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Dependence structure and dynamic connectedness between green bonds and financial markets: Fresh insights from time-frequency analysis before and during COVID-19 pandemic

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ABSTRACT

This paper examines the interdependence between green bonds and financial markets in the time-frequency domain by utilizing the multivariate wavelet approach and dynamic connectedness through combining Ensemble Empirical Mode Decomposition (EEMD) with Diebold and Yilmaz (2012) spillover framework. The findings of wavelet multiple correlations indicate that the benefits of diversification opportunities are more evident in the short run. The evidence of wavelet multiple cross-correlations reveals that green bonds and financial markets are highly integrated in the long run. The results of the static connectedness framework explain that the direction and magnitude of spillover behave differently across markets. The world stock market is the net spillover transmitter, while the corporate bond market is the net spillover receiver among the selected markets. The green bond market is receiving more but transmitted less volatility in the present study. The evidence on dynamic connectedness measured by the rolling window approach shows that the interconnection between green bonds and financial markets is volatile over time. These pieces of evidence provide implications to global investors having a strong position in the green bonds market in terms of risk management and portfolio decisions.

1. Introduction

The importance of portfolio diversification rises during crisis times. The optimal risk-return trade-offs require a complete understanding of the different securities' dynamic comovement and connectedness in a portfolio. In such a context, recent empirical studies advocate the inclusion of new asset classes in the investment portfolio, such as energy indices (Asl et al., 2021; Elsayed et al., 2020; Kang et al., 2015; among others), cryptocurrencies (Damianov and Elsayed, 2020; Garcia-Jorcano and Benito, 2020; Mroua et al., 2020; among others), precious metal (Rehman and Vo, 2021; Hernandez et al., 2018; among others), Islamic indexes (Alkhazali and Zoubi, 2020; Kenourgios et al., 2016; Yarovaya et al., 2021; among others) and green bonds (Pham, 2021; Reboredo and Ugolini, 2020; Nguyen et al., 2020; Reboredo, 2018; among others).

Green bonds have emerged as a new financial tool to face social, environmental, and portfolio risk mitigation challenges. The global green bond and green loan issuance reached USD 257.7bn in 2019. The USA, China, and France accounted together for 44% of global issuance in 2019. The green bond issuance is estimated to reach USD 500 bn in 2021 (Climate Bond Initiative).[1] In recent years, the green bond markets have attracted substantial interest for sustainable development, resulting from pressure for companies to reduce their environmental impact and increase impact investment. Green bonds are generally considered as social and ecological tools to meet global green investment needs for sustainable development. According to Ehlers and Packer (2017), green bonds are vital to satisfy both issuers' and investors' expectations to achieve the funding needs of environmentally friendly projects.

Given that green investments are crucial in alleviating climate

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change risk and providing a means to achieve risk mitigation, examining the comovement between green bonds and financial markets during different market conditions is essential. Therefore, understanding the comovement between the green bond and financial markets is crucial for international investors. Furthermore, it would emphasize the diversification benefits of allocating green bonds to a portfolio and demonstrating how the price oscillations may impact green bond prices in the financial markets (Reboredo, 2018).

Recent studies on green bonds investigate the connectedness and comovement between the green bond and (i) green equity markets (Pham, 2021); (ii) corporate and treasury bond, stock, and energy commodity markets (Reboredo, 2018); (iii) economic and financial uncertainty (Pham and Nguyen, 2021); (iv) Oil price shocks and geopolitical risks (Lee et al., 2021), (v) black bonds (Broadstock and Cheng, 2019). However, only a few recent studies examine the effects of the COVID-19 pandemic on green bonds markets. For example, Naeem et al. (2021) study the efficiency of green bonds pre-and during the COVID-19 pandemic. Yi et al. (2021) investigated the connection between green and black bonds during the coronavirus. Taghizadeh-Hesary et al. (2021) examine the risks and returns of green bonds during the COVID-19 period for Asia and the Pacific region. This study is motivated by the lack of empirical research on the dynamics of green bonds during the COVID-19 pandemic and the ongoing debate about the impact of green investments on portfolio risk diversification during crisis times. Investors may see green bond issuance as a tool that allows companies to obtain capital with environmental, social, and impact investment objectives. Therefore, the dynamic of green bond returns can be different from other financial assets.

Against this backdrop, the main objective of this study is to investigate information spillovers and interdependence between green bonds and financial markets in the time-frequency domain by utilizing the multivariate wavelet approach, and dynamic connectedness approaches. This study addresses the following unanswered questions: Does interdependence exist between green bonds and financial markets before and during COVID-19 pandemic periods? Does the dynamic connectedness between green bonds and financial markets change across time? Is there a short-run or long-run time-frequency relationship between green bond returns and financial market returns? Finally, do green bonds and global financial markets co-move in the same way during COVID-19?

This study contributes to the existing knowledge in three different ways. First, we examine the interdependence between green bonds and other financial markets (treasury and corporate bond markets, stock markets, traditional energy, and clean energy markets) before and during the COVID-19 pandemic. Second, we examine the time-frequency relationship between green bonds and financial markets using wavelet coherency. This methodology allows us to explore the comovement and lead-lag connection for the frequency components of the green bond returns at various frequencies and exact moments in time. Specifically, the multivariate wavelet approach will give a clearer indication about the type of overall correlation that exists within the multivariate set at different timescales. The proposed Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross-Correlation (WMCC) consist in one single set of multiscale correlations which are not only easier to handle and interpret but also may provide a better insight of the overall statistical relationship about the multivariate set under scrutiny. In addition, the WMC and its companion WMCC not only offer a more useful way to establish the overall multiple relationships but also, they have important advantages over the usual wavelet methods that use simple correlations and cross-correlations between all possible pairs of variables (Fernández-Macho, 2012, 2018). These methods also overcome the limitation of standard wavelet correlation analysis, which usually needs to calculate, and compare a large number of wavelet correlation and cross-correlation graphs (Fernández-Macho, 2012). Furthermore, the Diebold and Yilmaz (2012) connectedness approach measures the total connectedness and pairwise risk transmission between asset returns. Practitioners and researchers widely use Diebold and Yilmaz's (2012) spillover framework because it provides both static and dynamic methods of time-series connectedness analysis. Third, the sample period of this study includes some significant events such as the 2014–16 oil price decline, the announcement of COVID-19 as a global epidemic on March 12 by the World Health Organization, and the oil price crash on April 20, 2020. Therefore, the sample period can lead to different time-frequency comovement between the green bond and the financial markets.

This study shows that the lead/lag relationship between green bonds and financial markets has equal forces and is independent of the time scale. We find a weak cross-correlation between green bond returns and financial market returns in the short investment horizon. Therefore, the benefits of diversification opportunities become more significant in the short run. Empirical findings from the dynamic returns spillover connectedness show that clean green energy plays a dominant role in transmitting volatility while the role of green bonds is negligible. Finally, the interdependence between green bonds and financial markets is volatile over time. The highest connectedness is observed in the first quarter of 2020 due to the COVID-19 pandemic.

The rest of this paper is organized as follows. Section 2 exposes the related literature. Section 3 discusses the empirical methods. Section 4 defines the data and some preliminary results. Section 5 discusses the empirical results. Finally, Section 6 concludes the paper.

2. Literature review

The emerging literature on green bonds focuses primarily on company performance. Ehlers and Packer (2017) compared the credit spreads of green and conventional bonds. They found that green bonds are priced at a premium on average relative to conventional bonds, while their performance has been similar to other bonds. Baulkaran (2019) analyzes the shareholder wealth effects of green bond issuance by publicly traded corporations. The sample includes 54 firms that issue corporate green bonds and have at least 250 trading days returns data before and ten days after the announcement. Empirical results show that the cumulative abnormal returns are positive and statistically significant and the firm risk (beta and total risk) declines following green bond issuance. Russo et al. (2021) explore the determinants of green bond issuance using a sample of 306 corporate green bonds issued by 85 companies between 2013 and 2016. The empirical results show that project-specific characteristics have a positive impact on green bond performance. Also, the label “Pure Green” contributes to determining the green bond performance. Tang and Zhang (2020) find no evidence of a significant premium for green bonds, using green bond issuance by firms in 28 countries during 2007–2017. The empirical results suggest that the firm's issuance of green bonds is beneficial to its existing shareholders.

In the last few years, international investors have increased interest in including green financial instruments in their portfolios. Pham (2016) examines the volatility connectedness of the conventional and green bond market using daily data from April 2010 to April 2015. Empirical results demonstrate the existence of volatility clustering in these markets. Thus, a shock in the conventional bond market tends to spill over into the green bond market. Reboredo (2018) investigates the dependence structure using static and dynamic copula functions between the green bond market and related financial markets (the corporate and treasury fixed-income markets, the stock and energy commodity markets). He finds that the green bond market and corporate and treasury fixed-income markets are strongly dependent on average and at the tails of their joint distribution, indicating that green bonds have no diversification benefits for investors' fixed-income markets. However, green bond comovement with stock and energy commodity markets is weak, suggesting that green bonds have sizeable diversification benefits for investors in the stock and energy markets.

On the other hand, Broadstock and Cheng (2019) explore the determinants of correlation shapes between green and black bond markets. They use daily data from November 28, 2008, to July 31, 2018, and combine the dynamic conditional correlations with the dynamic model averaging methods. They find that the connection between green and black bonds is sensitive to macroeconomic factors. Reboredo and Ugolini (2020) examine the connectedness between the green bond and other financial markets using a structural VAR model identified through heteroskedasticity. They find that green bond is under significant influences from the fixed-income markets. Also, green bonds are weakly connected with the stock, energy, and corporate bond markets, implying that green bonds have substantial diversification benefits. In a similar vein, Pham (2021) investigates the frequency connectedness and cross-quantile dependence between the green bond and green stock markets from August 2014 to August 2020. Empirical findings show that the dependency between the green bond and green stock during normal market conditions is relatively weak. Alternatively, green bonds and green stocks are more connected during turmoil market movements. Kocaarslan (2021) analyzes the economic foundation behind the interactions between green bonds, conventional bonds, stocks, and energy commodities. The author finds an increase in the US dollar value enhances the dynamic conditional correlation between green and conventional bond markets. The green and the conventional bonds are seen as similar in risk-return behavior, especially during crisis times. In addition, appreciation of the US dollar reduces the dynamic conditional correlation of green bonds with energy commodities and stock markets. Le et al. (2021) investigates the time and frequency domain connectedness and spillover effects among fintech, green bonds, and cryptocurrencies. Using the DY (2012) approach, they find that volatility shocks transmitted from green bonds to other markets and vice versa are shallow than the other assets. The gold, oil, and green bonds are valuable as good hedgers compared to fintech and common equities.

Pham and Nguyen (2021) examine the impact of stock return volatility and economic policy uncertainty oil volatility on the dynamic green bond returns using data from October 2014 to November 2020. Using Markov switching dynamic regression and connectedness network, empirical results demonstrate time-varying dependence between green bonds and economic uncertainty in the volatile regime. However, the green bonds are weakly connected with economic uncertainty in tranquil periods with low uncertainty. Lee et al. (2021) examine the causal relation among green bonds, oil price shocks, and geopolitical risks in the context of the United States over 2013–2019. Using Granger causality in quantile, empirical results show bidirectional and asymmetric causality from oil price to the green bonds and unidirectional causality from variation in geopolitical risk to the green bond. Gao et al. (2021) investigate risk-spillover network connectedness among main financial markets and China's green bond. Using data from April 8, 2015, to April 8, 2020, the authors find significant spillovers between the green bond market, stock market, and commodities market. Finally, Gu et al. (2021) study the impact of public environmental concern on corporate green investments from the perspective of chief executive officer (CEO) turnover. The empirical findings show that the public's environmental concern pressure raises the CEO turnover probability in heavy polluting businesses.

The more recent literature has focused on the impact of the COVID-19 pandemic on green bond markets. Yi et al. (2021) study the effect of COVID-19 on China's green bond market. Using event study and green bond data for China over the period from August 27, 2019, to June 1, 2020, they find that the outbreak of COVID-19 has significant impacts on the volatility of the green bond market and increases the cumulative abnormal returns of the green bonds significantly. Naeem et al. (2021) investigate the comparative efficiency of green and conventional bond markets before and during the COVID-19 pandemic by applying asymmetric multifractal analysis. They find that multifractality in green and conventional bond markets is different for upward and downward trends. The multifractality tends to be more pronounced during dropping market trends for the conventional and green bond markets. In addition, the multifractality in the traditional market of bonds is lower than in the green bond market. Arif et al. (2021) studied green bonds' hedging and safe-haven properties for conventional equity, fixed income, commodity, and forex investments during the pandemic. They find that the green bond index could be a diversifier asset for medium- and long-term equity investors. In addition, it can serve as a hedging and safe haven tool for currency and commodity investments. Taghizadeh-Hesary et al. (2021) investigate the risk and return of green bonds focusing on Asia and the Pacific region during the COVID-19 pandemic and using data composed of 1174 observations divided into Asia and Pacific, Europe, and North America regions. Empirical findings show that green bonds issued in Asia and the Pacific have higher returns and risks than green bonds issued in the European or North American region.

Given the previous studies suggest that international investors utilize the green bond market to achieve risk mitigation, an empirical examination of the green bond return dynamics before and during the pandemic warrants investigation. Thus, this study contributes to the existing literature by studying the time-frequency relationship between green bond returns and global financial market returns before and during the COVID-19 pandemic.

3. Empirical methods

In this section, three main methodologies are discussed: (i) Wavelet Analysis, which describes the time-frequency properties of the underlying series. The conventional methodology generally focuses on time domain to assess the dynamics of connectedness among variables, the frequency domain is increasing its importance as investors have heterogenous interests in investment time horizons. Indeed, some investors prefer to make short-term investments (hours, days) while the others focus on medium or long-term investments (from several weeks to monthly and yearly investment). Wavelet analysis is an innovative approach that considers multi-dimension analysis. Particularly, the comovement between variables is assessed at different frequencies and over time, therefore, providing better insights about the relationship. Additionally, the ability to successfully handle non-stationary time series is another benefit of wavelet analysis. (ii) Ensemble Empirical Mode Decomposition (EEMD) method is able to convert the non-linear and non-stationary asset data into a combination of simple modes with specific economic meaning, which can be applied for the analysis of stationary time-series. As a self-adaptive multiscale decomposition technique, empirical mode decomposition can decompose the asset returns into different components accurately (iii) Diebold and Yilmaz (DY) connectedness approach is employed to measure the total connectedness and pairwise connectedness between asset returns. The DY method used in this study have significant advantages over the traditional linear and Granger causality test often used in prior studies when timescales under study are stationary. DY (2012) suggests a unified framework for measuring the spill over and dependencies. This method allows one to track the spill overs at all levels, from pairwise to system wide, in a coherent, mutually consistent way even though their insights are restricted to only the time domain. Moreover, detecting which clean energy stock return is connected with other asset classes and uncertainties, as well as quantifying the strengths of these connections, aids us in building a network spillover. The DY-Spillover network approach helps to identify the degree of interconnectedness and identifies the spillover network channels, which can be largely attributed to the investigated variables. Finally, the application of wavelet methodology describes the evidence of a co-movement between the global green bond market and treasury, corporate bond, stock, energy, and clean energy markets at various time-frequency scale. DY-Spillover network approach explains the dynamic connectedness between green bonds and financial markets that vary across time and provide information about the potential benefits of green bonds during crisis periods.

3.1. Wavelet multi-scale analysis

Conventional time-domain methods such as correlation coefficient and cointegration analysis did not provide time-frequency data properties and failed to provide a complete picture of market integration. In other words, conventional models capture the relationship between variables mainly in two investment periodicities, short and long terms. At the same time, the behavior of stock markets is heterogeneous and varies across time-scale. In contrast, the wavelet technique has the inherent ability to decompose the particular time series into various time-frequency scales. Moreover, the decomposition and localization property of wavelets make it a more useful method to handle the heterogeneous behavior of stock markets. Hence, the application of Wavelet Multiple Correlation (WMC) and Wavelet Multiple Cross-Correlation (WMCC) with Maximal Overlap Discrete Wavelet Transform (MODWT) across various time-scale is the proper perspective to capture the heterogeneous nature of sample markets.

