Are green bonds a different asset class? Evidence from time-frequency connectedness analysis

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Abstract

This paper investigates the time-frequency connectedness across the global green bond market and several mainstream financial and energy markets in an attempt to figure out whether green bonds represent a different asset class. The connectedness methodology proposed by Baruník and Křehlík (2018) is employed for that purpose. This approach enables quantifying the dynamics of connectedness in terms of return and volatility over time and across time scales simultaneously. The empirical results indicate that connectedness between the global green bond market and the conventional financial and energy markets mainly occurs at shorter time horizons, suggesting that shocks are rapidly transmitted across markets with an effect lasting less than a week. A strong connectedness in return and volatility is found between green bonds and Treasury and investment-grade corporate bonds, principally because of the numerous characteristics they share. This finding implies that green fixed-income securities are not a different asset class, but they closely mirror the performance of government and high-quality corporate bonds. In contrast, there is a quite limited connectedness between the green bond market and the general stock market, the renewable energy equity sector and the crude oil market regardless of the time horizon considered. This evidence shows that green bonds appear as a valuable tool to fight against climate change without having to sacrifice part of the return generated by traditional assets, particularly ordinary bonds. Furthermore, it can have useful implications for investors and policy makers.

Keywords: Green bonds, conventional financial markets, crude oil market, transmission of shocks, return and volatility connectedness, time-frequency space.

JEL Codes: C58, G12, G15, Q50

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1. Introduction

The acceleration of climate change over the past few years has shown that it is imperative to take actions immediately to reduce greenhouse gas emissions and avoid devastating effects on ecosystems and human life. The development of clean energy sources is viewed as a key strategy to decarbonize the energy system and ensure environmental protection (Van Hoang et al., 2019). An immense amount of capital is required to fund the massive transformational projects necessary to boost the transition towards a low-carbon economy. As argued by Baker et al. (2018), green bonds could play a pivotal role to mobilize financial resources to environmentally beneficial projects and, hence, to combat climate change. Green bonds are a category of fixed-income securities whose only difference from regular bonds is that the proceeds of green bonds are committed to finance projects that have positive environmental effects. An important catalyst for the growth of the green fixed income market was the publication of the Green Bond Principles (GBP) by the International Capital Markets Association (ICMA) in January 2014. These principles brought transparency to the market providing a framework to determine eligibility of projects and reporting requirements.

Green bonds have become one of the fastest-growing segments of international capital markets in the space of a decade. Since the European Investment Bank launched in 2007 the first green bond, called *climate awareness bond*, the market for this asset class has grown exponentially, reaching an issued total volume of around USD 800 billion in the period 2008-2019. According to Climate Bonds Initiative (CBI), worldwide green bond issuance in 2019 was around USD 259 billion, reflecting a growth of 51% over 2018 and marking a new record in green finance. This market is expected to continue growing as, in line with the International Renewable Energy Agency (IRENA, 2019), the transition towards a decarbonized global energy system aligned with the 2015 Paris Agreement goals will require to scale up investments in the renewable energy sector to USD 110 trillion by 2050.[1] Another sign of the enormous potential of this market is that, despite the recent boom, it still represents a very small fraction, just around 3.7% at the end of 2019, of the more than USD 100 trillion world fixed income market according to Moody's Investors Service data.

Understanding the interdependence between the green bond market and the major financial and energy commodity markets over different investment horizons is crucial for various economic

[1] The Paris Agreement of December 2015 set the objective of holding the global average temperature rise in the 21th century well below 2 degrees Celsius above the level of the pre-industrial age, doing everything possible to reduce that increase to 1.5 degrees Celsius in order to avoid dangerous climate change.

agents. For investors, it is critical in order to determine the suitability of green bonds at diverse time horizons as a useful alternative investment and hedging asset. Policy makers are concerned about the resilience of the green bond market to shocks in other markets due to their interest in the development of a strong sustainable financial system that enhances the effectiveness of governments' climate policies and also for market supervision purposes. Therefore, apart from their importance in terms of portfolio diversification and risk management, green bonds can become an essential tool in the fight against climate change, contributing greatly to finance the vast amount of sustainable projects needed to the decarbonization of the global economy.

Connectedness among green bond and conventional financial and energy markets may differ across time scales due to the heterogeneity of the multiple agents who interact in these markets. Economic agents operate on diverse time scales or frequencies, ranging from a few seconds to various years, as they have very different preferences, objectives, levels of assimilation of information and risk aversion and even institutional constraints (Chakrabarty et al., 2015). This heterogeneity can lead to antagonistic responses to the same news in the markets. As contended by Berger and Czudaj (2020), negative news can be regarded as sell signals for short-term agents, while they are buying opportunities for agents with longer horizons. Accordingly, it appears reasonable to expect that shocks can be transmitted across markets with different strength at distinct frequencies. Hence, to study separately short-, medium- and long-term connectedness among green bond and traditional financial and energy markets emerges as an issue of unquestionable interest.

The central purpose of this research is to determine whether green bonds can be categorized as an alternative class of asset with singular features that allow investors to achieve sizeable diversification benefits and downside protection, especially in times of financial turbulence. To that end, we investigate connectedness across the global green bond market and a set of mainstream financial markets, including the global Treasury and corporate bond, equity and currency markets, as well as the crude oil market, over time and across different frequencies simultaneously. In particular, the connectedness method introduced by Baruník and Křehlík (2018) is applied. The Baruník-Křehlík (hereafter BK) methodology can be viewed as the frequency-domain version of the spillover index approach of Diebold and Yilmaz (2012). Just as the Diebold-Yilmaz method focuses solely on the time domain by considering a single time horizon, the BK framework is based on the combination of spectral representation of variance decompositions with the spillover index approach of Diebold and Yilmaz (2012, 2014). The

BK methodology decomposes aggregate connectedness into a number of frequency bands, thus enabling the identification of the particular frequencies that have a greater weight in the total connectedness within a system of variables.

Green bonds are priced using the same valuation models than any other financial asset. Accordingly, green bond prices are impacted by changes in discount rates associated with fluctuations in interest rates and the market's perception of risk. These common pricing factors should lead to a close link between green bond prices and prices of non-green bonds and other financial assets, in such a way that green bonds will react in a similar manner to exogenous shocks than their conventional counterparts. Nevertheless, green bonds attract a special type of investors driven, at least partly, by non-pecuniary motives, particularly pro-environmental preferences, who want to be part of the transition to a more climate-resilient economy. These investors perceive green fixed-income securities as less risky in the long-term due to their lower environmental risk, which may alter drastically the performance of these bonds during periods of instability in the conventional financial markets. Specifically, green bonds are largely held by institutional investors, including insurance companies, pension funds and sovereign wealth funds, with sustainable and responsible investment mandates. These institutional investors have a long-term and more strategic outlook and tend to adopt "buy-and-hold" investment strategies in their portfolios, so that green bonds will exhibit lower volatility than other assets in times of high risk aversion. Based on this fact, green bonds might behave more similarly to other green financial instruments, such as clean energy stocks, and show a greater decoupling from ordinary bonds. As a result, green bonds could provide a certain protection against increased uncertainty and instability in traditional markets and better resist financial crisis compared with their mainstream counterparts. Accordingly, the net response of the green fixed income market to economic and financial shocks, mainly during episodes of market turmoil, must be treated as an empirical issue that needs to be examined.

This paper contributes to the extant literature in at least two ways. Firstly, to our best knowledge, this is the first study to analyze the time-frequency dynamics of connectedness in return and volatility across the global green market and a number of conventional financial and energy commodity markets. To this end, the connectedness methodology of Baruník and Křehlík (2018) is applied. The key distinguishing feature of the BK approach is that it provides a unified framework that allows quantifying the strength and direction of connectedness across a group of variables over time and across investment horizons simultaneously. Secondly, this is also the first work that addresses connectedness among the green bond market and several financial and energy markets also including the alternative energy equity market. Green bonds and renewable energy stocks have in common a beneficial effect on the environment. They can be regarded by environmentally conscious investors as close complements and/or substitutes, and green bonds can provide substantial funding for many projects of clean energy companies. Given these shared features, it seems natural to examine the dynamic interactions between both environmentally friendly financial assets.

