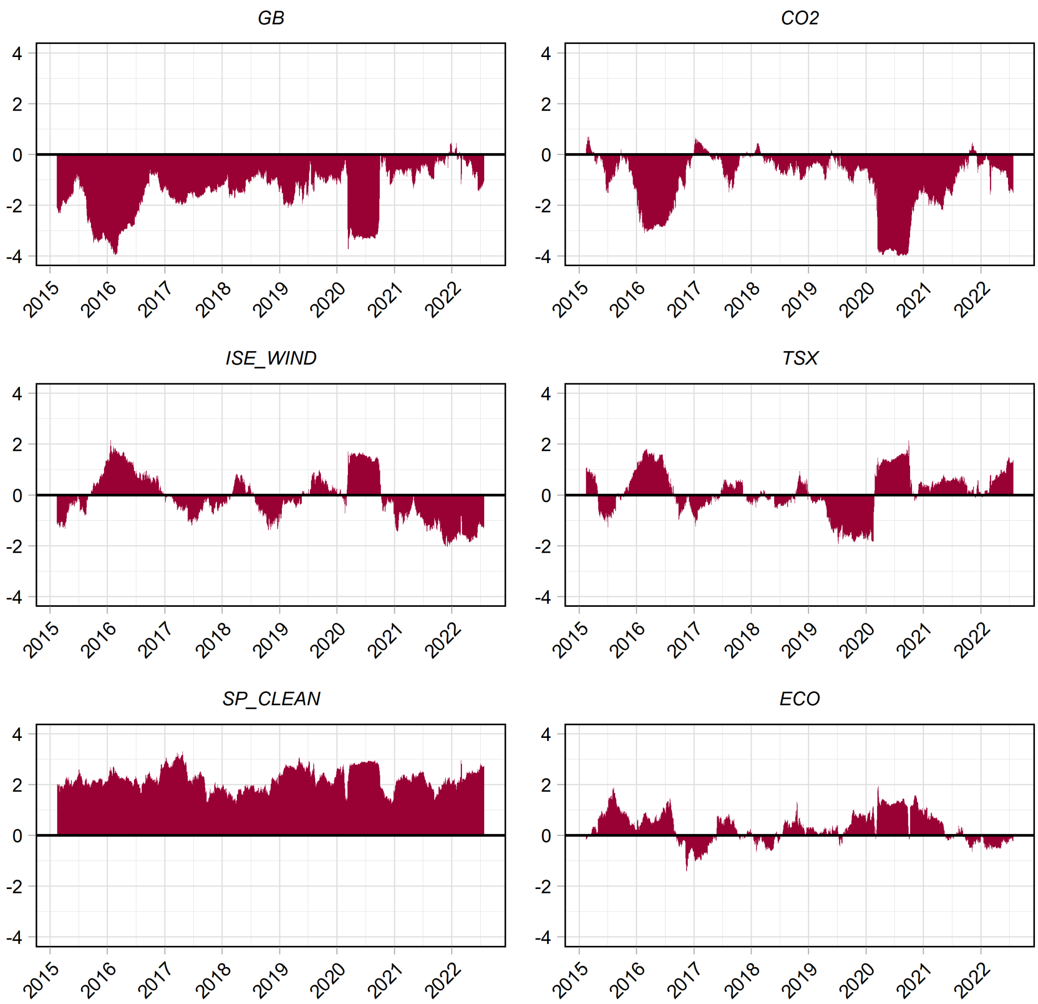

Figure D.7. Net directional connectedness DY12 without RENIXX and MAC_-SOLAR.