3.1.1. Wavelet multiple correlation (WMC) and wavelet multiple cross-correlation (WMCC) methods

We present the multivariate case using Fernández-Macho's (2012) methodology based on the wavelet-based pairwise correlation. Let the multivariate data generating process (DGP) of a random variable $Y_t = \{y_{1t}, y_{2t}, \ldots, y_{nt}\}$and its corresponding scale $\phi_j$can be presented as $W_{jt} = \{w_{1jt}, w_{2jt}, \ldots\ldots, w_{njt}\}$. Wavelet coefficients are derived by using the application of MODWT to each Y_{it}. MODWT transformation of a given data series into wavelet coefficients provides a multiresolution analysis without making strong assumptions about DGP.

The WMC signified by the symbol $\lambda_Y(\phi_j)$and described by Fernández-Macho (2012). A subsequent procedure based on DGP is used to obtained WMC. Given each wavelet scale ϕ_j, the linear combination w_{ijt}, $i = 1, 2, \ldots\ldots, n$ is used to estimate the maximum value of the square root of the coefficient of determination. The coefficient of determination (R_i^2) with a dependent variable X_i and a set of predictors $\{X_k, k \neq i\}$is expressed as $R_i^2 = 1 - 1/\rho^{ii}$, ρ^{ii} is the *i-th* diagonal component of the inverse of correlation matrix P. Hence, WMC can be computed as

$$\lambda_Y(\phi_j) = \sqrt{1 - \frac{1}{max\ \ diag\ \ P_j^{-1}}} \tag{1}$$

Where P_j is the correlation matrix of W_{jt}. The estimated coefficient of R_i^2which is computed from the regression of dependent variable X_i and a set of predictors $\{X_k, k \neq i\}$ have the same value as the square correlation for the observed realizations of $X_i$and its fitted realization $\widehat{X}_j$. Therefore, WMC again can be expressed as:

$$\lambda_Y(\phi_j) = corr(w_{ijt}, \widehat{w}_{ijt}) = \frac{cov(w_{ijt}, \widehat{w}_{ijt})}{\sqrt{var(w_{ijt})var(\widehat{w}_{ijt})}} \tag{2}$$

Form Eq. (2), var(w_{ijt}) and $cov(w_{ijt}, \widehat{w}_{ijt})$are computed as:

$$var(w_{ijt}) = \overline{\delta}_j^2 = \frac{1}{T_j}\sum_{t=j-1}^{T-1} w_{ijt}^2 \tag{2.1}$$

$$cov(w_{ijt}, \widehat{w}_{ijt}) = \overline{\gamma}_j = \frac{1}{T_j}\sum_{t=j-1}^{T-1} w_{ijt}, \overline{w}_{ijt} \tag{2.2}$$

Where w_{ij} maximizes the coefficient of determination and $\widehat{w}_{ij}$provides the consistent fitted values. WMCC is calculated from (2) by simply adding the lag term θ in between the observed and fitted estimates for the selected criterion variable and expressed the outcome as:

$$\lambda_{Y,\theta}(\phi_j) = corr(w_{ijt}, \widehat{w}_{ijt+\theta}) = \frac{cov(w_{ijt}, \widehat{w}_{ijt+\theta})}{\sqrt{var(w_{ijt})var(\widehat{w}_{ijt+\theta})}} \tag{3}$$

Where all parameters can be explained as above.

3.2. Ensemble empirical mode decomposition (EEMD) method

EEMD method is based on the empirical mode decomposition (EMD) method presented by Huang et al. (1998) and extended by Wu and Huang (2009). This method is widely used in finance and energy (Yu et al., 2010; He et al., 2016; Ji et al., 2014). The EEMD method overcomes the model mixing problem of the EMD method by adding white noise series into the original time series. Under this method, asset returns are decomposed into uncorrelated time-scale components to analyze asset prices' internal behavior on a different time scale.

The asset returns series $z(t)$is the sum of intrinsic mode function (IMF) and error term:

$$z(t) = \sum_{i=1}^{n} f_i(t) + \upsilon_n(t) \tag{4}$$

Where $f_i(t)$denotes the *ith* IMF, $\upsilon_n(t)$ represents the error term, and n is the number of IMFs.

The IMF and error terms for the asset return series are computed by utilizing the following four steps:

1. A white noise term is added to the original asset price returns $z(t)$to obtain the new return series $Z(t)$. Standard error between the new return series $Z(t)$and the original return series $Z(t)$is computed by using the following formula of Wu and Huang (2009):

$$\varepsilon_n = \frac{\mu}{\sqrt{N}} \tag{5}$$

Where μ is the amplitude of the new return series, and N is the number of ensamples.

2. A cubic function is used to generate the upper envelope $m_{\max}(t)$ and the lower envelope$m_{\min}(t)$of $Z(t)$. The average of two fitted envelope lines $\gamma(t)$is computed as follows:

$$\gamma(t) = \frac{|m_{\max}(t) + m_{\min}(t)|}{2} \tag{6}$$

3. The following formula is used to remove the effect of $\gamma(t)$ from new return series$z(t)$

$$\eta_1(t) = z(t) - \gamma(t) \tag{7}$$

There is necessary to repeat the above data generating process until the obtained average curve is zero. Thus, the return series $\eta_k(t)$obtained by the process k is computed as follows:

$$\eta_k(t) = \eta_{(k-1)}(t) - \eta_1(t) \tag{8}$$

The result of each shifting process must be IMF. The value of restricted standard deviation (SD) is used to examine the shifting process, which is defined as:

$$SD = \sum_{k=1}^{T} \frac{|\eta_{(k-1)}(t) - \eta_k(t)|^2}{\eta^2{}_{(k-1)}(t)} \tag{9}$$

Where t is the time period of the new series, and the value of SD generally lies between 0.2 and 0.3.

4. There is no need to repeat this process when the formula mentioned above is satisfied. Thus, $f_1(t) = \eta_k(t)$is the first series of IMF. Then, the following formula is used to subtract the first IMF from the new data series: $\Upsilon_1(t) = Z(t) - f_1(t)$. This entire process is repeated until the remaining series value is less than the predetermined value of the substantial consequence. At the same time, the number of IMFs extracted from asset return series is generally less than $\log_2 T$, where T is the length of asset return series.

3.3. Diebold and Yilmaz (DY) connectedness approach

The dynamic connectedness method in a comprehensive framework is initially proposed by Diebold and Yilmaz (hereafter DY, 2009, 2012). Practitioners and researchers widely use this connectedness approach because it provides both static and dynamic methods of time-series connectedness analysis. Under this approach, the VAR model is employed for static analysis, while the rolling-window VAR approach is used for dynamic analysis. It helps us to identify the degree of interconnectedness and identifies the spillover network channels among sample variables. Furthermore, this approach has used generalized forecast error variance decomposition (GFEVD) in a VAR framework instead of Cholesky factorization. Following DY (2012), a covariance stationary VAR(m) model is written as:

$$Z_t = \sum_{j=1}^{m} \vartheta Z_{t-j} + \upsilon_t \tag{10}$$

Where $Z_t$is the $n \times 1$vector of observed variables at time t;$\vartheta$is the $n \times n$ coefficient matrix and $\upsilon_t$is the matrix of serially uncorrelated error terms. Under this approach, in the presence of covariance stationary VAR system, the moving average (MA) representation is formulated as $Z_t = \sum_{j=0}^{\infty} \Lambda_j \upsilon_{t-j}$, where $n \times n$ coefficient matrix Λ_j follows a recursive process $\Lambda_j = \psi_1 \Lambda_{j-1} + \psi_2 \Lambda_{j-2} + \ldots\ldots\ldots + \psi_m \Lambda_{j-m}$, with Λ_0 being the $n \times n$ identity matrix and $\Lambda_j = 0$for $j < 0$.

DY (2012) used the GFEVD framework developed by Koop et al. (1996) and Pesaran and Shin (1998) to eliminate the influence of VAR ordering on the variance decomposition. Following this framework, H-step ahead GFEVD is written as:

$$\widetilde{\pi}^{l}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \vartheta^{2,l}_{ij,t}}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \vartheta^{2,l}_{ij,t}} \tag{11}$$

With $\sum_{j=1}^{n} \widetilde{\pi}^{n}_{ij,t}(H) = 1$ and $\sum_{ij=1}^{n} \widetilde{\pi}^{n}_{ij,t}(H) = n$. $\vartheta_{ij,\ t}{}^{l}$ represents generalized impulse response functions and $\widetilde{\pi}^{l}_{ij,t}(H)$ shows generalized forecast error variance decomposition.

Based on GFEVD, the total connectedness index that represents the interdependence of variables is formulated as:

$$C^{l}_{t}(H) = \frac{\sum_{ij=1, i\neq j}^{n} \widetilde{\pi}^{n}_{ij,t}(H)}{\sum_{ij=1}^{n} \widetilde{\pi}^{n}_{ij,t}(H)} * 100 \tag{12}$$

Total directional connectedness to asset i from all other assets j is defined as:

$$C^{l}_{i\leftarrow jt}(H) = \frac{\sum_{j=1, i\neq j}^{n} \widetilde{\pi}^{n}_{ij,t}(H)}{\sum_{j=1}^{n} \widetilde{\pi}^{n}_{ij,t}(H)} * 100 \tag{13}$$

Similarly, total directional connectedness from asset i to all other assets j is computed as:

$$C^{l}_{i\rightarrow jt}(H) = \frac{\sum_{j=1, i\neq j}^{n} \widetilde{\pi}^{n}_{ji,t}(H)}{\sum_{j=1}^{n} \widetilde{\pi}^{n}_{ji,t}(H)} * 100 \tag{14}$$

Net total directional connectedness, which is the difference between total directional connectedness 'To' others and 'From' others, is defined as

$$C^{l}_{it} = C^{l}_{i\rightarrow jt}(H) - C^{l}_{i\leftarrow jt}(H) \tag{15}$$

Finally, net total directional connectedness is a breakdown to compute net pairwise directional connectedness, which is given as:

$$C_{ij}(J) = \left(\frac{\widetilde{\pi}_{ji,t}(J) - \widetilde{\pi}_{ij,t}(J)}{N} \right) * 100 \tag{16}$$

Net total directional connectedness examines the influence of asset i on asset j or vice versa. Finally, DY (2012) assumes the variance decomposition matrix as the adjacency matrix of a weighted directed network to describe the network analysis of all market connectedness.

4. Data and descriptive analysis

In the present study, we examine the dependence structure and dynamic connectedness of the green bond market with other financial markets comprised of (i) treasury and corporate bond markets (ii) stock markets (iii) energy and clean energy markets. It is stated that the financial instruments traded in those markets are considered to be portfolio complements/substitutes of green bonds (Reboredo, 2018; Reboredo and Ugolini, 2020). Four types of global green bond indices, such as the S&P Dow Jones Green Bond Index; Bloomberg Barclays Green Bond Index; Solactive Green Bond Index, and the Bank of America Merrill Lynch Green Bond Index, have been developed to measure the financial performance of green bonds market. All of these indices have their methodology and criteria for including bonds in their index methodology. However, all these indices have a similar structure and show the highest degree of correlation nearer to one. We use Bloomberg Barclays Green Bond Index to represent the global green bond market for the present analysis. This index includes corporate, government-related, and securitized bonds, categorized as green by MSCI ESG Research and fixed-rate coupons. Its value is rebalanced every month and calculated in

USD.

The variables used to represent the above-enlisted financial markets are as follows: Bloomberg Barclays Global Treasury Index describes the treasury market. This benchmark measures the global investment-grade debt of developed and developing asset markets issued in 24 local currencies. Bloomberg Barclays Global Corporate Index is used to represent the corporate bond market. This index includes global corporate bonds from developed and developing market issuers within the industrial, utility, and financial sectors. Similarly, the MSCI world stock price index has used a proxy for the stock market. This index covers 85% of the free float-adjusted market capitalization of 23 developed countries' financial markets. MSCI World Energy Price Index is used to represent the global energy market. The index is composed of more than 1400 stocks listed on exchanges in 23 developed market countries. Finally, WilderHill's clean energy price index is used to signify the clean energy market. The index tracks the clean energy sector, especially the business sector, that may get substantial benefits from societal transition toward clean energy usage, zero carbon emission from renewables, and conversation.

Furthermore, four additional series: CBOE volatility index (VIX); world financial stress index (FSI); Twitter Economic Uncertainty index (TEU), and economic activity (business condition) index, are used to measure financial uncertainty, financial stress, and economic uncertainty respectively. The data on daily observations for the period 30/9/2014 to 30/6/2020 is collected from various sources.[2] Green bond, financial markets, and VIX data have been collected from DataStream, whereas FSI is sourced from the Office of Financial Research (OFR). Finally, the Twitter Economic Uncertainty index (TEU) is collected from the economic policy uncertainty website, while the economic activity (business condition) index is obtained from Aruoba et al. (2009). The sample period covers significant events such as decline in oil prices for the year 2014–16; commodity price shocks caused by the transition of China's economy in 2015; the US shale-energy revolution 2015–16; outbreak of the COVID-19 pandemic in 2020 and the oil price crash on April 20, 2020.

Fig. 1 shows the time-series plots of the green bond index and financial market indices along with auxiliary variables over the sample period. Green bonds, treasury, corporate bonds, and stock markets indices show similar fluctuations over the entire period. However, from these plots, two structural breaks are discernible. One structural break is observed in the mid of 2018, and the other structural break is shown at the start of 2020. The reason for the first structural break is that the green bond was issued at a premium, and other financial assets were dived due to excess liquidity. The second structural break arises due to the outbreak of the COVID-19 pandemic, which creates uncertainty in financial markets. The conventional energy and clean energy index plots show a similar trend of evolution over the study period. Similarly, the plots of uncertainty indices show a structural break in 2020 except TEU index, which confirms the structural break in 2016, arising from the European debt crisis and the US shale-energy revolution. The plots of return series presented in Fig. 2 show that the average returns of all markets are close to zero and share a similar feature of high volatility at the start of 2020 due to the COVID-19 pandemic.

Table 1 illustrates the descriptive analysis of the daily return series. The statistics explain that the average return series is positive except for the world energy index, and TEU exhibits the highest mean value. Clean energy returns are riskier than conventional energy returns, as implied by the highest value of standard deviation. Green bond and financial markets returns are skewed to the left as indicated by the significant negative values of the skewness except for positively skewed uncertainty returns. As observed for kurtosis, all return series exhibit leptokurtic distribution. Test statistics of Jarque and Bera normality tests reject the null hypothesis of the normality at a 1% significance level, indicating that returns series do not follow the normal distribution. The stationarity of all returns series is checked by applying Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Zivot Andrew (ZA) tests. The calculated values of the parameters remain higher than the critical values across all the tests except ZA, suggesting that each return series is non-stationary at a level. In contrast, the ZA test result indicates that return series are stationary at the level. Moreover, thetest statistics of L-B and ARCH-LM tests clearly show that all return series are suffering from the problem of autocorrelation and heteroscedasticity.

Subsequently, the pairwise correlation is tested between return series and illustrated in Fig. 3. The highest correlation is observed between treasury and green bonds, 0.84, followed by treasury and corporate bonds, 0.82. Similarly, the magnitude of the correlation is least between world stock and VIX, −0.68, followed by clean energy and VIX, −0.59. The robustness of the results is tested by using three different correlation methods, viz.; Pearson correlation analysis, Spearman correlation analysis, and Kendall correlation analysis. Broadly, the inferences are the same. In Fig. 4, we see that the correlation ranges from −0.49 to 0.65 (Pearson), −0.53 to 0.65 (Spearman), and − 0.39 to 0.53 (Kendall). Finally, both parametric and non-parametric correlations with network plotting are used, and robust results are obtained. These results are presented in Fig. 5.

Note: The red line shows a negative correlation, while the green line shows a positive correlation.