Our empirical analysis reveals various interesting findings. Connectedness in terms of return and volatility across green bonds and the selected mainstream financial and energy markets mainly occurs at the highest frequency band (up to five days). This implies that shocks are transmitted very quickly across markets and have a very short-term effect as that most of the response takes place in less than a week. However, connectedness at intermediate and lower frequency bands is rather limited, suggesting that the behavior of financial and energy markets at longer time horizons is primarily driven by their own fundamentals. Connectedness is particularly intense between the global green fixed-income market and the global Treasury and investment-grade corporate bond markets. This result can be attributed to the great similarities between green bonds and regular government and high-credit quality corporate bonds. There is also a significant connectedness, especially in the short-term, between the green bond market and the U.S. dollar currency market, although less important than in the case of ordinary bonds. On the contrary, there is only weak connectedness between the green bond market and the general stock market, the renewable energy equity sector and the crude oil market regardless of the time scale. This finding suggests that green bonds offer interesting diversification benefits for investors in general and renewable energy stocks as well as oil-related assets irrespective of their investment horizon. Overall, our results indicate that green bonds do not represent a different asset class, but they closely mirror the performance of government and investment-grade corporate bonds. Despite their environmentally friendly nature, green bonds exhibit a behavior closer to that of regular bonds than to that of other green financial products such as clean energy equities.

The rest of the article is set out as follows. Section 2 provides a brief review of the most prominent literature on the nexus between green bonds and other asset classes. Section 3 describes the methodology employed, while Section 4 introduces the dataset. Section 5 presents and discusses the most relevant empirical results and, finally, some concluding remarks are included in Section 6.

2. Literature review

Since the green bond market has just over a decade of life and its most spectacular growth has taken place from around 2014, the academic research about green bonds is rather limited. Much of this literature has devoted to measure the magnitude of the green bond premium, calculated as the difference of yield between green bonds and regular bonds with similar characteristics in terms of maturity, coupon rate, currency and credit rating.[2] So far, the results of this body of work have not been conclusive. For example, Baker et al. (2018), Hachenberg and Schiereck (2018), Gianfrate and Peri (2019) and Zerbib (2019) find a moderate negative premium in green bonds, indicating that investors are ready to sacrifice some return in exchange for the environmental features of green bonds. In contrast, Bachelet et al. (2019) and Karpf and Mandel (2017) document a positive green bond premium, implying that green bonds are traded at higher yields than their mainstream counterparts.

From another angle, Pham (2016) analyzes the volatility characteristics of the green fixed-income market in comparison with the broader standard fixed-income market. Her results indicate that the volatility clustering in the labeled segment of the green debt market is stronger than in its unlabeled analogue and the general bond market. There are also important volatility spillovers between the green bond market and the traditional fixed-income market. In a related research, Broadstock and Cheng (2019) investigate the determinants of correlation patterns between U.S. green and conventional bond markets using a two-stage methodology. The DCC (Dynamic Conditional Correlation) model of Engle (2002) is first employed to estimate dynamic conditional correlations between green and regular bond prices. Then, the dynamic model averaging framework of Koop and Korobilis (2012) is applied to identify the main macro and market-level determinants of such dynamic correlations. The empirical evidence shows that several macroeconomic conditions, such as news-based sentiment towards green fixed-income securities, crude oil prices and economic activity, are greatly influencing the connection between U.S. green and standard bonds.

Nevertheless, there are only a few recent papers on the co-movement of green bond prices with other relevant financial and energy asset classes. In a very influential contribution, Reboredo (2018) analyzes the dependence structure between the global green bond market and conventional fixed income, equity and energy markets using bivariate copulas. His empirical results indicate that the green fixed-income market is highly integrated with Treasury and

[2] For an updated systematic review of the literature on the existence of a green premium in the green bond market, see the paper by MacAskill et al. (2020).

investment-grade corporate bond markets. Contrarily, prices of green bonds weakly co-move with the stock and energy markets, thus offering interesting diversification opportunities for investors in these markets. Furthermore, green bonds are affected by significant spillovers from Treasury and corporate bond markets, while fluctuations in stock and commodity energy markets exert a negligible influence on the price of green bonds.

In the same vein, Reboredo and Ugolini (2020) address the process of price transmission among the green bond and various financial markets, including Treasury, investment-grade and high-yield corporate bond markets as well as equity, currency and energy markets, than can largely influence the performance of green bonds. To accurately capture the multivariate dependence pattern among markets, a structural VAR (vector autoregressive) model with an identification strategy based on the heteroscedasticity of the return series is used. Their findings reveal that the global green bond market is strongly related to the global government bond and U.S. currency markets and also, although to a lesser extent, to the investment-grade corporate bond market, receiving considerable spillovers from these markets, but transmitting insignificant effects in reverse. However, the green fixed income market is tenuously tied to the high-yield corporate bond, stock and energy markets. In another recent study, Reboredo et al. (2020) explore network connectedness among green bonds and a number of asset classes over several time horizons in the European Union and the U.S. markets. To that end, the spillover index method of Diebold and Yilmaz (2012, 2014) is conducted at different time scales using wavelet multiresolution analysis to decompose the original time series. The empirical results show considerable connectedness across green bonds and Treasury and investment-grade corporate bonds over all horizons in both the European Union and the U.S., although the linkage is slightly higher in the short-term. In particular, it is found that Treasury and corporate bonds are significant drivers of the dynamics of the green bond market, while the influence of shocks in green bond prices on other asset classes is very small. In contrast, green bonds exhibit a weak connection with high-yield corporate bonds, general stocks and energy stocks regardless of the time horizon and the geographic location. These authors also conclude that oil price uncertainty and, to a lesser extent, stock market uncertainty have a notable effect on net spillovers involving green bonds in all the time scales both for the European Union and the U.S.

From a different perspective, Liu et al. (2021) study the dynamic dependence structure and risk spillovers between the green bond market and a number of global and sectoral clean energy markets over time using copula models and conditional Value-at-Risk (CoVaR) methods, respectively. Their results reveal positive time-varying average and tail dependence between green bonds and alternative energy markets. Extreme downward and upward movements in the clean energy market have a spillover effect on the green bond market and vice versa. In addition, the risk spillovers from the renewable energy market to the green bond market are asymmetric, being greater for downside risks than for upside risks.

Our paper clearly falls within the strand of literature focused on the nexus between the green bond market and the major conventional financial and energy markets. In particular, this study is closely related to that of Reboredo et al. (2020) as both works assess connectedness between green fixed-income securities and various asset classes over a number of investment horizons. However, it is worth mentioning that there are some remarkable differences between our contribution and that of Reboredo et al. (2020). From a methodological standpoint, the present paper applies the time-frequency connectedness model of Baruník and Křehlík (2018), while Reboredo et al. (2020) employ a two-step approach. Specifically, they first apply multiresolution analysis based on the discrete wavelet transform to decompose the original time series into different frequency components. Then, they quantify the degree of connectedness between green bonds and a set of asset classes for each time scale or frequency applying the spillover index technique of Diebold and Yilmaz (2012). The main distinctive feature of the BK approach is that it offers a unified framework that enables assessing connectedness over time and across different frequency bands simultaneously using the original time series. Instead, the two-step procedure described above involves a double filtering process of the original series. The series are first filtered when applying the wavelet multiresolution analysis and then they undergo a second filtering in the estimation of the VAR parameters required for the implementation of the Diebold-Yilmaz approach. Therefore, the estimated VAR coefficients computed on data from the wavelet multiresolution analysis might be very persistent and influenced by the specific wavelet function used, which might affect the connectedness results. Furthermore, the fact that each time scale from the multiresolution analysis has a different power spectrum, i.e., the portion of total variance explained by each time scale is distinct, makes it difficult to identify the particular time horizons that contribute most to total connectedness within a system. However, when using the BK framework, spillovers are directly decomposed into frequency bands, so that the identification of the most relevant horizons is easier with this method.

Our research also differs from that of Reboredo et al. (2020) in terms of the geographical areas covered (the global market versus the European Union and the U.S.) and the variables used in the empirical analysis. One critical contribution of this paper is the inclusion of the alternative energy equity sector within the set of financial and energy markets whose connectedness is assessed. No study to date on connectedness across green bonds and other asset classes has explored whether there is a significant transmission of information between green bonds and renewable energy stocks and between these two green investment instruments and the major conventional financial and energy markets. However, given that green bonds and renewable energy equities represent the top two green financial products and green bonds provide an important amount of capital for clean energy firms, this topic deserves greater attention and this work attempts to fill this gap in the literature.