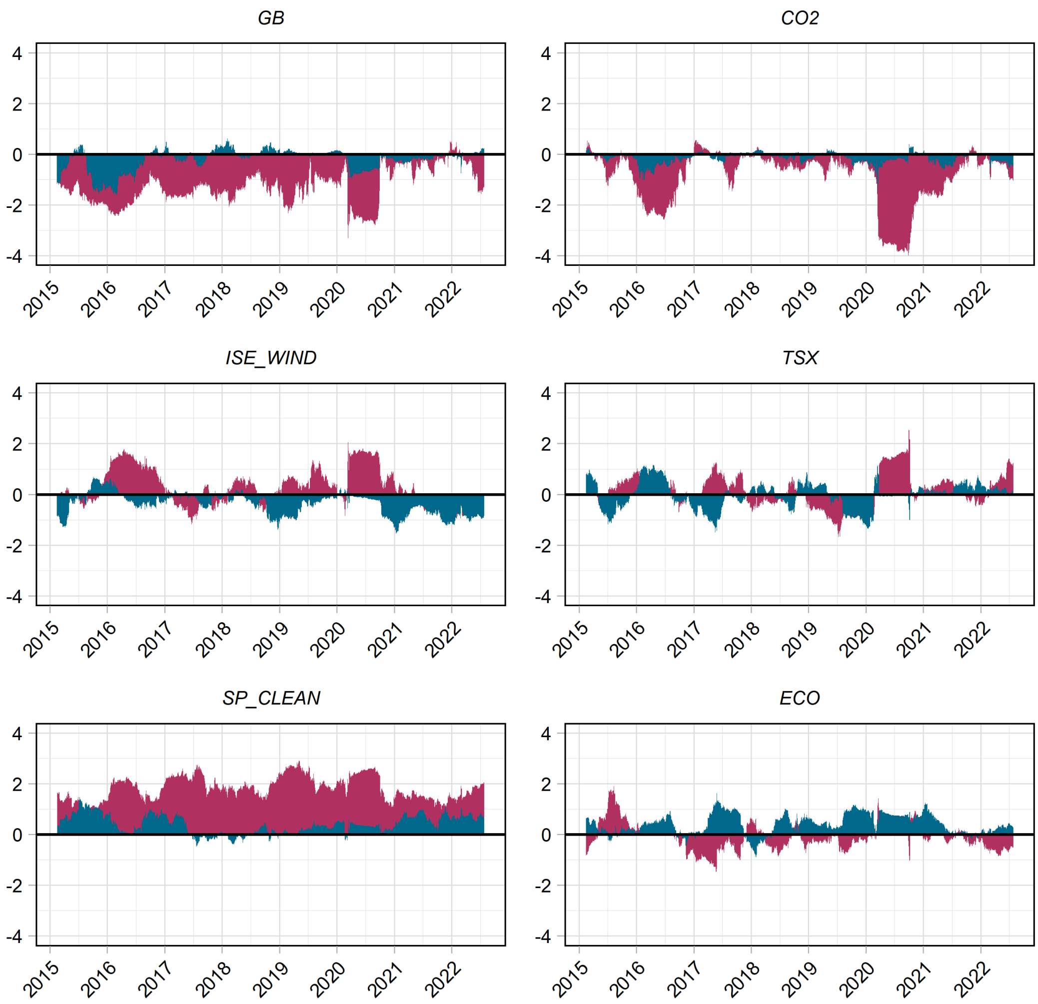

Figure D.8. Net directional connectedness BK18 without RENIXX and MAC_-SOLAR.