5. Empirical results and discussion

5.1. Wavelet multi-scale analysis

5.1.1. Wavelet multiple correlation (WMC)

Fig. 6 shows the graphical results of WMC for the selected market at multiple scales. The visual inspection of Fig. demonstrates that multiple correlations (MC) get stronger at lower frequencies (highest wavelet scale). MC starts with a level of 0.90 and then converges to its minimum value of 0.89 for a wavelet scale of 2 trading days. The fall in the level of MC implies that there is the possibility of divergence between the green bond and financial market returns at a short time horizon. In other words, the diversification opportunities for financial investors become high in the short run. Beyond the wavelet scale of 2 trading days, the MC level increases and reaches its maximum value of 0.98 at the highest scale. Thus, there is a possibility that diversification opportunities of green bonds with other financial markets decrease over the long run. In other words, hedging benefit of green bonds against the swing of the stock market would be higher for short term investors in comparison with long term investors. Therefore, these results of diversification benefits support the findings of Reboredo (2018), Reboredo and Ugolini (2020), and Nguyen et al. (2020). The findings mentioned above become clearer from Table 2, which is the rendition of Fig. 6 provides exact correlation values at multiple scales. The results enlisted in Table demonstrate the lowest value of multiple correlations, 0.903 at the highest frequency (lowest scale), 0.956 at a medium frequency (medium scale), and 0.982 at the lowest frequency (highest scale).

5.1.2. Wavelet multiple cross-correlation (WMCC)

Figs. 7 and 8 display the results of WMCC for green bond and other

[2] Starting date of data series is determined by the availability of green bond index series.

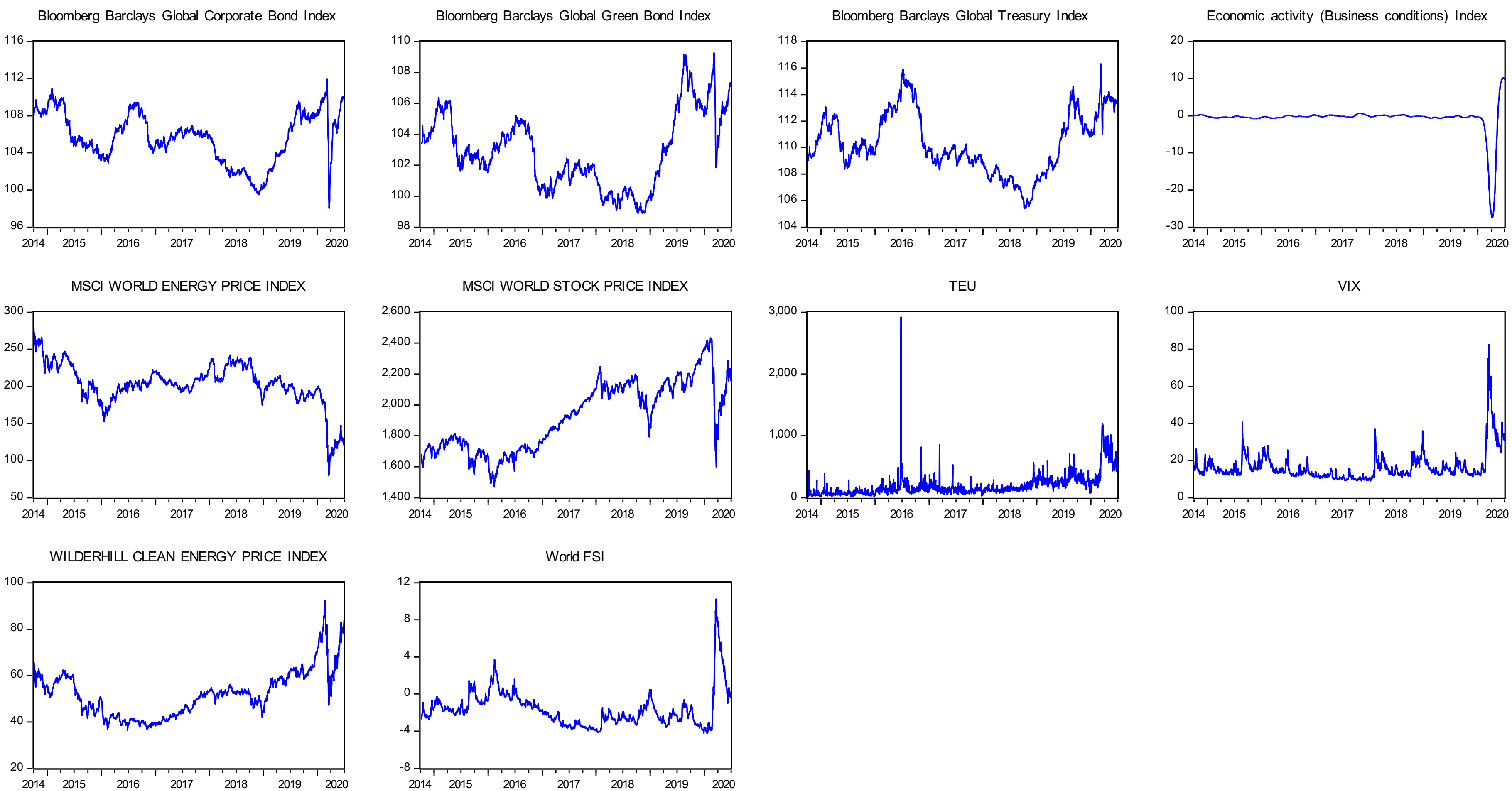


Fig. 1. Time-series plots of original data series.

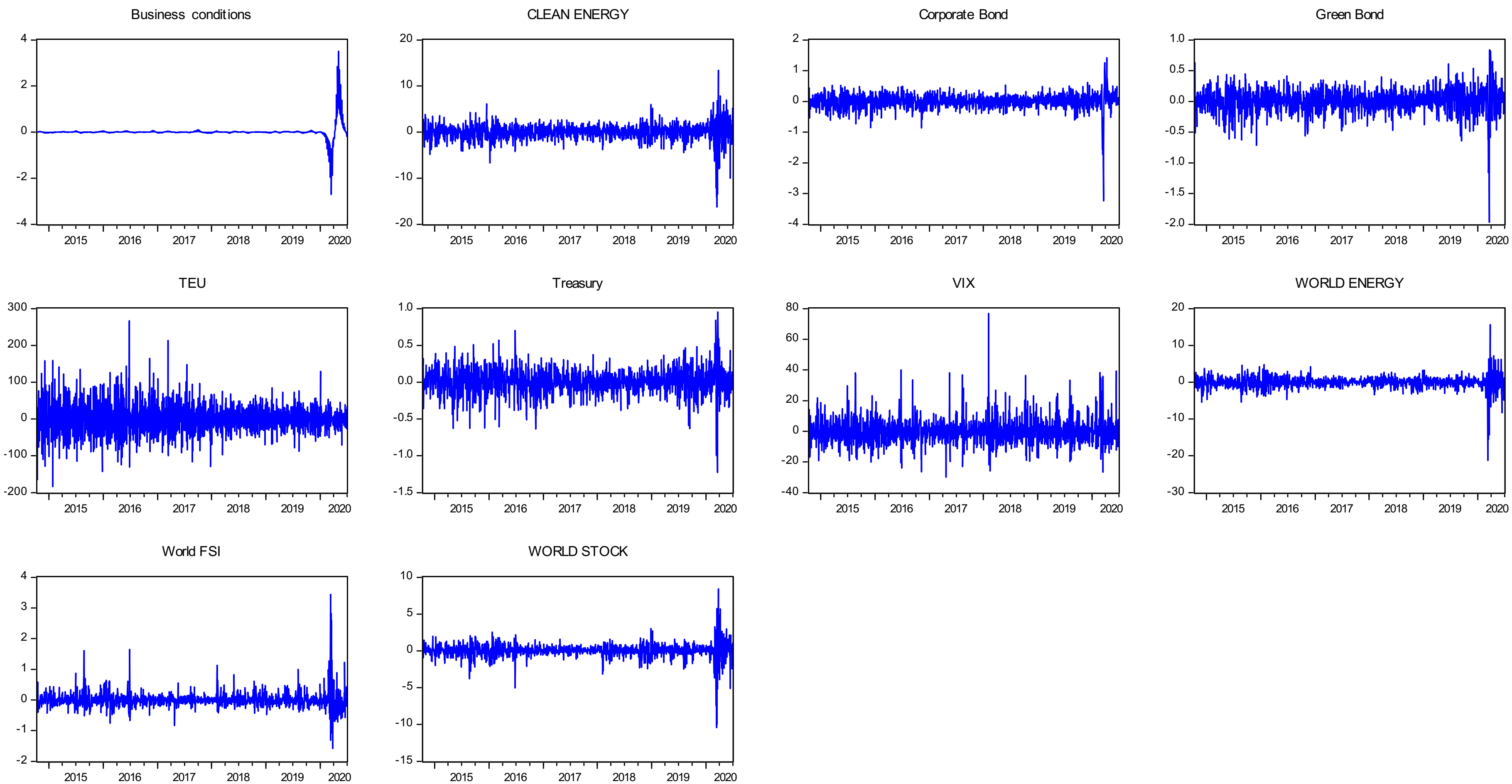


Fig. 2. Time-series plots of returns series.

Table 1
Descriptive analysis.

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	PP	KPSS	ZA	L-B	L-B^2	ARCH-LM(10)	Obs.
World Stock	0.021	0.047	8.406	−10.441	0.980	−1.566*	28.245*	40,203.7*	−10.7922	−1695.11	0.026472	−11.764*	133.7*	1981.6*	547.7*	1491
World Energy	−0.048	−0.017	15.67	−21.232	1.684	−1.936*	35.369*	66,021.2*	−11.1694	−1611.06	0.099408	−11.639*	101.1*	1288.5*	406.4*	1491
Clean Energy	0.029	0.057	13.399	−16.239	1.790	−1.201*	17.168*	12,828.7*	−10.9103	−1632.72	0.200647	−11.798*	121.7*	1655.9*	490.5*	1491
Green.Bond	0.002	0.01	0.841	−1.97	0.191	−1.215*	13.282*	6934.3*	−10.9583	−1437.88	0.145087	−11.779*	101.6*	1094.5*	359.0*	1491
Treasury	0.002	0.006	0.955	−1.226	0.175	−0.426*	7.610*	1365.5*	−11.9944	−1267.69	0.118899	−12.417*	57.2*	1342.5*	389.2*	1491
Corporate.Bond	0.001	0.01	1.416	−3.241	0.243	−2.431*	31.961*	53,575.7*	−11.2217	−1347.19	0.113506	−12.161*	318.0*	1225.2*	486.8*	1491
Business conditions	0.007	−0.001	3.503	−2.708	0.234	3.781*	89.327*	466,530.7*	−6.8559	−547.078	0.124041	−10.814*	7368.3*	1684.9*	1137.5*	1491
VIX	0.014	−0.395	76.825	−29.983	8.353	1.361*	10.797*	4237.3*	−12.5903	−1452.99	0.051928	−13.527*	37.3*	185.2*	68.6*	1491
World.FSI	0.001	−0.013	3.454	−1.58	0.265	3.528*	41.298*	94,213.8*	−9.8021	−1620.43	0.033622	−10.475*	143.6*	1443.5*	377.9*	1491
TEU	0.034	-1.081	267.149	−183.702	41.450	0.429*	5.782*	526.5*	−15.1268	−1607.91	0.039103	−15.337*	246.5*	168.5*	115.2*	1491

Note: * denote null hypothesis is rejected at 1% level.

selected financial markets returns at lags up to 30 trading days across various time scales (frequencies). The graphical representation (Fig. 7) shows that the cross-correlation becomes more robust as we move from highest frequency to lowest frequency. Specifically, there is significant evidence of weaker cross-correlation at the highest frequency. The world stock and treasury markets showed greater prospects of leading or lagging the remaining financial and green bonds markets. Moreover, cross-correlation steadily increases from 0.34 to 0.61 as we move from highest to medium frequency, corporate bonds having the greater potential to lead or lag the remaining markets. There is evidence of significant cross-correlation at the lowest frequency across all time lags, with the green bonds are potential leaders or followers at this investment horizon. This states that any potential shocks that hit the green bond market may in turn be transmitted to other financial markets and vice versa for these investment horizons. Furthermore, cross-correlation is insignificant at a scale of 10 to 20 and a lead of 10 and 30 trading days, thereby offering more significant benefits for portfolio diversifications.

Corroborating with previous literature on the contagion theory, the correlation across markets appears to peak as the effect of extreme economic events (Benhmad, 2013; Mun and Brooks, 2012; Narayan et al., 2014; Silvennoinen and Thorp, 2013; Stevenson, 2016). Mun and Brooks (2012) and Öztek and Öcal (2017) stated that this alteration of correlation was caused by the heightened volatility in the financial market. Since the negative asset returns are normally expected as the consequence of the crisis, together with the increasing linkage between them justifies the recorded positive relationship across assets.

Fig. 8 shows that all plots are symmetrical, indicating that the lead/lag relationship between green and financial markets has equal forces and is independent of the time scale. An insignificant level of cross-correlation is observed at levels 1 and 2, which justifies the weak cross-correlation between green bonds and financial markets returns in the short investment horizon. This result supports the empirical finding of Pham (2021) that shows that the spillover effects between the green bond and equity market are short-lived, as the degree of connectedness dissipates in the medium- and long-term investment horizons. From an economic perspective, this evidence indicates diversification benefits, which can be achieved by formulating a portfolio combination of weakly correlated assets to obtain optimal risk-adjusted returns (Nguyen et al., 2020). However, the level of cross-correlation slightly increases as we move from levels 3 to 4 and 5 (medium-term investment horizon). Finally, the level of cross-correlation reaches its maximum value of unity at levels 7 and 8. Thus, selected markets become fully integrated at long-term investment horizon and a clear indication of market maturity. This result supports the finding of Reboredo (2018), who shows that the green bond market and fixed-income markets are strongly dependent, both on average and at the tails of their joint distribution. At the time of the inception of the green bonds market, its share in the global financial market was relatively smaller than in other financial markets. After that, the green bonds market appeared to be an emerging market and attracted a broader group of investors. As a result, the correlation between green bonds and other conventional assets increases over time (Pham, 2016). Therefore, increasing the integration of green bonds with other financial markets over time is substantially associated with an increasing share of green bonds in the global financial markets since 2014. Furthermore, the positive correlation between the green bonds and other assets can be possibly explained by market maturity. Le et al. (2020); Taghizadeh-Hesary and Yoshino (2019) reported that green bonds were crucial to achieving sustainable development goals, yet it still represented a small share of the financial market. As a newly developed financial instrument that had not made mainstream finance, it was highly likely to be affected by the general market development. Nevertheless, green bonds have undergone massive development, becoming the fastest-growing segment of the market, from 2014 onwards. Total green bond issuance reached an unprecedented record of $255 billion in 2019 (Climate Bonds Initiative, 2019). Consequently, the alternation in the correlation of green bonds with other markets is

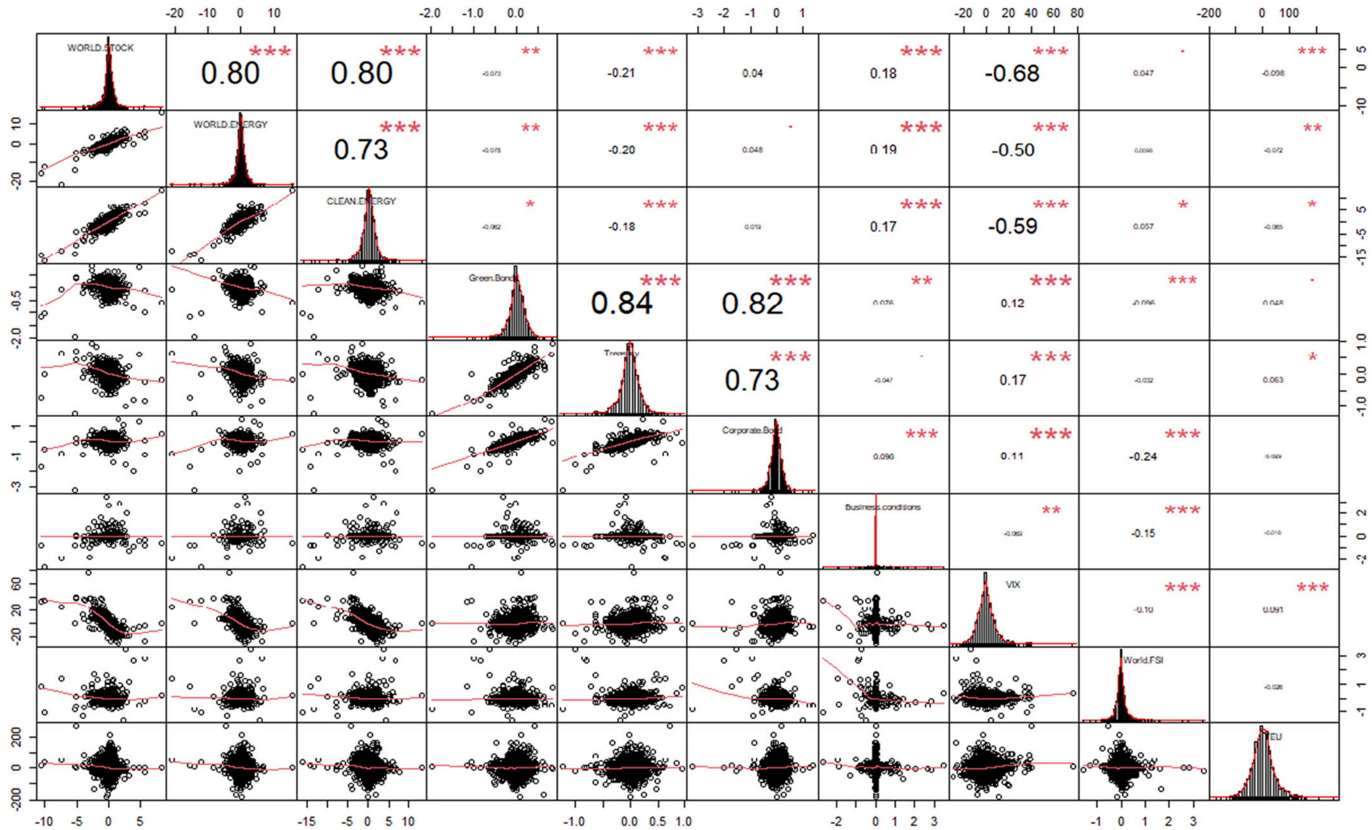


Fig. 3. Plots of pairwise correlation.