3. Methodology

In this section, we summarize the main features of the methodology of Baruník and Křehlík (2018) used in this study to measure the degree of connectedness between the global green bond market and a number of major conventional financial and energy markets in the time-frequency space. Given that the BK framework has its origin in the spillover index approach of Diebold and Yilmaz (2012, 2014), we first introduce the basic characteristics of the Diebold-Yilmaz technique. The Diebold-Yilmaz spillover index method is built on the generalized version of the variance decomposition of forecast errors of a VAR system proposed by Koop et al. (1996) and Pesaran and Shin (1998) and provides a useful framework to quantify the magnitude and direction of spillovers in the time domain. The fundamental advantage of this generalized approach lies in that its results are invariant to the order of the variables in the VAR process. Spillovers are a popular measure of interdependence or connectedness in a dynamic system of variables within the framework of the literature focused on the mechanism of transmission of information across assets or markets. A change in returns in one asset or market can affect returns in other assets or markets, thus generating the phenomenon known as return spillovers. However, information flows can be transmitted not only in terms of return, but also in terms of volatility. Volatility spillovers occur when volatility in one asset or market triggers volatility in other assets or markets and can also represent an important channel of transmission of information flows. Although a number of alternative econometric methodologies have been proposed in the literature to estimate return and volatility spillovers, the Diebold-Yilmaz approach has become the most commonly used by researchers over the last years. Understanding return and volatility spillovers across assets and/or markets have relevant practical implications for diverse areas, such as portfolio diversification, financial contagion, hedging, market efficiency and systemic risk.

The starting point of the Diebold-Yilmaz method is a covariance stationary VAR(p) process with n variables whose infinite moving average representation is given by:

$$X_t = \sum_{i=0}^{\infty} A_i\, \varepsilon_{t-i} \tag{1}$$

where X_t denotes a $n\ x\ 1$ vector of endogenous variables, A_i are $n\ x\ n$ coefficient matrices, with A_0 being an identity matrix, and ε_t is a vector of error terms. The moving average representation plays a crucial role for understanding the dynamics of the system of variables as it makes possible calculating the variance decompositions.

Under the generalized VAR framework, the portion of H-step-ahead forecast error variance of the ith variable explained by shocks to the variable jth can be computed as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_j\right)} \tag{2}$$

where Σ represents the covariance matrix of the error vector ε_t, σ_{jj} stands for the standard deviation of the error term in the jth equation of Σ, e_i is a $n\ x\ 1$ selection vector that takes the value of one for the ith element and zero otherwise, and A_h denotes a matrix of moving average coefficients at lag h. Thus, it is possible to construct a $n\ x\ n$ matrix $\theta(H) = \left[\theta_{ij}(H)\right]_{nxn}$, where each entry shows the contribution of the variable jth to the forecast error variance of the variable ith.

Following Diebold and Yilmaz (2012), each component of the generalized variance decomposition matrix can be normalized by dividing by the row sum as follows:

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

In this way, a number of system-wide and directional spillover indices that capture the mechanism of transmission of shocks from different perspectives can be calculated using the normalized components of the variance decomposition matrix.

The BK framework can be thought of as an extension of the Diebold-Yilmaz approach that uses the spectral representation of variance decompositions based on frequency responses to shocks, rather than on impulse responses to shocks, to measure connectedness in the frequency domain. According to Baruník and Křehlík (2018), the frequency response function, $\Psi\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-ih\omega} \Psi_h$, can be computed as the Fourier transform of the coefficients Ψ_h, where ω is the frequency and $i = \sqrt{-1}$.

The power spectrum $S_x(\omega)$, which shows how the variance of a series x_t is distributed over the frequency components ω, is a critical tool to understand frequency dynamics. It can be obtained as the Fourier transform of the $MA(\infty)$ filtered series as:

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h}) e^{-ih\omega} = \Psi(e^{-i\omega}) \Sigma \Psi'(e^{i\omega}) \quad (4)$$

Using the spectral representation for covariance, the generalized variance decomposition at a given frequency ω can be derived as:

$$\left(\theta(\omega)\right)_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} \left(\Psi(e^{-ih\omega})\Sigma\right)_{i,j}^{2}}{\sum_{h=0}^{\infty} \left(\Psi(e^{-ih\omega})\Sigma\Psi(e^{ih\omega})\right)_{i,i}} \quad (5)$$

where $\left(\theta(\omega)\right)_{i,j}$ stands for the portion of the spectrum of the ith variable at a given frequency ω that is due to shocks in the jth variable. As illustrated in Eq. (5), the variance decomposition in the BK framework does not depend on the forecast horizon H.

In the context of economic applications, it is often more informative to measure short-, medium- and long-term connectedness separately than focusing on a single specific frequency. Following Baruník and Křehlík (2018), the generalized variance decomposition at a certain frequency band $d = (a, b)$ is defined as:

$$(\theta_d)_{i,j} = \frac{1}{2\pi} \int_a^b \Gamma_i(\omega) \left(\theta(\omega)\right)_{i,j} d\omega \quad (6)$$

where $\Gamma_i(\omega)$ denotes the power of the ith variable at the frequency ω and is given by:

$$\Gamma_i(\omega) = \frac{\left(\psi(e^{-i\omega})\Sigma\psi'(e^{i\omega})\right)_{i,i}}{\frac{1}{2\pi}\int_{-\pi}^{\pi} \left(\psi(e^{-i\lambda})\Sigma\psi'(e^{i\lambda})\right)_{i,i} d\lambda} \quad (7)$$

Just like in the time domain, the normalized generalized variance decomposition at the frequency band d can be obtained as:

$$\left(\tilde{\theta}_d\right)_{i,j} = \frac{(\theta_d)_{i,j}}{\sum_j (\theta_\infty)_{i,j}} \quad (8)$$

where $(\theta_\infty)_{i,j}$ denotes the contribution over all frequencies.

Analogously to the time domain method of Diebold and Yilmaz (2012), a number of alternative total and directional connectedness measures can be introduced in the frequency domain. For instance, the *within connectedness* at the frequency band d is given by:

$$C_d^W = 100 \left(1 - \frac{Tr\{\tilde{\theta}_d\}}{\sum \tilde{\theta}_d}\right) \quad (9)$$

where $Tr\{\cdot\}$ is the trace operator and $\sum \tilde{\theta}_d$ denotes the sum of all elements in the $\tilde{\theta}_d$ matrix.

The within connectedness measures solely connectedness that takes place within the frequency band of interest, without taking into account the importance of fluctuations at this band with respect to all fluctuations. In order to get a connectedness measure that captures the contribution of a certain band to total or aggregate connectedness, the *frequency connectedness* at band d, C_d^F, can be defined as:

$$C_d^F = C_d^W \frac{\sum \tilde{\theta}_d}{\sum \tilde{\theta}_\infty} \tag{10}$$

Importantly, the frequency connectedness allows decomposing the original Diebold-Yilmaz connectedness index into different parts. Hence, the total spillover index introduced by Diebold and Yilmaz (2012) can be obtained as the sum of the connectedness measures corresponding to all frequency bands. In addition, total frequency connectedness can be employed to compute directional connectedness measures, such as directional frequency connectedness from the other variables to the ith variable or from the ith variable to the rest of variables.

4. Data description

To investigate connectedness between the global green bond market and a number of key conventional financial and energy markets, time series data reflecting the performance of each market are required. Following Reboredo (2018) and Reboredo and Ugolini (2020), the *Bloomberg Barclays MSCI Green bond index* (GBI) is used as a proxy for the financial performance of the global green bond market. This index was launched in November 2014 and has become the most widely employed green bond index. All the securities that make up this index are rated investment-grade and have fixed-rate coupons.[3]

As for the mainstream financial markets, the global Treasury and corporate bond markets are accounted for the *Bloomberg Barclays Global Treasury total return index* and the *Bloomberg Barclays Global Aggregate Corporate index*, respectively. In particular, the Bloomberg Barclays Global Treasury total return index tracks local currency fixed-rate sovereign debt issued by investment grade developed and emerging countries. Instead, the Bloomberg Barclays Global Aggregate Corporate index is a reference indicator of global investment grade fixed-rate corporate debt. In turn, the overall stock market is approximated for the *MSCI world index*, which captures the performance of around 1,600 large and mid-cap stocks across 23

[3] It is worth highlighting that this index has been appointed as the best green bond index at the Environmental Finance Green Bond Awards for the years 2016, 2017 and 2018.

developed countries, covering around 85% of the free-float market capitalization in each country. Furthermore, the *trade-weighted U.S. dollar index (TWEXB)*, which is a weighted average of the value of the U.S. dollar relative to the currencies of major U.S. trading partners, is used to track the dynamics of the currency market. Since green bonds are issued in over 30 different currencies and the GBI is calculated in U.S. dollars, movements in the exchange rate of the U.S. dollar can cause fluctuations in the GBI simply by the effect of currency conversion. Additionally, the *RENIXX world index* is an indicator of the market performance of the global renewable energy industry. RENIXX world is the first international industrial stock index for clean energy and is composed of the 30 largest companies worldwide in the field of alternative energies. This index is considered to assess whether there is a significant transmission of information between clean energy stocks and green bonds as both financial assets belong to the category of renewable energy, being their ultimate goal obtaining funds to finance alternative energy projects. Lastly, the *Brent oil price* is utilized as a proxy for the global crude oil market.[4] Oil price dynamics can influence the financial performance of green bonds as lower crude oil prices lead to increased oil demand and reduce economic viability of many green projects financed through green bonds.