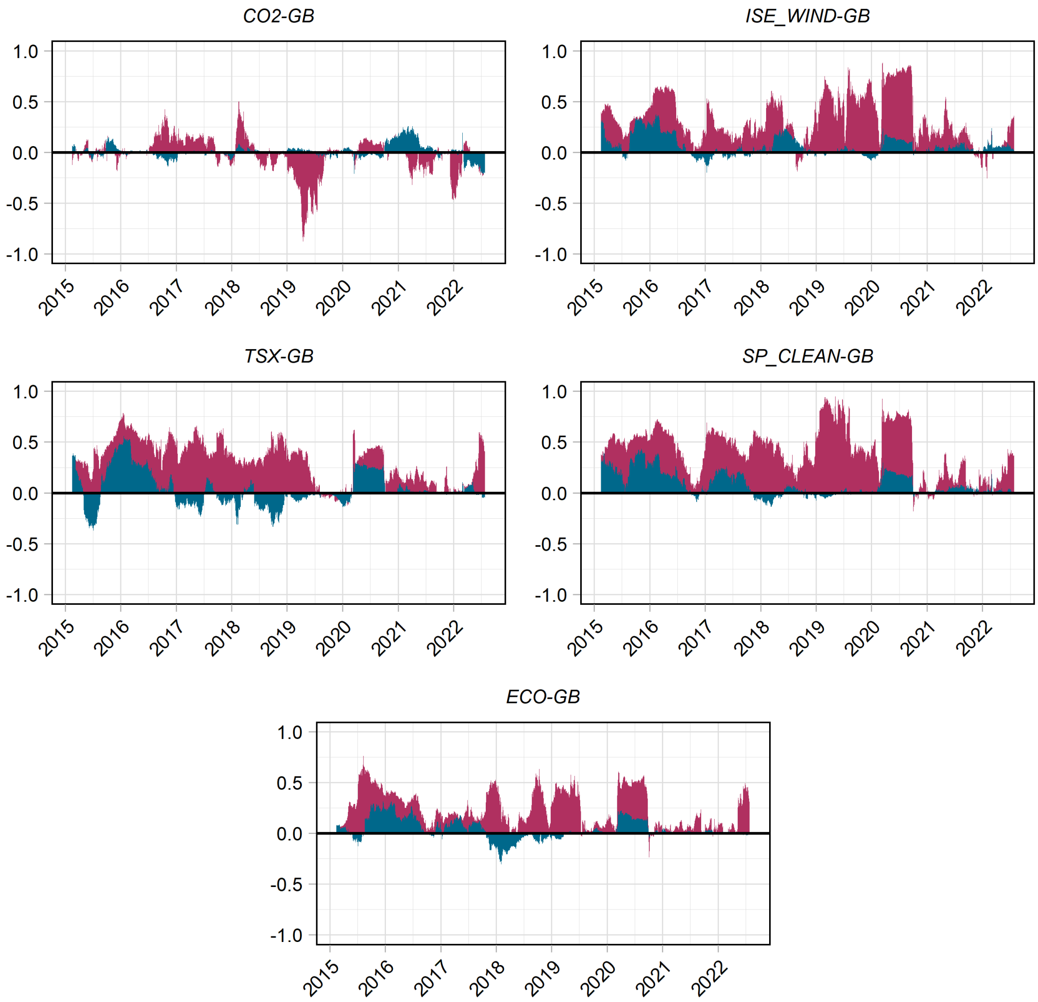

Figure D.9. Net directional pairwise connectedness between green bonds and the green financial system without RENIXX and MAC_SOLAR.

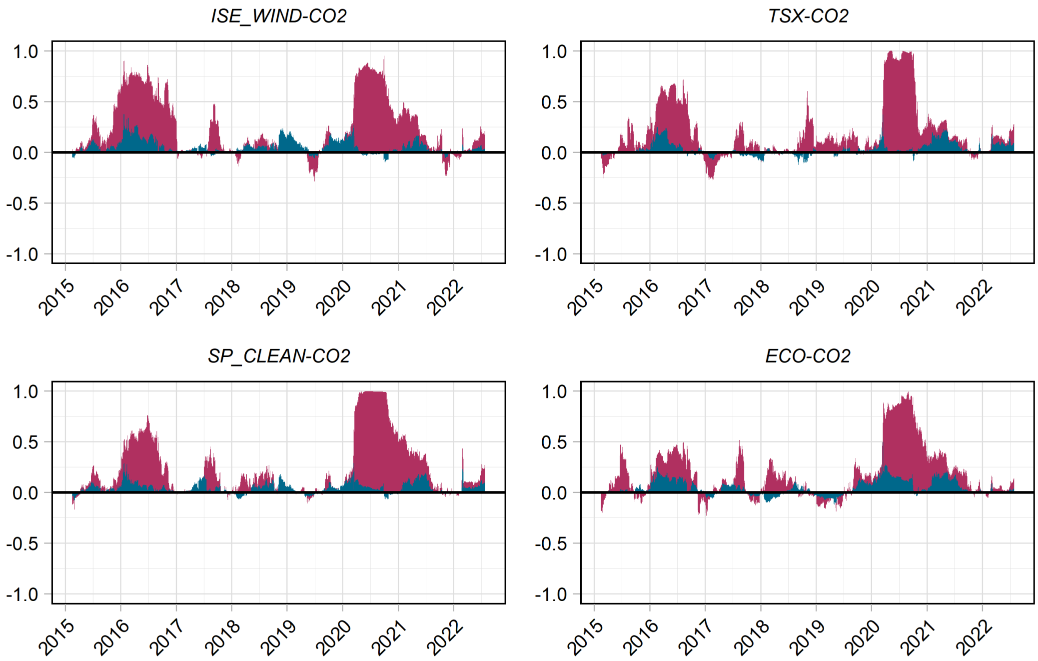

Figure D.10. Net directional pairwise connectedness between carbon market returns and the green financial system without RENIXX and MAC_SOLAR.

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