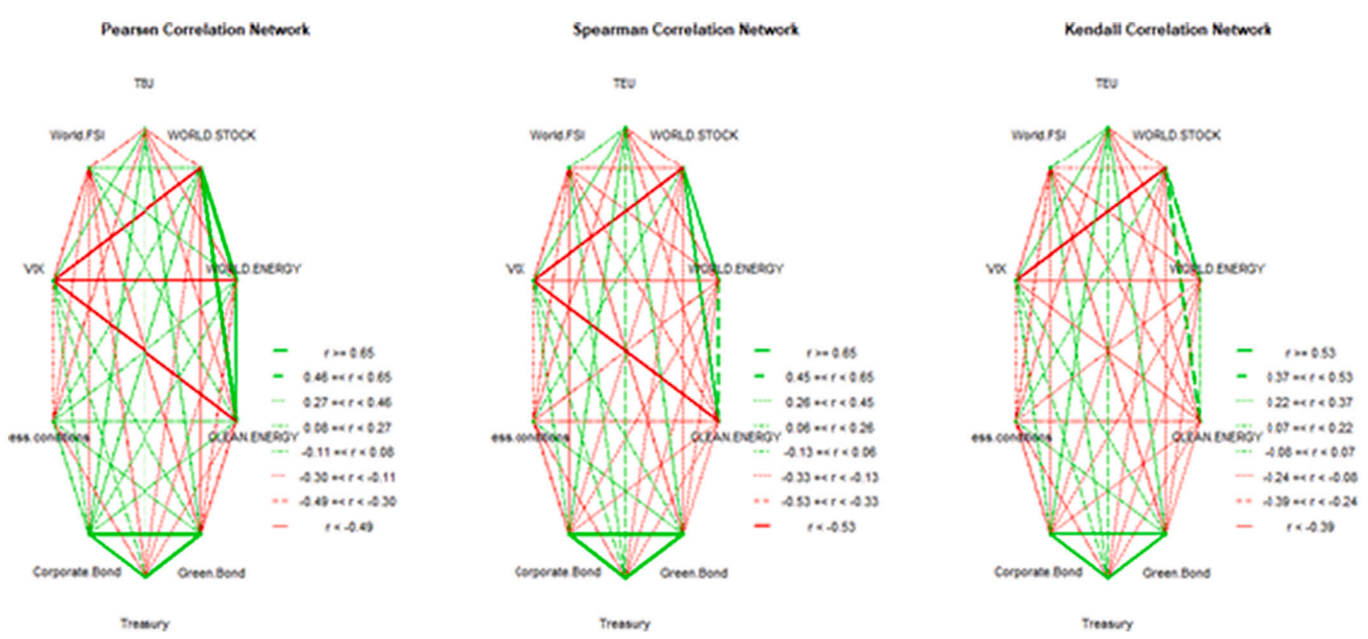


Fig. 4. Network analysis of pairwise correlation.

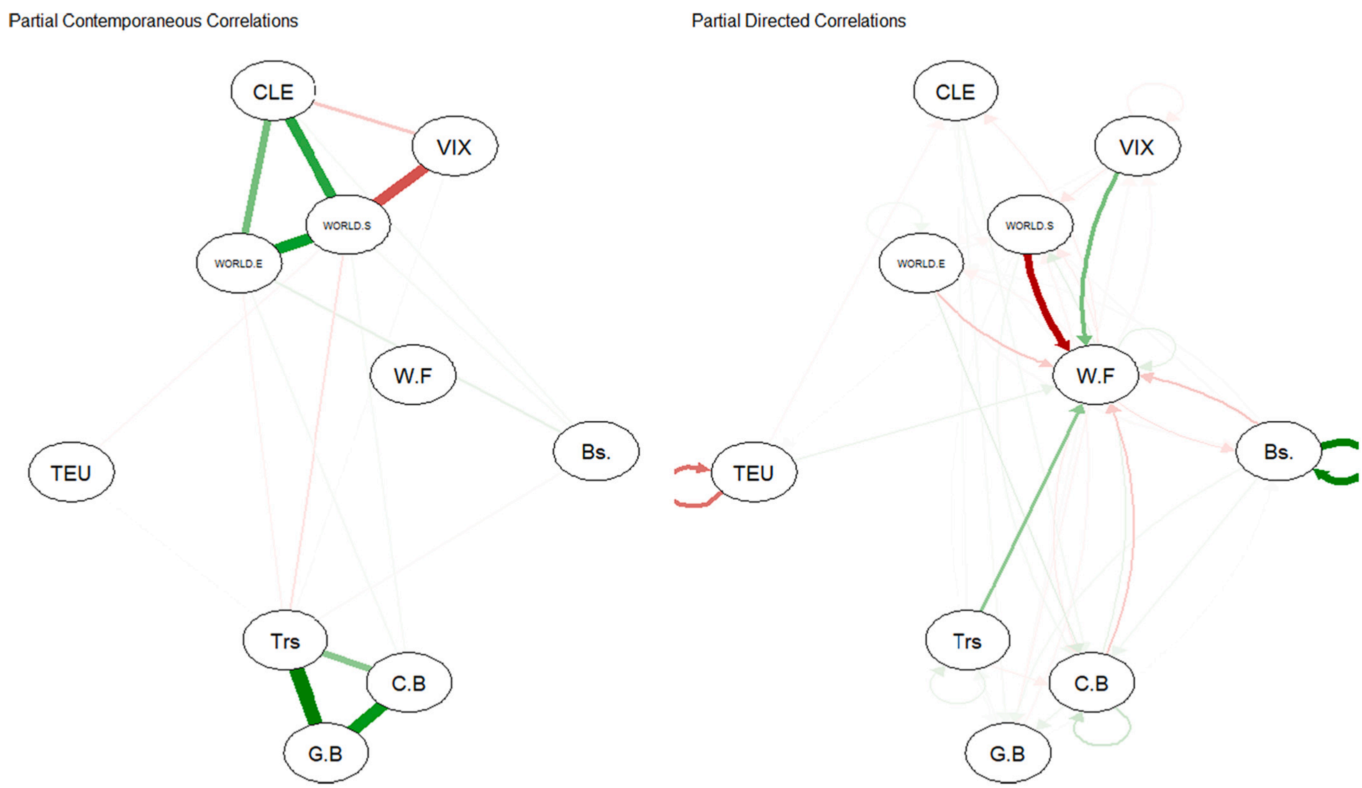


Fig. 5. Plots of partial contemporaneous correlation and partial directed correlation.

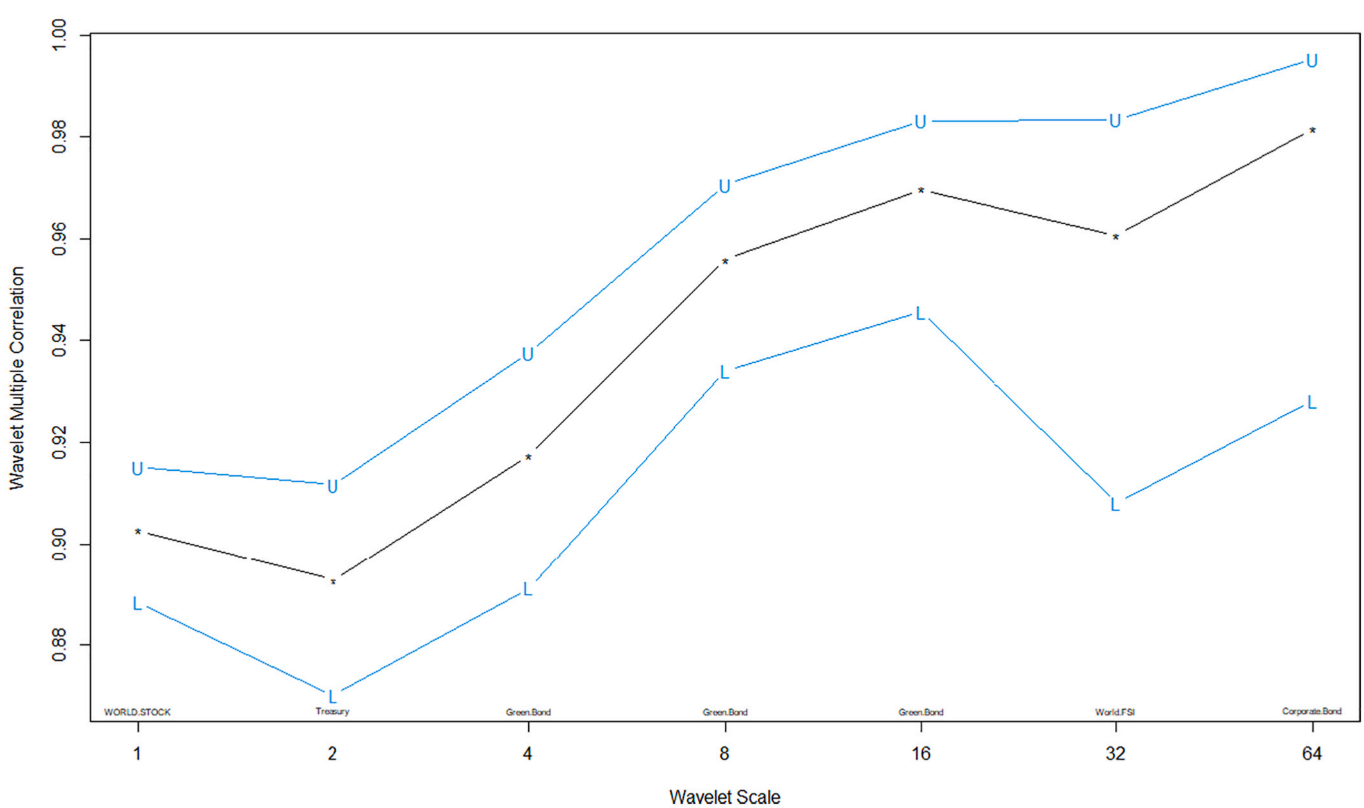


Fig. 6. Wavelet multiple correlation.
Note: The dotted lines show the upper and lower bounds at the 5% significance level.

Table 2
WMC between green bonds and financial markets.

	Correlation	Lower	Upper
[1,]	0.9026534	0.888427	0.915147
[2,]	0.8927376	0.870034	0.911663
[3,]	0.9174106	0.891161	0.937538
[4,]	0.9559158	0.934104	0.970618
[5,]	0.9697317	0.945643	0.983237
[6,]	0.9606996	0.908112	0.983452
[7,]	0.9815462	0.9282	0.995353

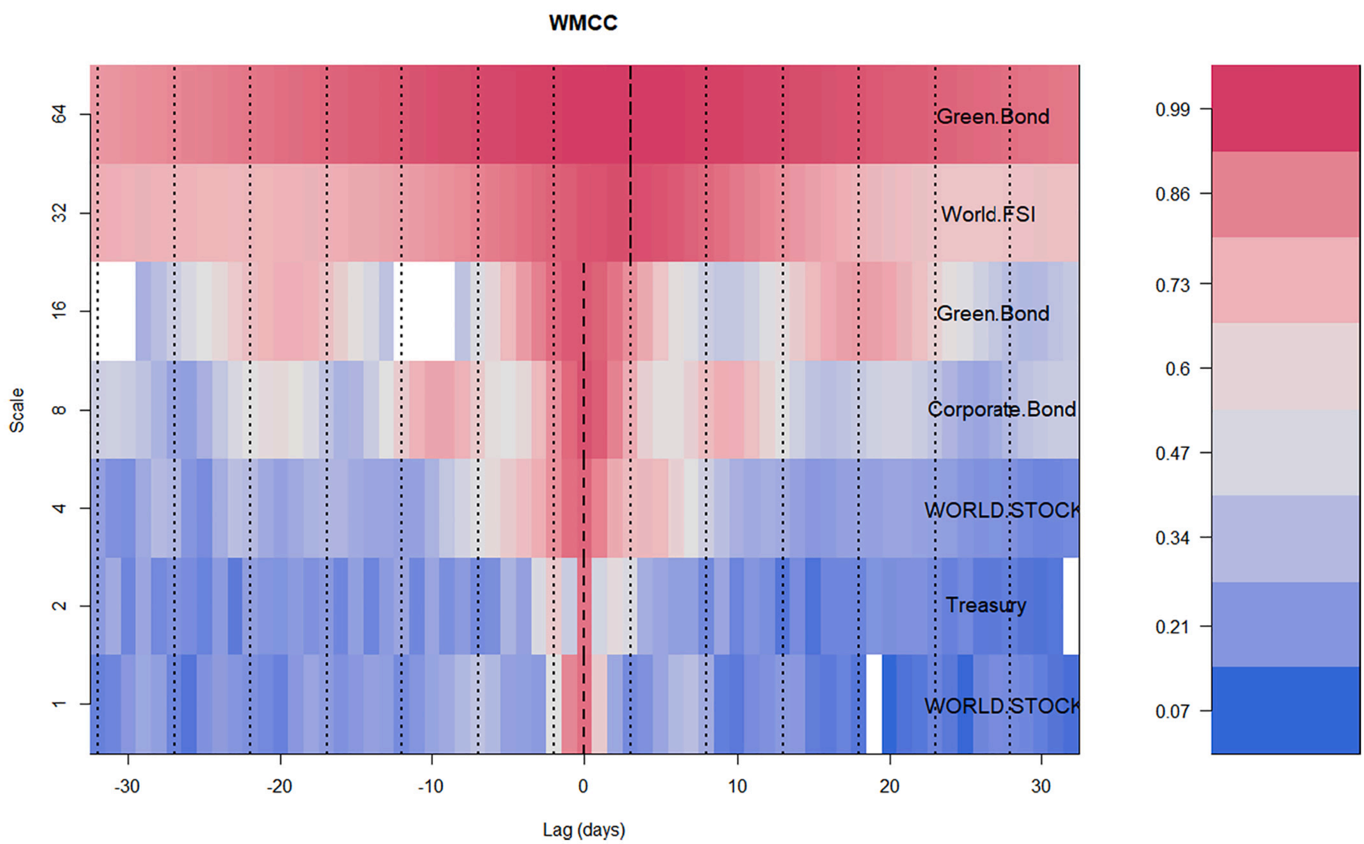


Fig. 7. Wavelet multiple cross-correlation.
Notes: The time scale is shown on the vertical axis, while lags are displayed on the horizontal axis. The color bar on the right-hand side of the graph offers the range of correlation from the low (dark blue color) to the high (dark red color). The dark lines denote the 95% confidence interval for WMCC. The negative time lags suggest that selected market returns lead at a particular scale, and the opposite is true for positive time lags.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