Daily closing prices of all these series are used. The sample period runs from October 14, 2014 to December 19, 2019, totalling 1348 daily observations. The starting date is conditioned by the availability of data for the green fixed-income market. Daily returns are calculated as first log differences of closing prices. The data on green, Treasury and corporate bond and global and renewable stock price indices are extracted from Bloomberg, while data on the Brent crude oil and the TWEXB are gathered from the FRED database.

Table 1 presents the descriptive statistics of return series. All mean daily returns are close to zero and small compared to their standard deviations, implying relatively high volatility in all markets. Based on standard deviations, the crude oil market is much more volatile than the rest of markets, probably due to the wild price swings of oil since the early 2000s. As expected, the volatility of the fixed income markets is considerably lower than that of the general and renewable energy stock markets. The skewness coefficient is negative for the majority of series, suggesting that they are skewed to the left. In turn, the kurtosis measure is always greater than 3, indicating that all series are leptokurtic. This deviation of normality is corroborated by the

[4] The Brent crude oil price is employed in this study because it has become the primary international benchmark for oil pricing in recent years. Nowadays, roughly two-thirds of all crude oil contracts around the world use the Brent oil as a reference.

Jarque-Bera (JB) test statistics, which reject normality of the distribution for all return series at the 1% level. In addition, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests as well as the Kwiatkowski-Phillips-Schmidth-Shin (KPSS) stationarity test confirm that all return series are stationary at the 1% level. Lastly, the Pearson correlation coefficients show that global green bond returns are highly positively correlated with global Treasury bond returns (+0.891) and global investment-grade corporate bond returns (+0.880), suggesting a strong co-movement between the different fixed income markets.

Insert Table 1 here

5. Empirical findings

In this section, we present the results of connectedness in terms of return and volatility based on the BK methodology. Since the central purpose of this study is to analyze the time- and frequency-varying nature of connectedness between the global green bond market and a group of conventional financial and energy commodity markets, we focus exclusively on the dynamic connectedness measures. Three different frequency bands, which can be interpreted as different horizons from an investment perspective, are considered to assess the time persistence of connectedness across green bond and mainstream markets. Following Baruník and Křehlík (2018), Jiang et al. (2019) and Wang et al. (2020), among others, the first spectral band captures movements from 1 up to 5 days, i.e., one business week, and, therefore, can be associated with the short-term. The second frequency band corresponds to movements between 6 and 22 days, i.e., from one business week to approximately one business months, and represents the medium-term. In turn, the third band captures movements in the time frame of 23 to 200 days, i.e., from more than one business months to around 9 business months, thus representing the long-term. Note that the edge of the lowest frequency band is determined by the length of the rolling window considered. [5] The findings of the Diebold-Yilmaz spillover index method are also reported to get a first overview of the time dynamics of spillovers across markets. In line with Ferrer et al. (2018), Li et al. (2020) and Lovcha and Perez-Laborda (2020), among others, the dynamic connectedness measures are obtained based on a rolling window size of 200 days. Moreover, a 100 day forecast horizon is employed following the seminal paper of Baruník and Křehlík (2018), even though the BK framework is independent of the chosen forecast horizon.

[5] Furthermore, it is worth mentioning that various alternative frequency bands have been considered to evaluate the robustness of our empirical results. In all cases, the results are quantitatively and qualitatively the same to those obtained with the particular specification of frequency bands used in our empirical analysis.

A VAR model with two lags based on the Schwarz information criterion is used to describe the dynamics in each window.

A variety of alternative symmetric and asymmetric GARCH-type specifications under different error distributions, such as normal, Student-t, generalized error distribution and skewed t-distribution, have been considered to estimate the conditional variance of the time series under scrutiny. The results show that the EGARCH (1,1) model with skewed t-distribution gives the best fit for most of the series when using the Akaike and Schwarz information criteria. [6] Consequently, the conditional variance of each series to be utilized in the volatility connectedness analysis is estimated through this specification. The univariate EGARCH model allows capturing the asymmetric effect of positive and negative innovations in the volatility process. It is also assumed that the residuals of the return series follow a skewed t-distribution (Hansen, 1994), which enables describing better the asymmetric and fat tail features of the return series.

5.1. Dynamic total return and volatility connectedness measures

Figure 1 plots the dynamics over time of the total spillover indices in return and volatility based on the Diebold-Yilmaz approach. Total return and volatility spillovers exhibit a similar pattern and are relatively significant for most of the sample period, even though the value of return spillovers is slightly bigger than that of volatility spillovers. In particular, total return spillover effects range from 43.04 to 57.07%, while total volatility spillovers fluctuate between 30.59 and 46.51%. This evidence suggests that there is a significant transmission of information in both return and volatility across the global green bond market and the set of conventional financial and energy markets under analysis throughout the whole sample period. Interestingly, there is considerable time variation in system-wide return and volatility spillovers, with the highest levels being observed in the first part of the sample (between late 2016 and early 2017). There is a decline in connectedness from 2017 onward, which can be explained by a combination of several factors. First, international equity and fixed income markets benefited from an environment of synchronized global economic growth and modest inflation since early 2017. Second, the level of stock market volatility was historically low. More precisely, during most of 2017, the VIX index had lowest values than in March 2007, just before the start of the subprime mortgage crisis in the U.S. Third, measures of business and consumer confidence hit record high levels during this period. This accumulation of positive news could lead to a

[6] The estimation results of the different GARCH-type models are not shown here for the sake of brevity, but they are available from the authors upon request.

relaxation in the perception of risk in financial and energy markets by market participants, resulting in a lower degree of transmission of shocks across markets during the last part of the sample.

Insert Figure 1 here

Figure 2 displays the time-frequency dynamics of total return and volatility connectedness calculated on the basis of the BK methodology. As can be seen, the total connectedness measures in return and volatility follow a similar pattern, even though the value of return connectedness is slightly higher than that of volatility connectedness over the entire sample. Importantly, the measures of total connectedness both in return and volatility are much larger at the highest frequency band than at the intermediate and lowest bands. This means that the greatest portion of return and volatility connectedness is created at the highest frequencies (up to five days) over the full sample period. This result suggests that green bond and mainstream financial and energy markets process information rapidly and shocks are propagated across markets mainly in the very short-term, generating responses with persistence less than one week. It is also worth highlighting that the sum of short-term, medium-term and long-term connectedness depicted in Figure 2 is equal to the total spillover index for a single time horizon based on the Diebold-Yilmaz approach displayed above in Figure 1.

Moreover, short-term connectedness reaches its peak during the first part of the sample (late 2016 and early 2017), which is in line with the hypothesis of a certain relaxation in the perception of risk in markets from the beginning of 2017 due to the good progress of the world economy and increased business and consumer confidence. Our empirical evidence is also in tune with that of Reboredo et al. (2020). Despite using a different methodology and different geographical areas to quantify connectedness across green bonds and several asset classes, Reboredo et al. (2020) also document strong spillovers in the short-term between the green fixed-income market and various mainstream financial and energy markets in both the European Union and the United States.

The prevalence of the short-term as the main source of connectedness can be seen as consistent with a general scenario of decreasing uncertainty, growing and relatively stable financial markets and low levels of risk aversion. As contended by Baruník and Křehlík (2018), under these circumstances shocks are quickly transmitted across markets, but, in the absence of fundamental changes in investors' expectations, the impact of shocks has little persistence and disappears after a few days. Likewise, the low connectedness in return and volatility at longer horizons (more than 5 days) confirm that spillovers among green bonds and conventional markets are typically short-lived. Thus, it appears that the behavior of this group of markets in the medium- and long-term is mostly driven by their own idiosyncratic factors. Furthermore, this evidence suggests the existence of feasible diversification opportunities in the medium- and long-term in portfolios combining green bonds with traditional financial and energy-related assets.

Insert Figure 2 here

5.2. Directional connectedness network results

In this sub-section, we turn attention to directional information to gain a better insight into the intensity of directional connectedness among the green bond market and the conventional financial and energy markets. To that end, the network graphs that capture return and volatility connectedness between each pair of markets over the full sample period are plotted.

Figure 3 shows the network graphs depicting average pairwise directional spillovers in return and volatility over the whole sample based on rolling window estimates of the Diebold-Yilmaz approach. The node size is proportional to the contribution of each market to system-wide spillovers, while the node color refers to the direction of spillovers. In particular, the red color reflects the extent to which the market of interest acts as a transmitter of spillovers to the rest of markets, while the green color shows the degree to which that market is a net receiver of spillovers from the remaining markets. Hence, the predominance of red (green) color implies that the market of interest is a net transmitter (receiver) of spillovers. Moreover, the color and thickness of edges connecting pairs of markets represent the strength of spillovers. Specifically, edges in red color and full lines indicate spillovers greater than 20%, edges in green color and dashed lines imply that the magnitude of spillovers is between 10% and 20%, and edges in blue color and dotted lines reflect spillovers between 1% and 10%. Spillovers with value lower than 1% are omitted from the plots for the purpose of clarity.

There are strong spillover effects in both return and volatility between the global green bond market and the global Treasury and investment-grade corporate bond markets and, to a lesser extent, the foreign exchange market. This result is not surprising in view of the fact that a large fraction of green bonds is issued by the same governments, supranational institutions and companies that issue most of the conventional Treasury and investment-grade corporate bonds. Therefore, green bonds share remarkable similarities with regular bonds in terms of issuers, credit risk, coupon rates and maturity, which justifies the considerable connectedness between the green bond market and the standard fixed-income markets. One major implication of this finding is that green bonds allow environmentally conscious investors to maintain their commitment to the fight against climate change without sacrificing a significant part of financial return. It should be also stressed that the close tie between green bonds and Treasury and investment-grade corporate bonds is totally consistent with the evidence provided by Reboredo (2018) and Reboredo and Ugolini (2020).

Furthermore, noticeable return and volatility spillovers are observed in the two possible directions, i.e. running from standard government and investment-grade corporate bonds to green bonds and also running from green bonds to conventional government and corporate fixed income securities. The transmission of shocks from the green bond market to the traditional bond market could be striking a priori, given that the green fixed-income market only accounts for a tiny portion of the overall bond market. However, a possible explanation for these bidirectional spillovers is that, as mentioned above, there is a large common ground between green bonds and regular bonds in terms of issuers, credit quality, maturity, currency, etc. Consequently, green bonds and their mainstream counterparts tend to be affected by the same factors, so that they act simultaneously as receivers and transmitters of shocks. This finding means that investing in green bonds does not generate significant diversification opportunities for investors in ordinary government and high-credit quality corporate bonds. It is worth noting that our findings are different to those of Reboredo and Ugolini (2020), who detect sizeable spillovers from regular bond markets to the green bond market, but not in the opposite way. This dissimilarity in results can be explained by the difference in terms of empirical methodology between our study and that of Reboredo and Ugolini (2020).

Bidirectional return and volatility spillovers, but not as intense as in the previous case, are also found between the green bond market and the currency market. This relevant transmission of information may have its origin in the fact that green bonds are denominated in over 30 different currencies, in such a way that large movements in the exchange rate markets can have an impact on the value of green bond portfolios held by international investors. Simultaneously, the green bond market seems to have a certain ability to anticipate fluctuations in foreign exchange markets. This result is in fully accordance with Reboredo and Ugolini (2020), who document a close association between the green fixed-income market and the U.S. dollar currency market.

In contrast, spillovers in return and volatility between the green bond market and the general stock market, the renewable energy stock sector and the crude oil market are quite low or even non-existent over the entire sample. Specifically, there are no spillovers in return and volatility between green bonds and general stocks, which implies that green bonds offer attractive diversification benefits for stock market investors. The lack of a significant link between green bond and equity markets can be explained not only by the different types of assets traded in both markets, but also by the disparity in preferences, investment objectives and risk tolerance of the average investor in each of these markets. This evidence is in agreement with that of Reboredo (2018) and Reboredo and Ugolini (2020), who also report a weak connection between the green bond market and the overall stock market.

Spillover effects between the global green bond market and the renewable energy equity sector are rather weak in return and non-existent in volatility. One plausible explanation for this finding is that, apart from sharing the objective of supporting environmental sustainability, investors in the green bond market are different from investors in the clean energy stock sector. It must be borne in mind that green bonds are, above all, a category of bonds, so that green bond investors tend to have a more conservative profile and are more risk averse than investors in alternative energy stocks. Thus, this divergence in terms of investment profile and risk aversion could play a central role in the absence of a strong linkage between green bonds and renewable energy equities. A key implication of this finding is that investors with a marked environmental focus can regard green bonds as a useful complement to clean energy stocks in terms of diversification and hedging strategies without abandoning their core concerns about sustainability and climate change mitigation.

Lastly, the oil market exhibits the weakest connectedness with the rest of markets. Interestingly, there are no significant spillovers in return and volatility between green bonds and crude oil despite the substitutive character between renewable energy and oil and that green bonds are employed to finance many renewable energy-related projects. This decoupling indicates that the boom of the global green bond market over the past few years has taken place regardless of the behavior of crude oil prices. In this regard, it is worth pointing out that the revolution of the shale oil in the U.S. has transformed the dynamics of the oil market in recent years, contributing to explain the absence of a close linkage between the crude oil market and the general financial markets. The U.S. shale oil boom refers to the unprecedented surge in shale oil production in the U.S. since the late 2000s, which was caused by a technological breakthrough based on the combination of hydraulic fracturing and horizontal drilling. From investors' perspective, this finding indicates potential diversification benefits from including green bonds into a portfolio of oil-related assets. This evidence is consistent with that of

Reboredo (2018) and Reboredo and Ugolini (2020), who also fail to detect a high interdependence between the green bond market and the energy commodity markets.

Insert Figure 3 here

5.3. Hierarchical clustering analysis

As a robustness check of the above spillover results, a hierarchical clustering analysis is undertaken in this section. Hierarchical clustering is a well-known technique in biological sciences and has just been recently employed in the economic and financial literature (Smiech et al., 2020; Sim et al., 2021). This method allows grouping a set of assets or markets into subgroups that share numerous common features. In this section, the hierarchical clustering is conducted on the pairwise spillover results of the Diebold-Yilmaz approach, so that the set of markets under study are grouped in clusters with similar characteristics in terms of transmitted and received spillovers. The starting point of our hierarchical clustering analysis is the $n \times n$ asymmetric matrix whose elements capture the spillover effects between all possible pairs of markets resulting from the Diebold-Yilmaz approach.

Following Borg and Groenen (2005), any square asymmetric data matrix Q can be uniquely decomposed into the sum of a symmetric matrix and a skew-symmetric matrix as follows:

$$Q = S + K \tag{11}$$

where S denotes a symmetric matrix and K is a skew-symmetric matrix. [7] The element s_{ij} of S shows the average amount between objects i and *j,* while the element k_{ij} of K describes the departures from symmetry between i and *j,* i.e., the difference with respect to the mean s_{ij}. In the context of the present study, the elements s_{ij} are calculated as averages $(\theta_{ij} + \theta_{ji})/2$ and the elements k_{ij} are computed as $(\theta_{ij} - \theta_{ji})/2$, being θ_{ij} and θ_{ji} the spillover received by the market i from the market j and the spillover transmitted from the market i to the market j, respectively. The S matrix represents the similarity or connectedness between the markets under study, while the elements of the skew-symmetric matrix reflect the lack of balance or reciprocity between transmitted and received spillovers.

Given that S and K are orthogonal matrices, the cross-products are all equal to zero. Hence, the sum of squares of the matrix Q can be also decomposed into a sum of squares as:

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \theta_{ij}^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} s_{ij}^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij}^2 \tag{12}$$

[7] A skew-symmetric data matrix K is a square matrix in which $K^T = -K$.