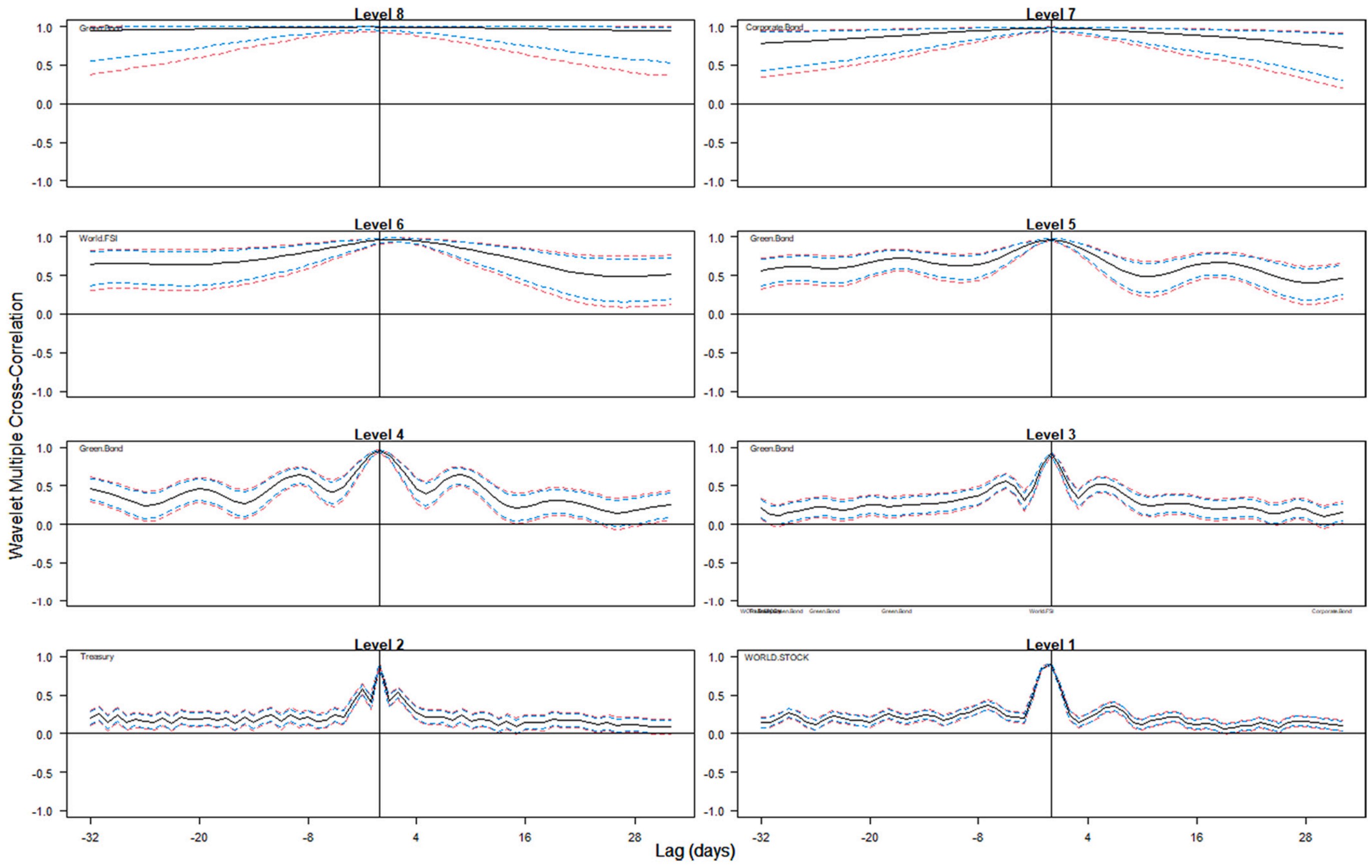


Fig. 8. Wavelet multiple cross-correlation.

Table 3
Full sample spillover connectedness results.

Returns	World Stock	World Energy	Clean Energy	Green Bond	Treasury	Corporat Bond	Business Conditions	VIX	World FSI	TEU	FROM	Net
World Stock	32.97	21.10	20.77	1.04	2.54	0.76	1.77	17.52	1.11	0.43	6.70	4.319
World Energy	24.13	37.41	19.31	1.27	2.54	0.56	2.23	11.39	0.79	0.38	6.26	2.378
Clean Energy	23.40	18.94	36.70	1.00	2.16	0.67	1.84	14.34	0.64	0.32	6.33	2.088
Green Bond	2.31	2.45	2.09	36.78	26.99	25.72	1.30	1.31	0.77	0.27	6.32	−0.389
Treasury	3.12	2.48	2.18	28.09	37.38	23.08	1.06	1.45	0.81	0.35	6.26	0.048
Corporate Bond	3.97	4.98	4.33	23.95	20.68	35.29	2.50	2.25	1.76	0.29	6.47	−1.069
Business Conditions	3.12	5.22	1.20	0.73	1.27	1.28	83.30	1.40	2.38	0.10	1.67	−0.197
VIX	22.98	12.47	16.69	1.05	1.90	0.92	0.35	42.96	0.19	0.51	5.70	1.198
World FSI	25.88	17.98	16.73	1.75	4.63	0.80	3.60	18.55	9.40	0.68	9.06	−8.167
TEU	1.32	0.75	0.88	0.45	0.39	0.24	0.07	0.83	0.49	94.58	0.54	−0.209
TO	11.02	8.64	8.42	5.93	6.31	5.40	1.47	6.90	0.89	0.33	55.32	

suggested.

5.2. Connectedness analysis

5.2.1. Static spillover connectedness

The results of DY static spillover connectedness across green bonds and financial markets returns and uncertainty returns are presented in Table 3. Empirical results state that the average value of the total connectedness of the system is 55.32%, indicating an acceptable level of connectedness among 10 variables. This finding is supported by the study of Lundgren et al. (2018). The off-diagonal elements of the 10 × 10 matrix illustrate the directional spillover between two markets. For instance, the value 24.13 in row 3, column 2 represents the share of spillover transmitted from world energy to world stock. The highest spillover is reported from the treasury to green bonds - the share of volatility transmitted from the treasury to green bonds is 28.09%.

Similarly, the value of the lowest spillovers 0.10%, is observed from business condition to TEU. The values enlisted in the second row from the bottom of Table 3 describe the total directional spillover from each market to other markets. The outcomes explain that total directional spillover in the “To” column span from 0.33% (TEU) to 11.02% (world stock). Thus, the contribution of world stock to other markets is highest, and TEU is lowest across the sample variables. The values in the second rightmost column of Table 3 illustrate the total directional spillover from other markets to each of the 10 markets. The results explain that total directional spillover in the “From” column varies from 0.54% to

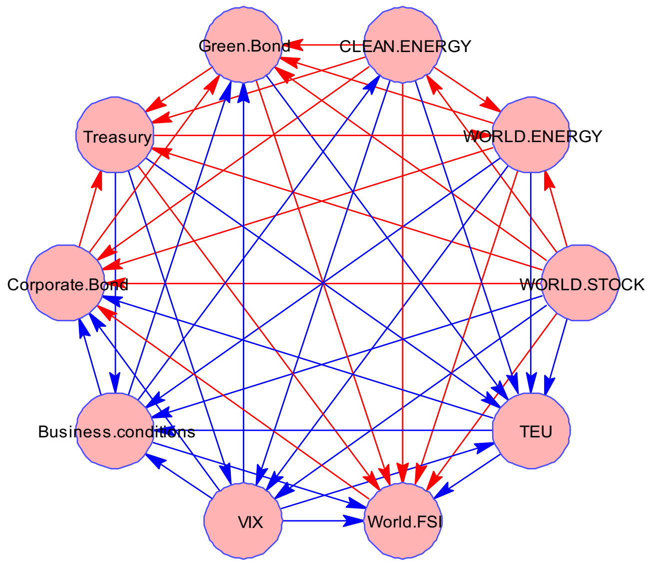


Fig. 9. Network plot of net pairwise directional spillover.

9.06% for TEU and world FSI. This implies that TEU is the most affected by the shocks from other markets while World stock is the least affected by the shocks from other markets.

The rightmost column provides the results of net directional spillover, and the positive value of the net spillover indicates that a particular market is a spillover contributor. That is, it transmits net volatility to other markets. On the other hand, the negative value of net spillover implies that a specific market is a net receiver. That is, it receives shocks from other markets. The results show that world stock, world energy, clean energy, treasury, and VIX are net contributors of shocks, while green bonds, corporate bonds, business condition, world FSI, and TEU are the net receiver of shocks. In other words, world energy markets, clean energy markets, treasury markets, and stock markets play a leading role in global financial markets. In contrast, the green bonds market and corporate bonds market is most affected by other markets' shocks. Our empirical evidence is consistent with the finding of Reboredo and Ugolini (2020) and supports the fact that the green bond market is still a small market, closely mirrors the evolution of the treasury market, is impacted by the evolution of the USD and exhibits a low degree of integration with other financial markets. As a result, the green bond market is a net price-spillover receiver with a weak capacity to transmit price spillover effects.

Subsequently, the net pairwise directional spillover across 10 variables using a network plot is estimated (see Fig. 9). The direction of arrows explains net directional spillover between variables. From the network plot, world stock is the leading net spillover transmitter, and its highest transmission is to green bonds, treasury, corporate bonds, world energy, clean energy, and world FSI. A corporate bond is the highest net spillover receiver and receiving shocks from all selected markets except green bond, where its role is net spillover transmitter. Similarly, green bonds transmitting shocks to the treasury, TEU and world FSI while receiving shocks from remaining markets.

5.2.2. Static multiscale spillover connectedness

To further clarify the connectedness results, we examine the multiscale spillover connectedness at different levels of IMFs, and the results are presented in Table 4. The average value of the total connectedness is less than 50% in the first three levels of the IMF: 49% at IMF1, 41% at IMF2 and 47% at IMF3. However, at higher levels of IMF, the average value of the total connectedness increases to more than 50%. For instance, the average value of total connectedness is 70% at IMF4, 62% at IMF5, 88% at IMF6, 75% at IMF7. Moreover, the net spillover results illustrate that world stock is a net transmitter of volatility at IMF1, IMF2, IMF6, and IMF 7 while at IMF3, IMF4, and IMF5, the net receiver of volatility. World energy and green energy are net transmitters of volatility at IMF1 to IMF5, and at remaining IMFs, both are the net receiver of volatility. A green bond is the net receiver of volatility at IMF1 and IMF3 to IMF6 and the net transmitter of volatility at IMF2 and IMF7. However, at IMF2, green bond and financial markets are all net transmitters of volatility, and at IMF6, all markets are the net receiver of volatility except world stock and corporate bonds.

In the next step, we have analyzed the net pairwise directional spillovers through network plots, as presented in Fig. 10. World stock is the net transmitter of volatility at IMF1 and IMF6; green bond is the net transmitter at IMF4 and IMF5; treasury and TEU are net receivers of volatility at IMF6. Moreover, the green bond is the net receiver of world energy and green energy volatility at IMF1, IMF2, IMF4, and IMF5 while net transmitter from remaining IMFs. Corporate bonds are the net receiver of volatility from all financial markets except green bonds at IMF1 to IMF5. TEU, World FSI, and VIX are the net receiver of volatility at IMF1, IMF3, IMF4, and IMF6.

Last but not least, at IMF1, world stock is playing a dominant role by transmitting volatility to all selected markets, followed by world energy that sending volatility to all financial markets except world stock. Similarly, the green bond is highly affected by the shocks from other financial markets, followed by the corporate bond receiving shocks from all financial markets except the green bond. All financial markets are the major cause of increasing economic uncertainty, financial stress, and financial uncertainty. At IMF2, a corporate bond is the highest receiver of volatility, followed by world energy, a net receiver from world stock, green energy, green bond, and treasury. In contrast, treasury is the highest transmitter of volatility, followed by green energy, net transmitter to world energy, green bond, and corporate bond. At IMF3, Green energy is the highest transmitter of volatility while the green bond is the least transmitter of volatility; at IMF4 green bond is the highest receiver of volatility while green energy is the least receiver of volatility, at IMF5, world stock is most affected by the shocks while green energy is the least affected by the shocks, at IMF6, world stock is the highest transmitter of shocks while treasury is the highest receiver of shocks, at IMF7, all financial market play their equal role in transmitting and receiving shocks. From this discussion, it becomes clear that green energy plays a significant role in transmitting volatility, while green bonds are most affected by the shocks from other markets at all IMFs.

5.3. Dynamic connectedness analysis

5.3.1. Dynamic returns spillover connectedness

A major drawback of static spillover analysis is that the link between

Table 4
Multiscale spillover connectedness results.