Therefore, the two components of spillovers can be treated independently. A related result is that the matrix S is the best symmetric approximation to the matrix Q in the least squares sense. Therefore, the matrix S plays a key role in clustering analysis, providing a simple and effective description of the process of transmission of information within our set of markets. The elements of S measure the average intensity of pairwise spillovers between markets. The larger the s_{ij}^2 value, the greater the transmission of information between i and j markets. To perform hierarchical clustering, S needs to be transformed in a distance matrix that contains the distances between all pairs of markets. To do this, the diagonal elements of S are first removed. Then, the formula $100 - s_{ij}$ is used for all non-diagonal elements of S. The resulting matrix can be viewed as a distance matrix and is employed to construct the clusters. The homogeneous clusters are generated under the assumption that the shorter the distance between a pair of markets, the higher the similarity between them.

Figure 4 displays the map of clusters across the green bond market and the selected conventional financial and energy markets based on the application of hierarchical clustering. Plot A refers to the clusters formed on the basis of return spillovers, while Plot B shows the clusters arising from volatility spillovers. The smaller the distance between two markets in the graph, the higher the similarity between them. Different colors are utilized to distinguish the clusters. The results of the clustering analysis are very similar when considering return spillovers or volatility spillovers. In particular, three clusters can be distinguished in Figure 4. The first cluster is composed of the green, Treasury and investment-grade corporate bond markets and, to a lesser extent, of the currency market. The close proximity of green, government and investment-grade corporate bonds confirms the evidence of previous network analysis based on the Diebold-Yilmaz approach (see Figure 3), showing that green bonds closely mirror the performance of Treasuries and high-quality corporate bonds. As expected, the level of connection between green bonds and the currency market is less relevant than in the case of ordinary bonds. The second cluster is made up of the general stock market and the renewable energy equity sector. This composition is not surprising as the clean energy sector is an important component of the overall stock market and, hence, it seems logical that there is a strong transmission of shocks between them. Finally, also in line with the network analysis results, the crude oil market seems to be totally disconnected not only from the green bond market but also from the conventional financial markets.

Insert Figure 4 here

5.4. Directional connectedness network results by frequency

Figure 5 and 6 plot the network graphs depicting average pairwise directional connectedness in return and volatility, respectively, based on the rolling window estimates of the BK framework for the three frequency bands over the entire sample. Plot A of each figure refers to the short-term (up to 5 days), while Plots B and C are associated to the medium-term (from 6 to 22 days) and the long-term (from 23 to 200 days), respectively. Considerations on size and color of nodes and color and thickness of edges are identical to those described in Figure 3. It can be observed that return and volatility connectedness follow a very similar pattern over the three time horizons. The most striking feature is that the magnitude of connectedness in both return and volatility is much higher at the shortest horizons (up to 5 days) than at the intermediate and longest horizons for the full sample period. This result confirms that most of the connectedness is generated at the highest frequencies, so that shocks are transmitted across green bond and conventional financial and energy markets primarily in the short-term, although their impact is short-lived (up to one trading week). In fact, the pattern of connectedness in the shorter horizon is quite similar to that given in the time-domain Diebold-Yilmaz approach (see Figure 3). The predominance of information transmission in the very short-term is also in accordance with the evidence on total connectedness reported in Figure 2.

The strongest connectedness in terms of return and volatility is observed in the short-term between the global green bond market and the global Treasury and investment-grade corporate bond markets, showing up in the two possible directions. This result can be thought of as a direct consequence of the fact that, apart from greenness criteria, green bonds have numerous common characteristics with conventional government and investment-grade corporate bonds, such as credit quality, issuers, coupon rates and maturity. Moreover, this pronounced short-term connectedness shows the inability of investors to benefit from diversification opportunities between green bonds and regular bonds with high credit quality in the short-tem. This evidence is in agreement with that of Reboredo et al. (2020), who document a close tie, particularly in the short-term, between the government and corporate bond markets and the green bond market in both the European Union and the United States. However, connectedness across green and regular bonds is weaker in the medium- and long-term, reflecting that idiosyncratic factors specific to each market play a more prominent role at longer horizons.

A significant connectedness, though not as pronounced as in the case of conventional bonds, is also found between the green fixed-income market and the currency market. This connectedness appears primarily in terms of return and is more apparent at shorter horizons.

The transmission of information across these two markets can be attributed to the fact that green bonds are issued in around 30 different currencies worldwide. Thus, exchange rate movements can affect the value of portfolios of green bonds denominated in a variety of currencies. Moreover, it appears that the green bond market is able to anticipate future short-term movements in forex markets. An interesting implication of this finding is that international investors in green bonds seem to be exposed to substantial fluctuations in the currency markets in the very short-term. Connectedness between the global green fixed-income market and the currency market weakens considerably, however, in the medium- and long-term, suggesting that these two markets are mainly driven by their own idiosyncratic circumstances at longer time horizons.

Nevertheless, no return and volatility connectedness is found between the world green bond market and the general equity market regardless of the investment horizon. This result is fully consistent with that obtained in the network analysis when considering a single time horizon or frequency (see Figure 3). The lack of connectedness can be related to large differences in terms of expectations, preferences, environmental commitment and risk aversion between the average investor in general equity and green bond markets, which causes the dynamics of both markets to be completely independent, irrespective of the time horizon. Similarly, Reboredo et al. (2020) conclude that the propagation of shocks across green bonds and general stocks in the European Union and the U.S. is negligible in the short, medium and long horizons. Likewise, there is a very weak connectedness across the global green bond market and the renewable energy equity sector. In fact, the only evidence of connectedness across these markets is observed in terms of return at shorter horizons, though its magnitude is rather limited. This near-total absence of connectedness across different time horizons, despite the environmental-friendly nature of both markets, can be attributed to the considerable disparity in risk profile and attitude toward risk between investors in green bonds and clean energy stocks.

Additionally, there are no return and volatility connectedness between the global green bond market and the crude oil market regardless of the time horizon, confirming that the development of the global green fixed-income market over the past few years has been totally decoupled from the oil price. In the same vein, Reboredo et al. (2020) provide evidence of a very weak transmission of shocks between the green bond market and the energy market across short, medium and long time scales in the European Union and the U.S. From a similar perspective, Ferrer et al. (2018) also find no significant connection across different time horizons between the crude oil market and another green financial asset such as the renewable energy stocks. It is also worth highlighting that the international oil market shows the lowest level of connection with the remaining conventional financial markets for all the investment horizons. This finding can be explained by the singular dynamics of the oil market during the last few years, which has been highly influenced by a major development such as the boom of shale oil production in the U.S. since the late 2000s. As a matter of fact, the U.S. became the world's biggest crude oil producer in 2018, surpassing Saudi Arabia and Russia, thanks to the shale oil revolution. Several recent works, including Bataa and Park (2017) and Kilian (2017), have demonstrated that the boom of the U.S. shale oil production has played a vital role in the development of oil prices since mid-2014.

Insert Figure 5 here

Insert Figure 6 here

5.5. Hierarchical clustering analysis by frequency

Finally, a hierarchical clustering analysis conducted on the connectedness estimates of the BK framework is performed to identify groups of markets with similar characteristics in terms of directional connectedness at different frequency bands. The explanation of hierarchical clustering provided in Section 5.3 is valid for this Section, with the only particularity that in this case the homogeneous clusters are constructed based on the results of the connectedness BK framework for the three different frequency bands considered. The output of the hierarchical clustering analysis between the green bond market and the selected traditional financial and energy markets is graphically represented in Figures 7 and 8. Figure 7 refers to the clusters constructed on the basis of results of return connectedness, while Figure 8 shows the clusters obtained when considering the results of volatility connectedness. Furthermore, Plot A of each figure reports the map of clusters for the short-term (up to 5 days), while Plots B and C refer to the medium-term (from 6 to 22 days) and the long-term (from 23 to 200 days), respectively. Different colors are used for separate clusters.

The results of the hierarchical cluster analysis are very similar for return connectedness and volatility irrespective of the time horizon and also entirely consistent with those of the clustering analysis based on the Diebold-Yilmaz approach displayed in Figure 4. Specifically, the whole set of markets under consideration can be classified into three clusters. The first cluster comprises the global green bond, Treasury and investment-grade corporate bond markets and, to a lesser degree, the currency market. This finding corroborates once again the close ties between green bonds and Treasury and high-credit quality corporate bonds. The second cluster is formed by the general stock market and the renewable energy equity sector. The rationale for this grouping is that the renewable energy sector constitutes a large component of the overall stock market in such a way that it is perfectly logical to find an important degree of connectedness between alternative energy stocks and general stocks. In addition, the third cluster only includes the crude oil market, which is consistent with the notion that the shale oil revolution in the U.S. has totally conditioned the dynamics of the global oil market in recent years, thus leading to a decoupling of the crude oil market from the traditional financial markets.