	World Stock	World Energy	Clean Energy	Green Bond	Treasury	Corporate Bond	Business conditions	VIX	World FSI	TEU	FROM	NET
IMF1												
World Stock	39.62	23.47	19.53	0.27	1.15	0.15	2.25	11.17	2.31	0.08	6.04	4.404
World Energy	25.16	46.25	17.44	0.56	1.05	0.24	2.99	5.45	0.71	0.16	5.38	2.343
Clean Energy	22.75	18.49	44.33	0.36	1.03	0.25	3.03	8.64	0.95	0.16	5.57	1.359
Green Bond	0.53	1.05	0.72	42.2	28.84	25.34	0.71	0.45	0.15	0.02	5.78	−0.244
Treasury	1.88	2.26	1.52	25.57	44.03	22.45	0.58	0.67	0.97	0.06	5.6	0.916
Corporate Bond	0.73	1	0.92	24.99	25.25	44.92	0.35	1.02	0.78	0.04	5.51	−0.153
Business conditions	3.21	2.03	1.21	0.72	1.23	2.6	87.04	0.26	1.59	0.12	1.3	0.064
VIX	21.78	10.62	14.51	1.17	1.81	1.32	0.22	47.8	0.69	0.06	5.22	−1.297
World FSI	27.62	17.6	12.91	1.32	4.5	0.95	3.34	11.31	20.21	0.23	7.98	−7.106
TEU	0.76	0.66	0.51	0.39	0.27	0.24	0.13	0.25	0.58	96.21	0.38	−0.286
TO	10.44	7.72	6.93	5.54	6.51	5.35	1.36	3.92	0.87	0.09	48.74	
IMF2												
World Stock	45.56	15.64	17.9	1.27	2.2	1.08	2.66	11.04	2.07	0.59	5.44	1.270
World Energy	16.06	52.77	13.06	2.24	2.4	1.47	4.36	5.38	1.47	0.79	4.72	0.694
Clean Energy	12.71	12.86	58.84	1.5	2.66	1.01	2.72	5.05	1.19	1.47	4.12	2.103
Green Bond	0.48	0.99	0.7	50.49	23.49	20.46	1.04	0.68	1.11	0.58	4.95	0.056
Treasury	0.87	1.49	2.37	23.13	54.14	14.75	1.06	0.69	0.96	0.54	4.59	0.687
Corporat Bond	1.19	4.01	2.95	14.23	14	55.8	2.31	2.7	2.23	0.56	4.42	0.085
Business conditions	2.5	1.67	3.06	4.27	1.99	2.99	76.66	1.66	4.98	0.22	2.33	−0.587
VIX	13.09	7.14	10.74	0.49	0.97	1.55	0.24	63.25	1.05	1.48	3.67	0.475
World FSI	19.71	9.52	11.01	2.59	4.6	1.21	2.66	13.47	32.54	2.69	6.75	−5.195
TEU	0.53	0.86	0.4	0.36	0.42	0.54	0.41	0.83	0.44	95.19	0.48	0.411
TO	6.71	5.42	6.22	5.01	5.27	4.51	1.75	4.15	1.55	0.89	41.48	
IMF3												
World Stock	43.83	7.87	13.03	1.59	3.33	1.01	6.95	9.4	11.21	1.79	5.62	−0.513
World Energy	7.72	42.29	14.5	1.66	1.56	2.53	15.16	5.22	8.19	1.15	5.77	0.133
Clean Energy	5.36	12.09	56.51	4.41	5.34	1.6	5.49	1.99	5.77	1.44	4.35	3.626
Green Bond	2.65	4.44	2.86	40.72	22.02	23.23	1.93	0.55	1.38	0.24	5.93	−0.854
Treasury	5.15	3.32	2.65	15.88	48.63	19.21	0.92	1.02	2.58	0.63	5.14	0.544
Corporat Bond	2.97	4.19	6.31	15.05	15.62	51.37	2.36	1.17	0.65	0.33	4.86	0.583
Business conditions	2.17	9.48	15.23	3.42	0.81	2.23	65.84	0.11	0.57	0.14	3.42	0.574
VIX	11.1	4.44	5.22	0.86	2.59	1.44	1.81	69.23	2.13	1.17	3.08	0.562
World FSI	10.19	9.19	15.66	3.58	4.36	2.53	4.81	15.95	32.21	1.53	6.78	−3.384
TEU	3.73	4.02	4.29	4.29	1.19	0.68	0.47	0.99	1.46	78.87	2.11	−1.271
TO	5.1	5.9	7.98	5.07	5.68	5.45	3.99	3.64	3.39	0.84	47.05	
IMF4												
World Stock	11.94	27.82	34.67	0.77	3.87	4.76	10.46	1.89	2.12	1.69	8.81	−2.080
World Energy	9.88	28.91	33.2	1.03	3.7	5.25	11.07	1.79	3.34	1.82	7.11	7.833
Clean Energy	9.98	28.08	35.85	0.89	3.86	4.22	11.46	1.67	2.04	1.93	6.41	12.77
Green Bond	3.12	5.4	10.82	36.87	13.05	19.03	7.5	1.07	1.99	1.15	6.31	−3.465
Treasury	9.89	17.7	22.09	6.3	15.8	9.07	11.99	1.2	3.35	2.61	8.42	−4.408
Corporat Bond	4.22	7.86	15.03	14.36	6.31	18.2	29.96	1.11	2.25	0.69	8.18	−2.475
Business conditions	1.56	3.09	0.52	0.63	0.21	4.48	84.66	0.81	2.79	1.25	1.53	9.205
VIX	10.78	23.84	32.07	1.12	2.45	2.22	9.72	11.61	3.21	2.97	8.84	−7.251
World FSI	10.82	27.03	32.54	0.79	3.59	5.45	10.67	2.86	4.2	2.05	9.58	−6.672
TEU	7.01	8.61	10.38	2.57	3.06	2.57	4.55	3.47	7.97	49.82	5.02	−3.403
TO	6.73	14.94	19.13	2.85	4.01	5.7	10.74	1.59	2.91	1.62	70.21	
IMF5												
World Stock	12.04	32.31	10.01	3.99	4.1	4.48	11.37	9.19	12.1	0.39	8.8	−4.122
World Energy	3.29	44.04	8.41	6.98	6.8	1.62	14.58	5.54	7.58	1.16	5.6	4.311
Clean Energy	9.25	6.86	47.91	1.23	2.85	3.21	2.51	11.34	12.59	2.24	5.21	2.500
Green Bond	1.61	9.7	10.51	25.16	5.76	16.92	13.9	1.69	8.03	6.73	7.48	−3.264
Treasury	2.86	5.09	15.71	6.36	27.85	20.45	8.38	0.71	3.38	9.23	7.22	−3.062
Corporat Bond	1.2	8.86	7.65	6.31	4.42	23.63	35.34	0.88	4.69	7.03	7.64	−1.345
Business conditions	2.99	0.54	8.53	11.14	0.06	1.66	62.41	0.48	10.99	1.2	3.76	6.201
VIX	11.18	10.64	10.96	0.98	4.06	4.9	3.1	44.56	8.5	1.12	5.54	−0.891
World FSI	8.7	23.55	4.88	2.1	5.23	7.96	8.07	13.32	25.66	0.53	7.43	−0.435
TEU	5.66	1.53	0.45	3.1	8.24	1.73	2.35	3.38	2.13	71.44	2.86	0.107
TO	4.67	9.91	7.71	4.22	4.15	6.29	9.96	4.65	7	2.96	61.53	
IMF6												
World Stock	17.21	13.78	3.67	6.32	1.72	9.3	14.18	13.9	16.26	3.66	8.28	16.377
World Energy	29.15	0.21	8.15	6.93	0.03	19.67	26.55	3.65	3.51	2.15	9.98	−7.316
Clean Energy	27.27	0.82	16.18	6.69	0.46	19.06	19.44	4.89	2.87	2.33	8.38	−2.697
Green Bond	19.76	2.27	6.01	9.78	1.35	23.62	31.23	2.91	1.66	1.44	9.02	−3.355
Treasury	29.81	0.19	7.43	3.73	1.89	23.63	24.7	4.24	2.57	1.81	9.81	−9.158
Corporat Bond	31.42	0.8	9.08	8.45	0.51	14.32	26.11	2.83	4.85	1.62	8.57	7.104
	25.26	0.1	5.3	4.93	0.07	16.43	41.19	3.43	2.05	1.25	5.88	15.99

(continued on next page)

Table 4 (*continued*)

	World Stock	World Energy	Clean Energy	Green Bond	Treasury	Corporate Bond	Business conditions	VIX	World FSI	TEU	FROM	NET
Business conditions												
VIX	32.76	1.85	6.95	6.67	0.64	12.45	26.43	4.68	5.04	2.52	9.53	−4.704
World FSI	22.23	6.69	3.6	7.49	1.65	11.83	23.43	8.21	10.1	4.77	8.99	−4.860
TEU	28.9	0.14	6.67	5.46	0.09	20.73	26.66	4.22	2.49	4.64	9.54	−7.381
TO	24.66	2.66	5.68	5.67	0.65	15.67	21.87	4.83	4.13	2.15	87.98	
IMF7												
World Stock	20.22	11.48	8.07	7.39	4.03	11.50	4.40	13.03	17.88	2.00	7.98	1.721
World Energy	11.52	16.36	8.83	10.06	6.94	8.57	1.98	10.13	16.04	9.56	8.36	−1.465
Clean Energy	6.83	11.05	14.06	12.84	2.30	6.81	2.09	9.76	7.90	26.38	8.59	0.669
Green Bond	3.36	8.78	0.61	24.42	26.58	14.37	2.91	2.36	14.17	2.44	7.56	0.020
Treasury	4.66	7.50	0.33	21.15	34.53	15.53	0.58	1.07	13.85	0.80	6.55	−0.376
Corporat Bond	11.87	5.11	12.94	11.09	5.64	17.43	4.33	13.68	5.84	12.08	8.26	−6.088
Business conditions	10.51	25.21	9.65	1.20	4.35	5.63	15.79	10.13	15.70	1.83	8.42	−0.425
VIX	11.44	15.47	20.81	2.00	2.36	1.14	1.38	22.8	12.28	10.32	7.72	2.430
World FSI	15.99	12.00	8.161	9.50	5.26	12.23	4.74	12.04	17.73	2.26	8.23	3.306
TEU	5.69	4.27	1.88	7.02	8.21	2.94	0.91	0.74	2.92	65.4	3.46	4.022
TO	8.191	10.07	7.13	8.23	6.57	7.88	2.33	7.29	10.66	6.77	75.13	

variables remains constant over time. The volatility jumps caused by economic and financial events are ignored in the static spillover index. Fig. 11 plots the total returns spillover estimated by rolling window analysis. It is evident from Fig. 11 that the total spillover index is time-varying and ranges from 62% to 90%. The fluctuations in the index value remain smooth throughout the sample period except in the third quarter of 2016 and the first quarter of 2020. The 2016 fluctuations might be the reason for the US-shale energy revolution and the increase in commodity demand in China. COVID-19 pandemic is the major cause of 2020 fluctuations that negatively impact global stock markets. The evidence supports the findings of Yi et al. (2021) and Taghizadeh-Hesary et al. (2021) that COVID-19 significantly affect the investment in green bond market.

The graphical illustration of the net returns spillover index for each considered variable is presented in Appendix 1. The close inspection of plots shows that clean energy, VIX, and world stock markets remain net transmitters of volatility throughout the sample period except in early 2020, where its strength of transmission decreases. Corporate bonds are the net transmitter of volatility from the first quarter of 2017 to the last quarter of 2019 but become a net receiver in the remaining sample period. Green bonds and treasury remain net transmitters for most of the sample period, while corporate bonds and world energy are net receivers. Business conditions, TEU, and world FSI appear to be net receivers for the whole sample period.

5.3.2. *Dynamic multiscale returns spillover connectedness at different IMFs*

Fig. 12 shows the graphs of multiscale connectedness and describes that for the first IMF, the range of spillover is 50% to 90%, and for the second IMF, the range is 59% to 90%. However, at IMF3, the range varies from 70% to 90%, and at IMF 4 and 5, the range mostly lies between 87% to 92%. At IMF6, the range exceeds 94%, and at IMF, it exceeds 92%. Our findings support the general argument that the total spillover index increases with higher IMF.

The graphs of multiscale net connectedness are displayed in Appendix 2. The results explain that at IMF1, world stock is the net transmitter until the first quarter of 2020; afterward, it either becomes a net receiver or net transmitter. At IMF2, world stock is the net transmitter of volatility from the first quarter of 2016 to the mast quarter of 2019 and becomes the net receiver in the remaining periods. From IMF3 to IMF7, it appears to be either a net receiver or transmitter throughout the sample period. At IMF1 to 7, all the remaining variables are a weak transmitter of volatility for most of the sample period.

6. Conclusion

This paper examines the dependence structure and dynamic connectedness between green bonds and financial markets by incorporating several global uncertainty indices using daily data from 30/9/2014 to 30/6/2020. Financial markets comprise three different markets (i) treasury and corporate bond markets (ii) stock markets (iii) energy and clean energy markets, while uncertainty indices cover financial uncertainty, financial stress, and economic uncertainty. The association between variables in the time-frequency domain is studied by applying a multivariate wavelet approach, whereas dynamic connectedness is examined by combining the Ensemble Empirical Mode Decomposition (EEMD) model with the Diebold Yilmaz volatility spillover approach. Following results are observed with the application of these approaches:

First, Wavelet Multiple Correlation (WMC) results reveal the significant change in the pattern of multiple correlations with the increase in time scale. As a result, the deviation between green bond and financial markets returns tends to decrease from short-run to long-run time intervals. Therefore, the benefits of diversification opportunities become more significant in the short run.

Second, Wavelet Multiple Cross-Correlation (WMCC) findings imply significant cross-correlation at the lowest frequency across all time lags. The cross-correlation level reaches its maximum unity value at 7 and 8 levels. Thus, selected markets become fully integrated at a long-term investment horizon, which indicates market maturity.

Third, the static connectedness framework results explain that world stock is the least affected by the shocks from other markets while the Twitter Economic Uncertainty index (TEU) is the most affected by the shocks from other markets. The results of net directional spillover show that world stock is the leading spillover transmitter while corporate bond is the main spillover receiver among the selected markets. The

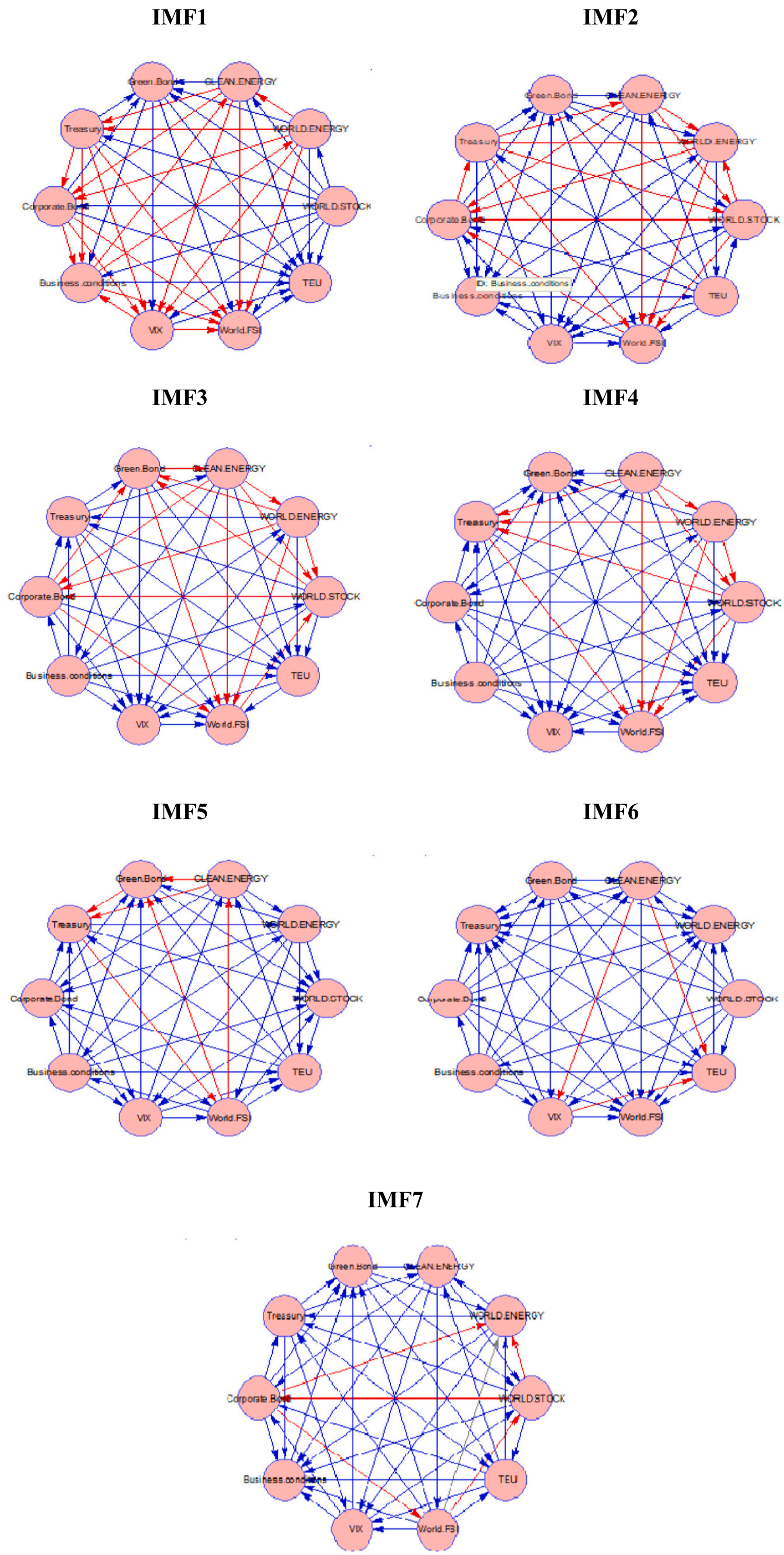


Fig. 10. Network plots of multiscale net pairwise directional spillover.

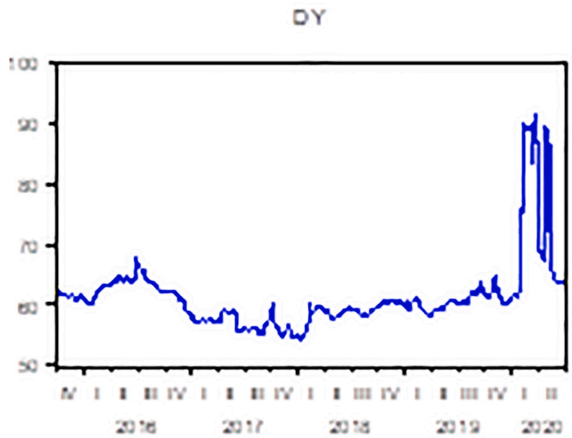


Fig. 11. Dynamic total spillover connectedness.

green bond market is transmitting less but receiving more volatility from other markets. The findings of the multiscale connectedness approach indicate a more complex volatility spillover network. Green energy plays a dominant role in transmitting volatility, while the role of the green bond is negligible at all IMFs. Most of the evidence confirms that world stock has different spillover effects on the remaining markets reruns.

Fourth, the evidence on dynamic connectedness demonstrates that the interdependence between green and financial markets is volatile over time. The highest connectedness is observed in the first quarter of 2020 due to the COVID-19 pandemic. Furthermore, world stock is the net transmitter of volatility for most sample period. In contrast, corporate bonds and world energy are the net receivers of volatility for most of the study period.

Our empirical findings have policy implications in terms of portfolio diversification and management. Empirical results on dynamic connectedness between green bond and financial markets provide new insights in terms of portfolio design for green investors around the word. Due to the low integration of green bonds with stock and energy markets, green bonds provide shelter to the price oscillations in these

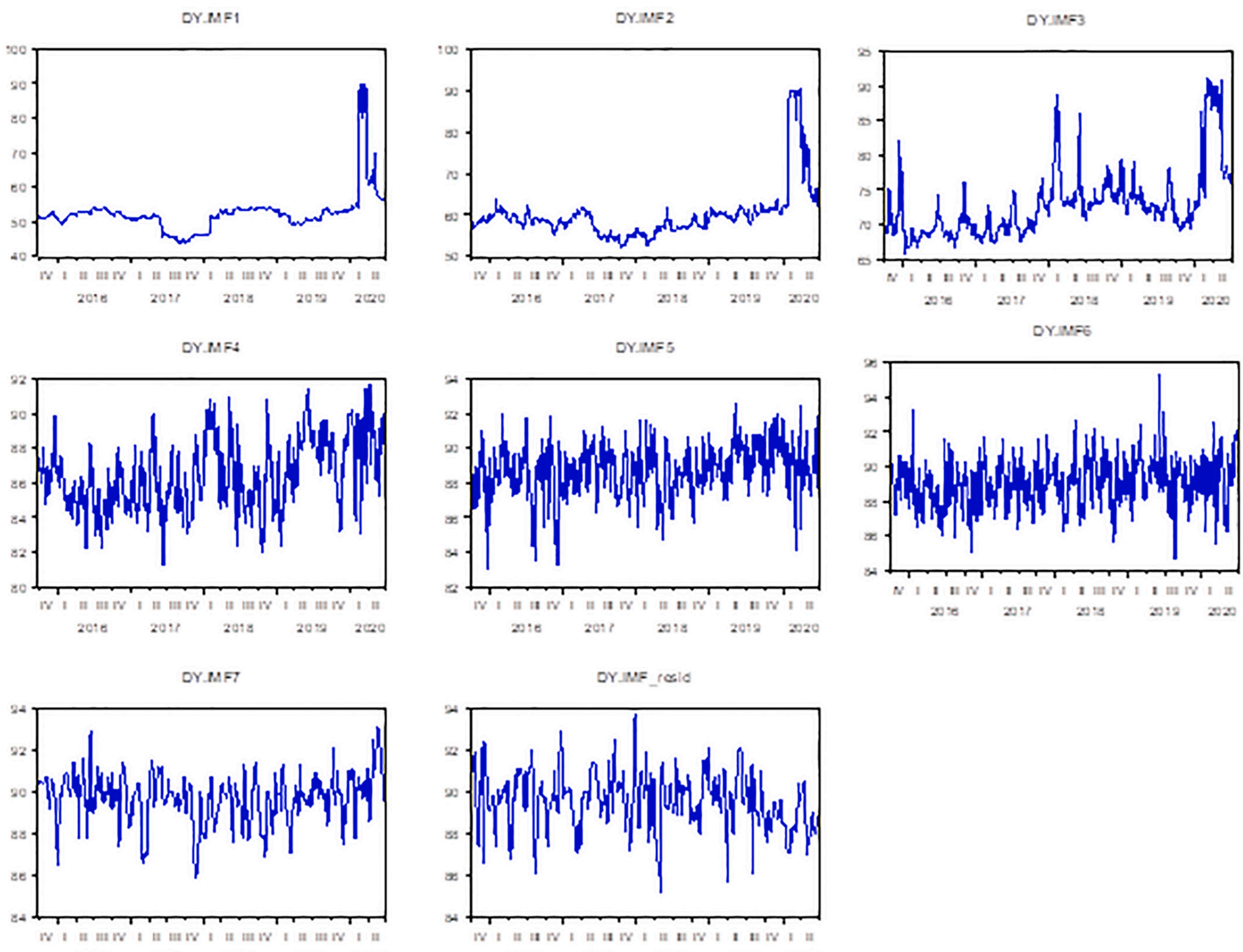


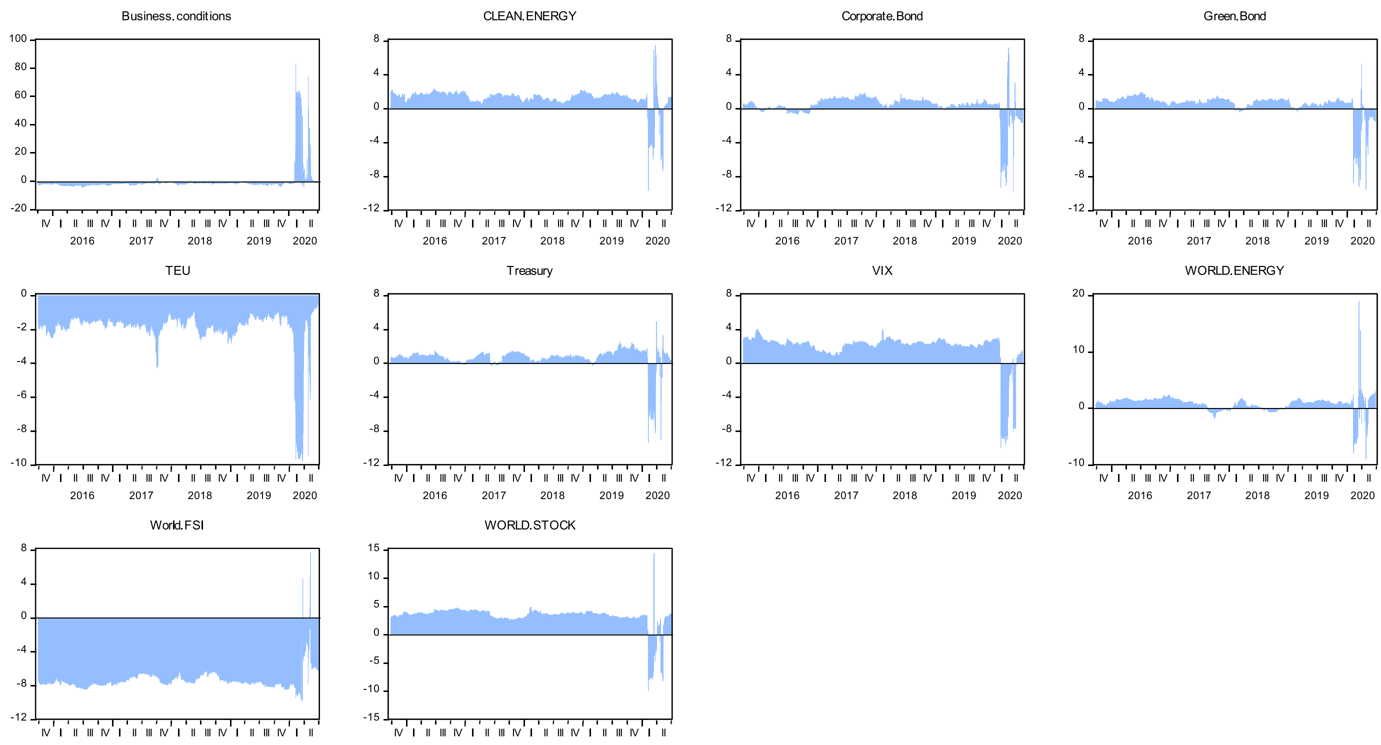
Fig. 12. Multiscale dynamic total spillover connectedness.

markets. It is thereby advised to combine green bonds and these markets in portfolios setting to obtain the diversification benefits. Additionally, the diversification benefit of green bonds is shown at all investment horizons, yet we notice the decreased hedging property of green bonds in the long run. In other words, the allocation across green bonds, stocks, and energy market would give more benefit to active investors (who actively trade in the short-term) as opposed to passive investors (who normally invest in the long-term). These empirical findings also have some policy implications for green bond issuers. As green bonds are a sound financial device for investors, issuers can use this financial vehicle to expand and diversify their investor base and enhance their corporate social responsibility, even though green bond emissions involve higher costs due to green certification. Finally, the growth of the green bond market is impressive recently, but it needs to be accelerated. Hence, it is imperative to promote policies supporting the development of the green bonds market.

Future research can explore the impact of technology development and crypto-assets markets on the dynamics of green bonds returns in the short and long term run during the COVID-19 pandemic. In addition, global behaviours and perceptions could be introduced (as discussed in Gozgor, 2021) as well as vaccine-related news to explore dynamics connectedness of global green bond markets during the COVID-19 pandemic.