Insert Figure 7 here

Insert Figure 8 here

5.6. Wavelet methods

In this sub-section, we evaluate the robustness of our empirical findings about interdependence between the global green bond market and the conventional financial and energy markets at distinct frequencies from a different perspective using wavelet analysis. In particular, two relatively novel wavelet tools, such as the wavelet correlation introduced by Rua (2010) and the wavelet-based Granger causality test developed by Olayeni (2016), are employed for that purpose. Firstly, the wavelet correlation measure of Rua (2010) can be thought of as a correlation coefficient that allows assessing the degree of comovement of two time series in the time and frequency domains simultaneously. This measure is analogous to the traditional correlation coefficient in the time domain and ranges between -1 and 1. Secondly, the wavelet-Granger causality method of Olayeni (2016) can be viewed as an extension to the time-frequency space of the traditional Granger causality test originally proposed in the time domain. The approach of Olayeni (2016) is based on the combination of wavelet techniques and Granger causality analysis and enables one to identify in what particular time periods and frequencies the causal relations are more intense. In line with the main aim of the paper, this robustness analysis focuses on the linkage between the green bond market and each mainstream market.

Figure 9 displays the results of the wavelet correlation and the wavelet-based Granger causality method of Olayeni (2016) between green bonds and each of the conventional financial and energy markets. Wavelet correlation and causal relations are illustrated through contour plots as there are three dimensions involved: frequency, time and magnitude of the correlation or causal link. The strength of wavelet correlation and causal effects is denoted by a color code, which ranges from dark blue (high negative wavelet correlation or lack of causal effects) to dark red (strong positive wavelet correlation or causal effects). The results of both wavelet techniques are broadly consistent with those of the BK framework. As evidenced by the large areas with predominant dark red color in some graphs of this figure, the strongest connection in terms of both wavelet correlation and causal links appears once again between green bonds and Treasury and investment-grade corporate bonds. This relationship tends to be more pronounced at higher frequencies (short-term), although there are also some areas with significant positive wavelet correlation and causal linkages in the two possible directions at intermediate (medium-term) and lower frequencies (long-term). Moreover, the wavelet methods show a clear prevalence of the dark blue color in the graphs of wavelet correlation and wavelet-based causal flows. This finding suggests a rather weak link between the green fixed income market and the general stock market, the clean energy equity sector and the crude oil market regardless of the frequency and time period. Therefore, this evidence confirms that the close association observed between green bonds and ordinary bonds is not the result of the application of a particular empirical methodology such as the BK framework, but it may be attributed to the numerous characteristics shared by green and regular fixed income securities.

Insert Figure 9 here

6. Concluding remarks

Green bonds have become one of the most promising financial mechanisms to raise money for environmentally friendly projects that accelerate the decarbonization of the economy necessary to mitigate climate change. The explosive growth of issued green bonds during recent years has prompted a surge of interest in understanding the transmission of information between the green bond market and the conventional financial and energy markets over different investment horizons. Such knowledge is critical to assess correctly the risk-return profile of green bonds and the resilience of the green fixed income market to economic and financial shocks as well as to properly promote transition to sustainable economic development. This paper intends to elucidate if green bonds are actually a different class of asset with a behavior substantially different from that of the most popular mainstream assets. For that purpose, we examine connectedness across the green fixed-income market and a set of traditional financial and energy commodity markets in the time-frequency space. To this end, the methodology proposed by Baruník and Křehlík (2018), which provides a unified framework to characterize the dynamics of connectedness in time and frequency simultaneously, is applied. Another major contribution of this work is the inclusion of the clean energy equity sector in the connectedness analysis to check whether the environmental-friendly nature shared by green bonds and renewable energy stocks translates into a significant level of interdependence between both green financial products.

Our empirical findings reveal that return and volatility connectedness between the global green bond market and the selected traditional markets primarily occur at shorter time horizons (up to five days), indicating that shocks are rapidly transmitted across markets with an effect lasting less than a week. The weaker connectedness in the medium- and long-term is, however, consistent with the notion that at longer horizons financial and energy commodity markets are mostly driven by their own idiosyncratic factors. The strongest connectedness is found between the global green bond market and the global Treasury and investment-grade corporate bond markets. This result can be related to the fact that green bonds share many similarities with regular high-quality bonds in terms of issuers, credit rating, maturity, currency, coupon rates, etc. Thus, this noticeable bidirectional connectedness suggests that green bonds cannot be regarded as a different asset class, but they are fundamentally substitutes and/or supplements of more traditional fixed income securities in investment portfolios. In short, one of the principal features of green bonds is that they allow investors to integrate climate risk in their portfolios while exhibiting a similar profile of risk and return to that of Treasury and investment-grade corporate bonds. There is also a significant connectedness in return and volatility, mainly at the short-term, between the global green bond market and the currency market, although to a lesser degree than in the case of standard bonds. The fact that green bonds are denominated in a wide range of currencies makes the value of many international green bond portfolios susceptible to large fluctuations in the forex market.

Nevertheless, connectedness in return and volatility across the green fixed income market and the general stock market, the renewable energy equity sector and the crude oil market is quite limited regardless of the time horizon considered. One interesting implication of this evidence is that, despite their similar environmental-friendly nature, green bonds and clean energy stocks are essentially different asset classes, with distinct risk and return characteristics and aimed at different types of investors. Therefore, the level of connectedness between these two climate-friendly financial products is not at all comparable to that existing between green bonds and regular bonds. Furthermore, the lack of connectedness between green bonds and the crude oil market suggests that the behavior of the global green bond market in recent years has been virtually unaffected by oil price developments. It is also worth mentioning that connectedness in return and volatility between the oil market and the remaining financial markets is negligible for all time scales. The shale oil boom in the U.S. since the late 2000s may have played a key role in this decoupling.

A number of useful implications for several economic actors in terms of portfolio investment and hedging strategies, financial stability preservation and sustainability policy emerge from our empirical evidence. Investors and portfolio managers should keep in mind that the inclusion of green bonds in portfolios mostly composed of traditional financial assets, particularly Treasury and investment-grade corporate bonds, does not offer significant diversification benefits, especially in the very short-term. In contrast, green bonds, aside from their environmental or climate benefits, appear as an attractive diversification opportunity for investors in general stocks, renewable energy stocks and oil-related assets, mainly at horizons longer than one week. It should be also highlighted that green bonds represent a viable alternative to renewable energy equities to diversify the portfolio risk of investors with environmental concern without renouncing the commitment to fight against climate change. Moreover, the weak linkage between green bonds and other kinds of assets, like general and clean energy stocks and oil-related assets, gives issuers of green bonds the ability of expanding their base of investors by attracting investors seeking to diversify the risk of their portfolios made up of conventional assets. In addition, the similar profile of risk and return of green bonds compared with ordinary bonds indicates that it is perfectly possible to back the fight against climate change through investment in green fixed income securities without sacrificing a significant part of financial performance. On the other hand, policy makers concerned about preserving financial stability should be aware that the green bond market is vulnerable, particularly in the short-term, to the same risk factors that affect conventional financial markets. Therefore, it is really difficult to avoid that the green fixed income market experiences huge losses in the short-term during episodes of major financial turmoil. Finally, a large part of the success of sustainability policies supporting the expansion of the green bond market as a powerful tool to raise funds to combat climate change depends on those policies having a marked long-term orientation not disrupted by turbulence in financial markets lasting a short time. To sum up, green bonds, beyond their diversification and hedging properties, can help meet the growing demand for environmentally and socially responsible investment by funding projects that contribute to environmental sustainability and, therefore, they could play a relevant role in the solution to the climate change crisis.