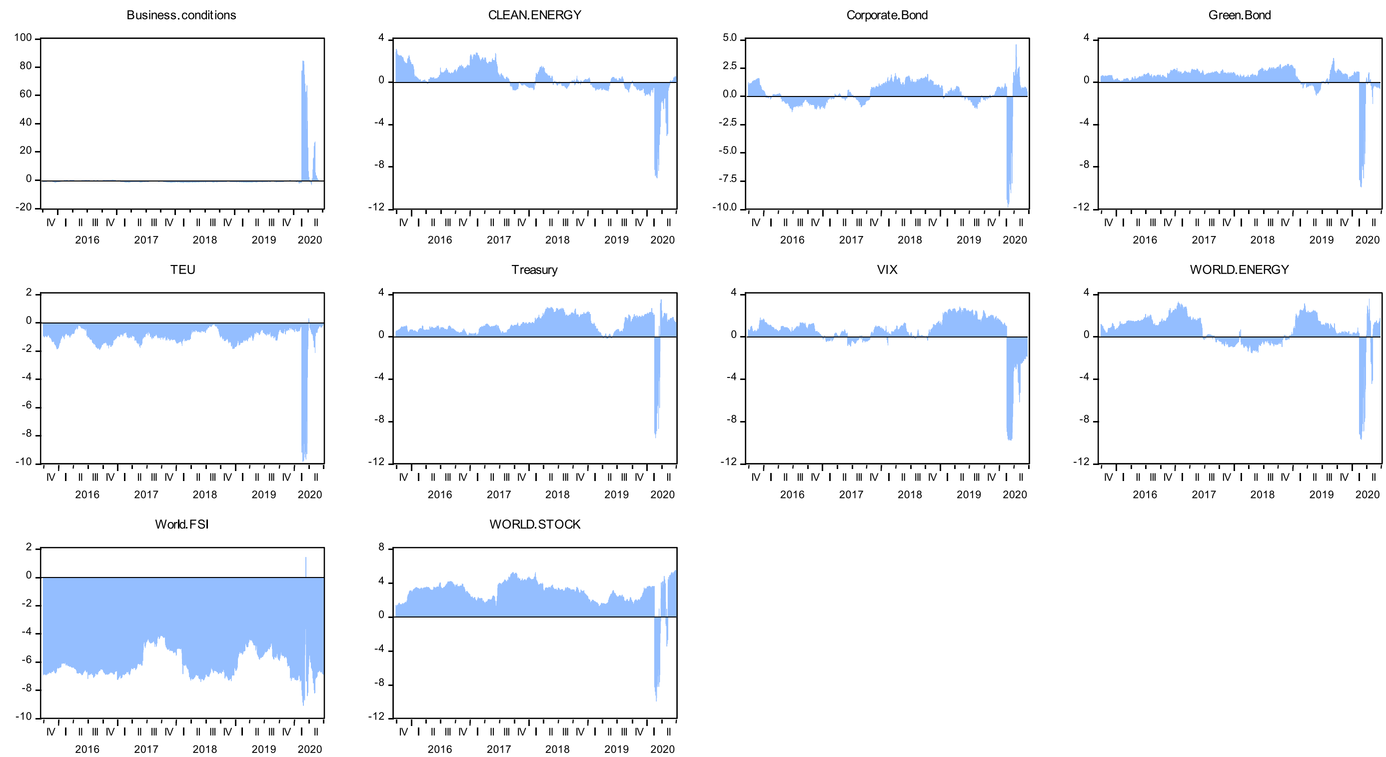
Appendix 1

NET Spillover: DY

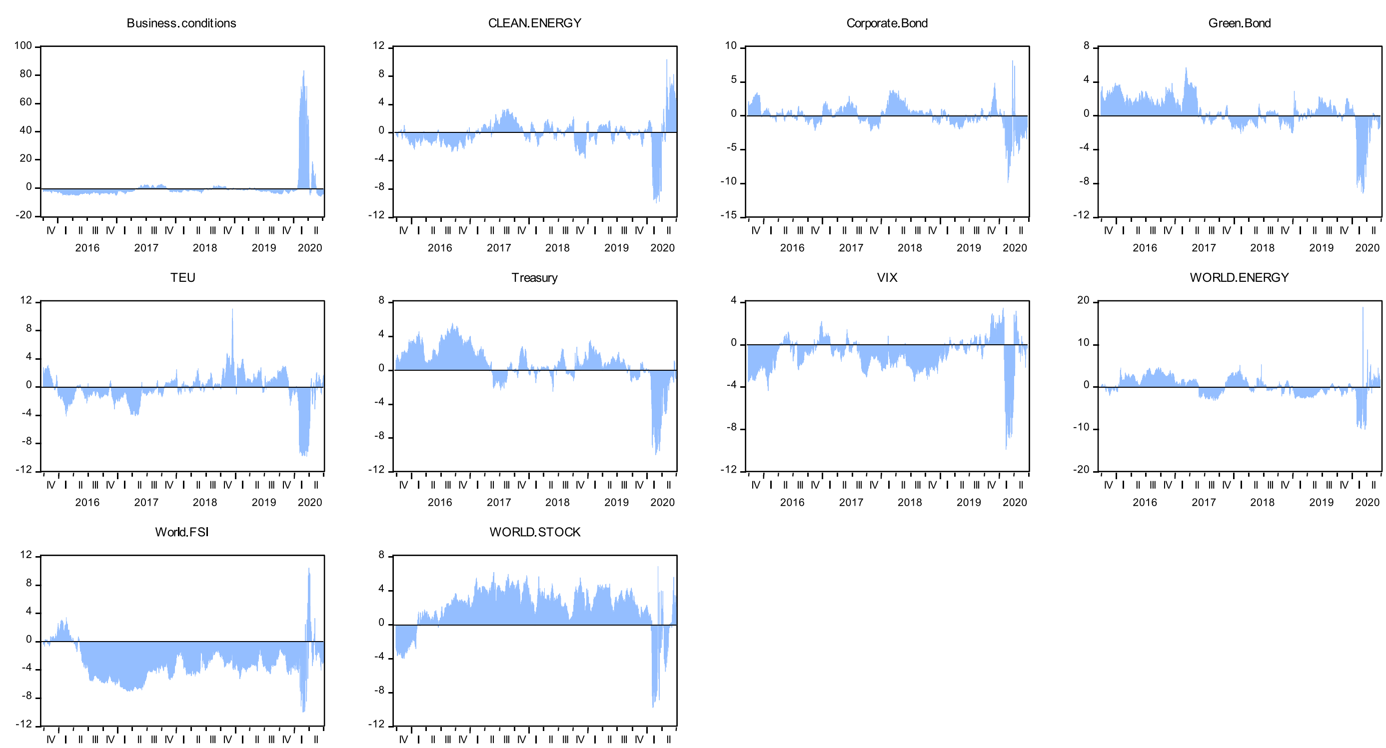


Appendix 2

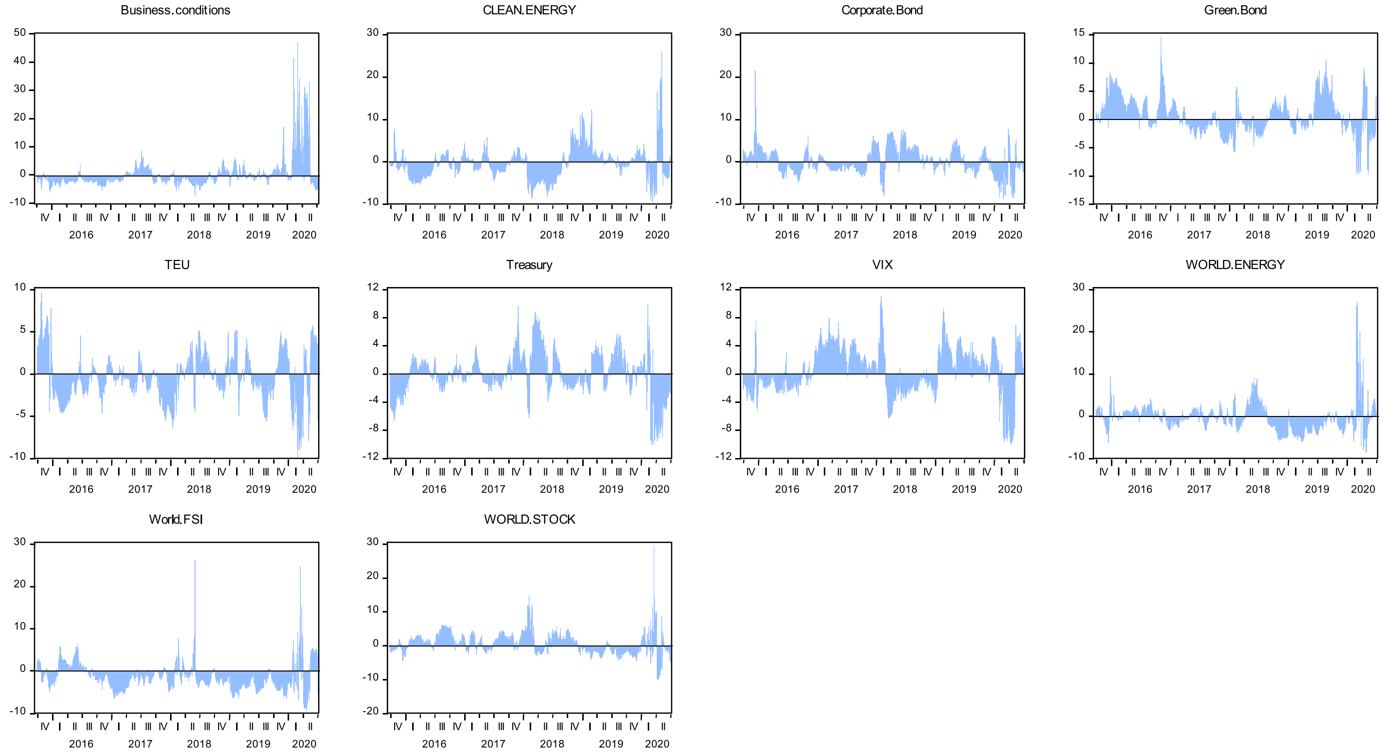
NET Spillover: DY-IMF1



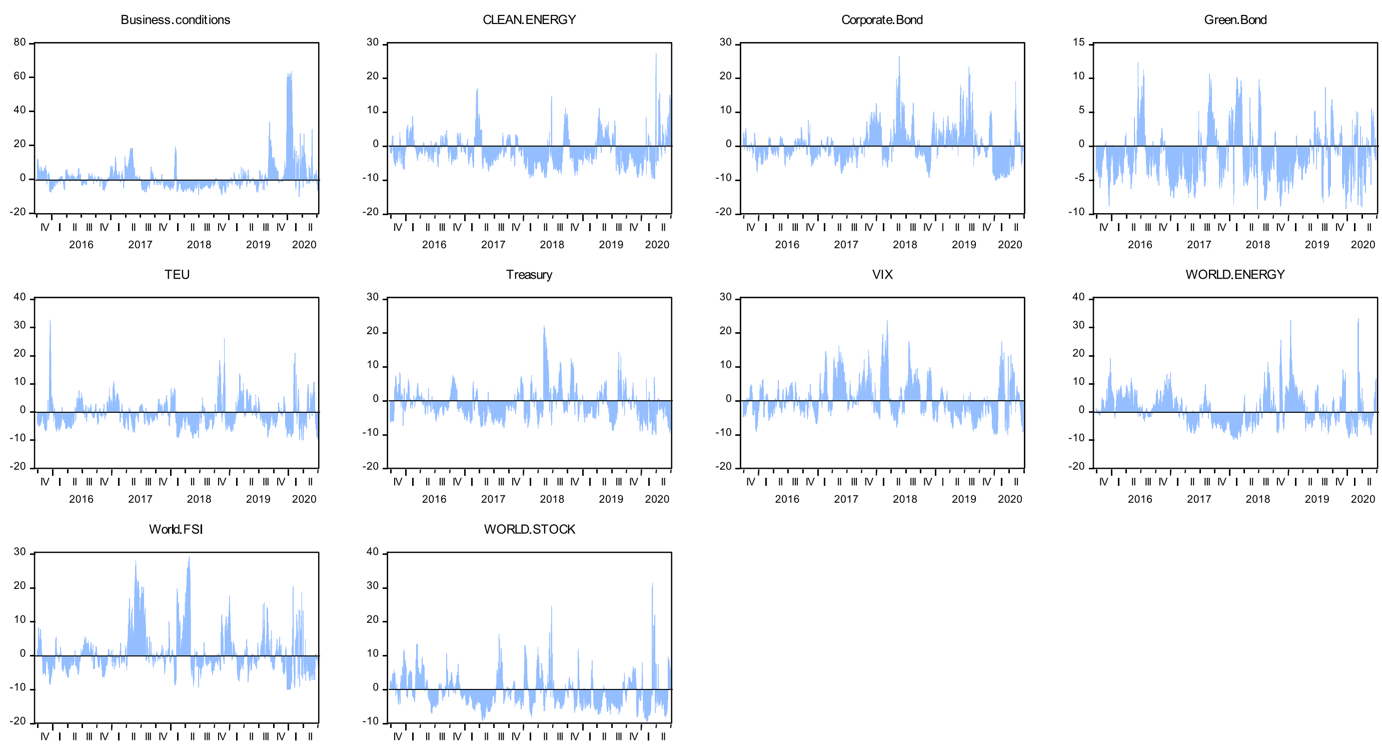
NET Spillover: DY-IMF2



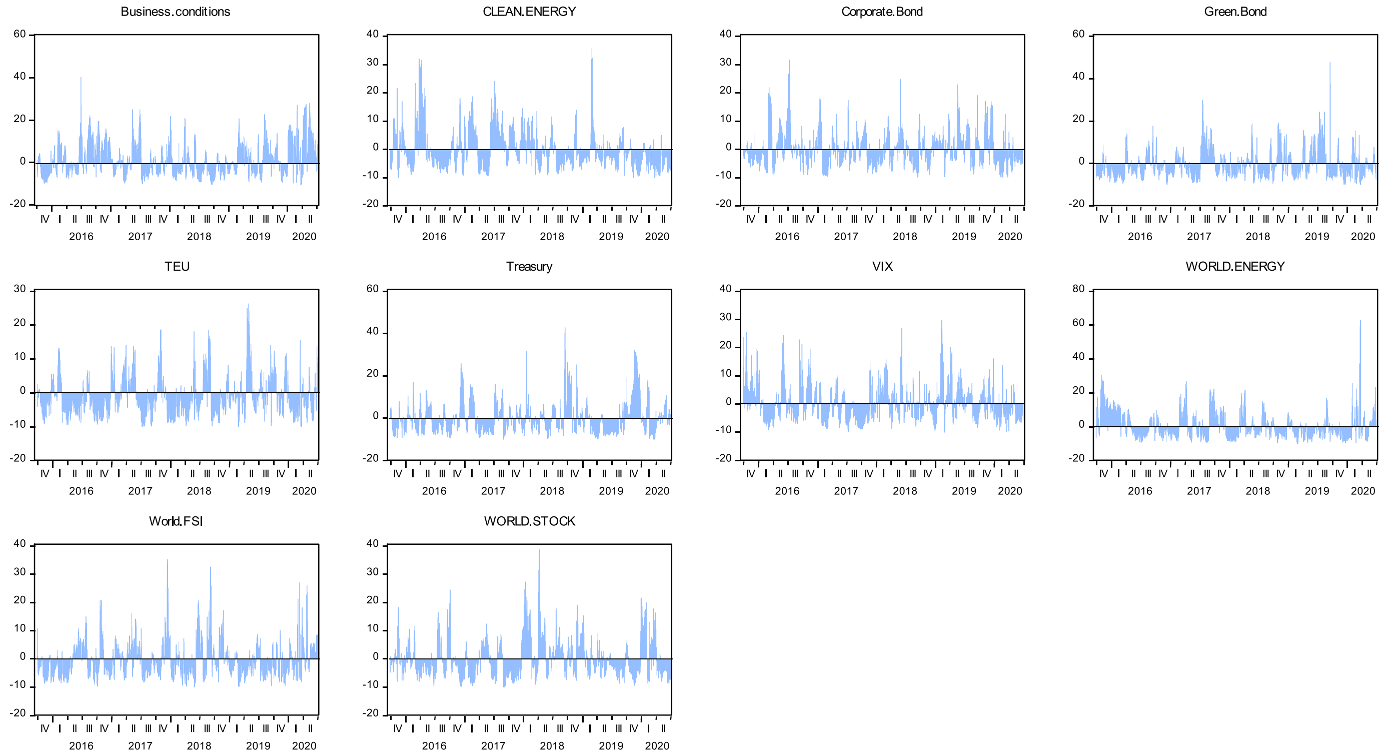
NET Spillover: DY-IMF3



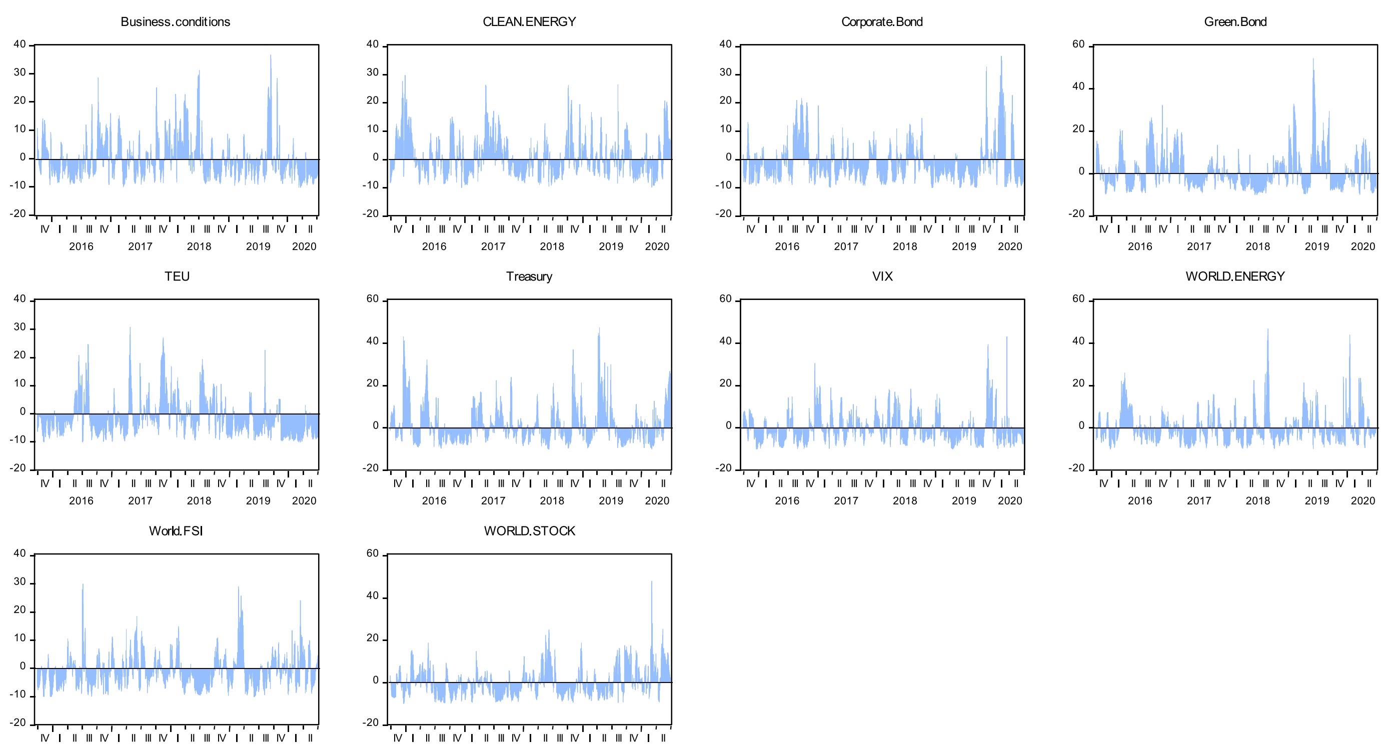
NET Spillover: DY-IMF4



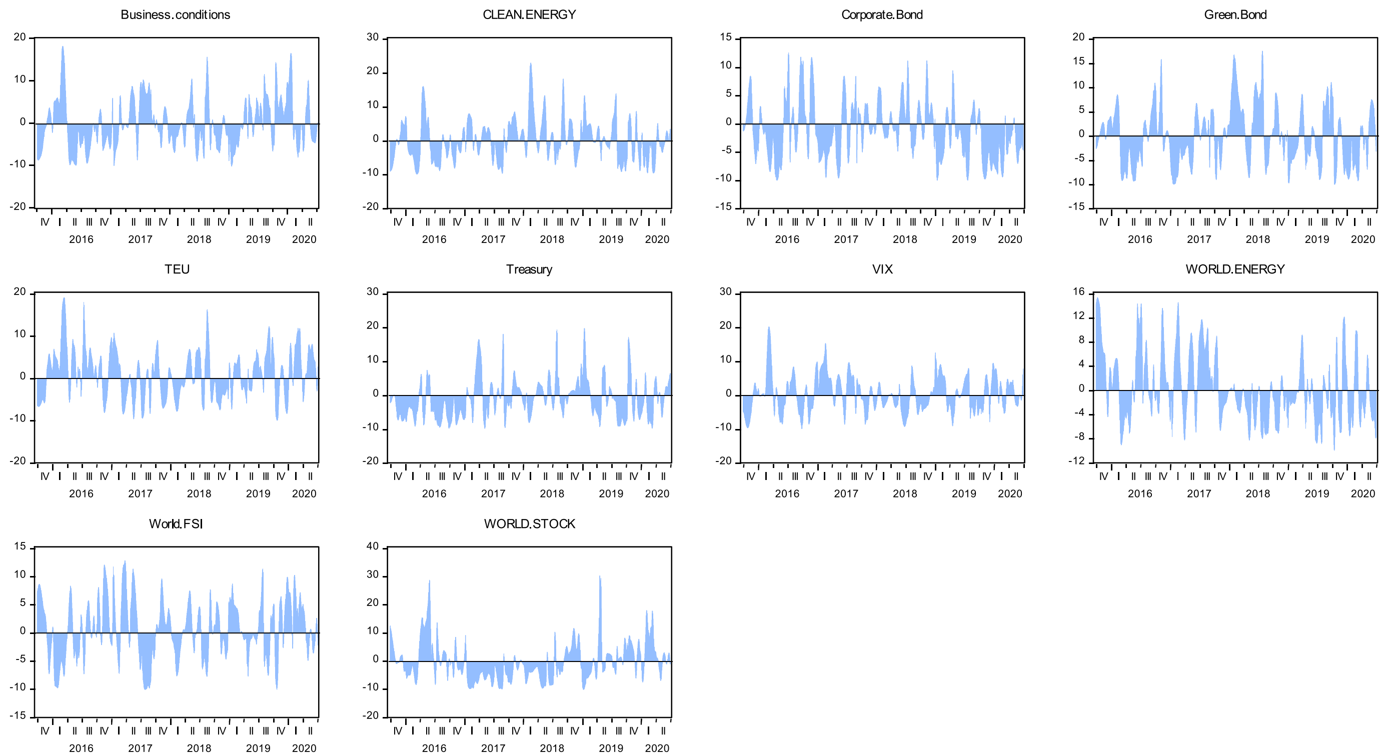
NET Spillover: DY-IMF5



NET Spillover: DY-IMF6



NET Spillover: DY-IMF7



Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.105842.

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