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Table 1. Descriptive statistics and correlations for asset returns

	Green Bond	Renewable	Stock	Treasury	Corporate	TWEX	Oil
A. Descriptive statistics							
Mean	0.004	0.044	0.026	0.005	0.011	0.016	-0.022
Minimum	-1.602	-6.144	-5.029	-2.074	-1.080	-1.992	-8.083
Maximum	1.600	7.457	3.040	1.909	1.055	1.652	11.070
Std. Dev.	0.333	1.217	0.708	0.361	0.247	0.297	2.227
Skewness	-0.153	-0.230	-0.730	-0.053	-0.378	0.040	0.309
Kurtosis	4.574	7.485	7.296	5.578	4.514	6.207	5.098
J-B	142.7***	1129.1***	1143.7***	369.7***	159.1***	571.7***	265.5***
ADF	-38.03***	-31.86***	-31.12***	-36.16***	-38.67***	-35.52***	-35.73***
PP	-38.11***	-31.71***	-30.82***	-36.17***	-38.62***	-35.50***	-35.78***
KPSS	0.194	0.097	0.043	0.124	0.295	0.239	0.204
B. Correlation matrix							
Green Bond	1.000						
Renewable	-0.242***	1.000					
	(-9.107)						
Stock	0.022	0.477***	1.000				
	(0.796)	(19.78)					
Treasury	0.891***	-0.303***	-0.125***	1.000			
	(71.59)	(-11.58)	(-4.593)				
Corporate	0.880***	-0.153***	-0.050*	0.839***	1.000		
	(67.70)	(-5.649)	(-1.819)	(56.36)			
TWEX	-0.668***	-0.040	-0.367***	-0.575***	-0.521***	1.000	
	(-32.73)	(-1.471)	(-14.40)	(-25.62)	(-22.27)		
Oil	-0.033	0.220***	0.321***	-0.099***	-0.081***	-0.265***	1.000
	(-1.199)	(8.230)	(12.38)	(-3.644)	(-2.966)	(-10.01)	

Note: This table displays the summary statistics of daily returns of global green bonds and a number of asset classes (global stocks, renewable energy stocks, Treasury bonds, investment-grade corporate bonds, trade-weighted U.S. dollar index, denoted by TWEX, and Brent oil price) over the period from October 15, 2014 to November 29, 2019, with a total of 1333 daily observations. Panel A shows the descriptive statistics and unit root tests, while Panel B presents the correlation matrix, which reports the Pearson linear correlation coefficients between all pairs of variables. In particular, Std. Dev. stands for the standard deviation, J-B refers to the Jarque-Bera test statistics for normality. ADF, PP and KPSS are the statistics of the ADF (Augmented Dickey-Fuller), PP (Phillips-Perron) unit root test and the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) stationarity test, respectively. Natural logarithmic first difference returns (multiplied by 100) are used. In addition, t-statistics of correlation coefficients are in parenthesis. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Figure 1. Dynamic total spillover indices based on the Diebold-Yilmaz approach

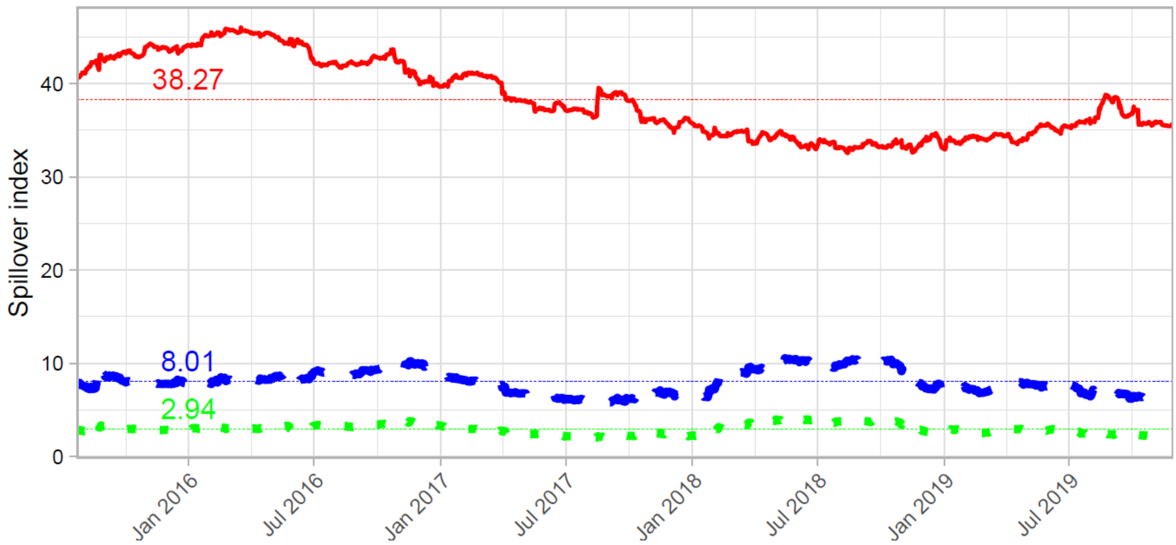
A) Total return spillover index

B) Total volatility spillover index

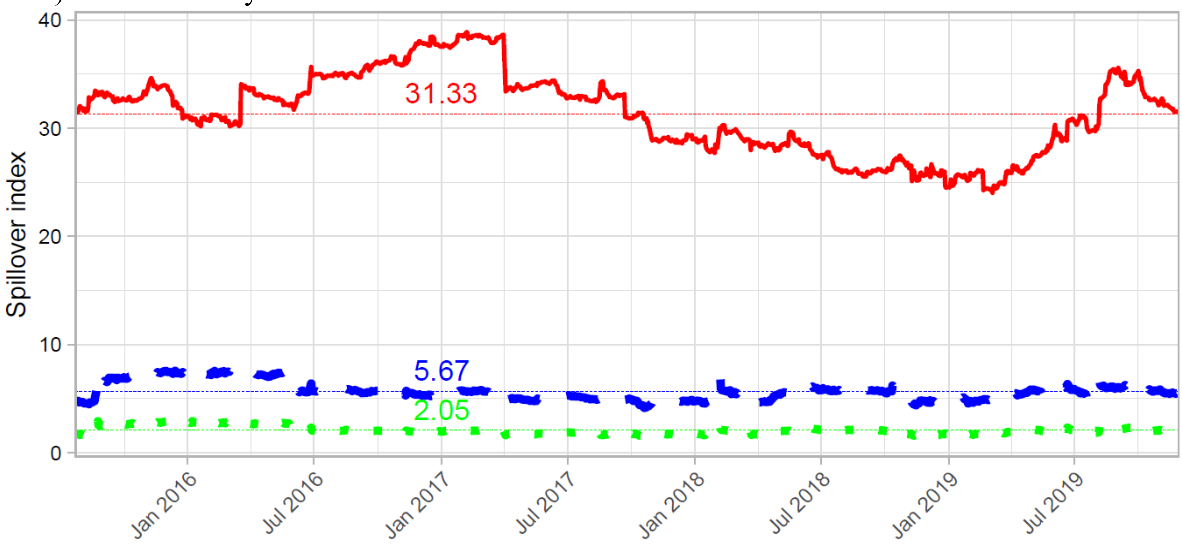
Note: This figure depicts the time-varying total return spillover index (Plot A) and total volatility spillover index (Plot B) between green bond returns and the rest of asset classes over the full sample period using the approach of Diebold and Yilmaz (2009). The red dotted line shows the average total spillover over the entire sample period. These dynamic total spillover indices are calculated using a rolling window size of 200 days and a forecast horizon of $H = 100$ days.

Figure 2. Dynamic total connectedness measures based on the Baruník-Křehlík framework

A) Total return connectedness



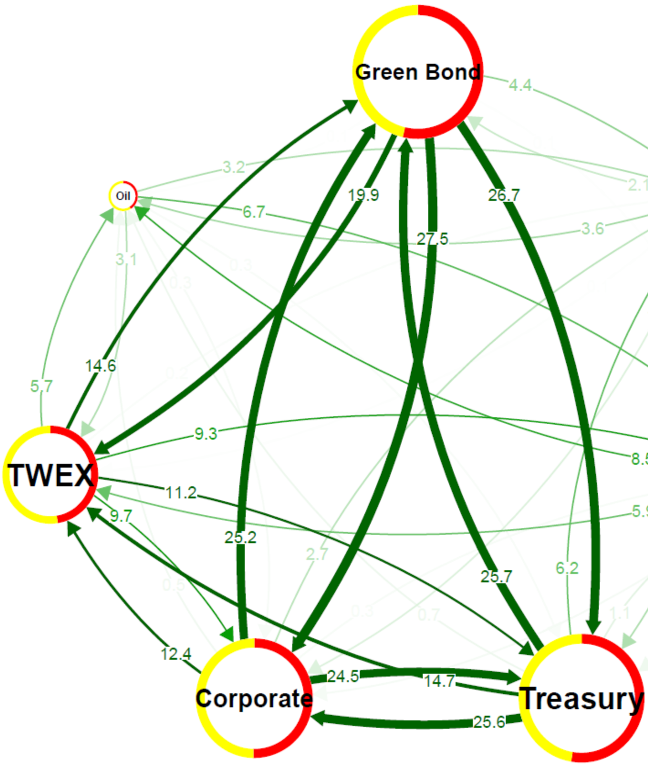
B) Total volatility connectedness



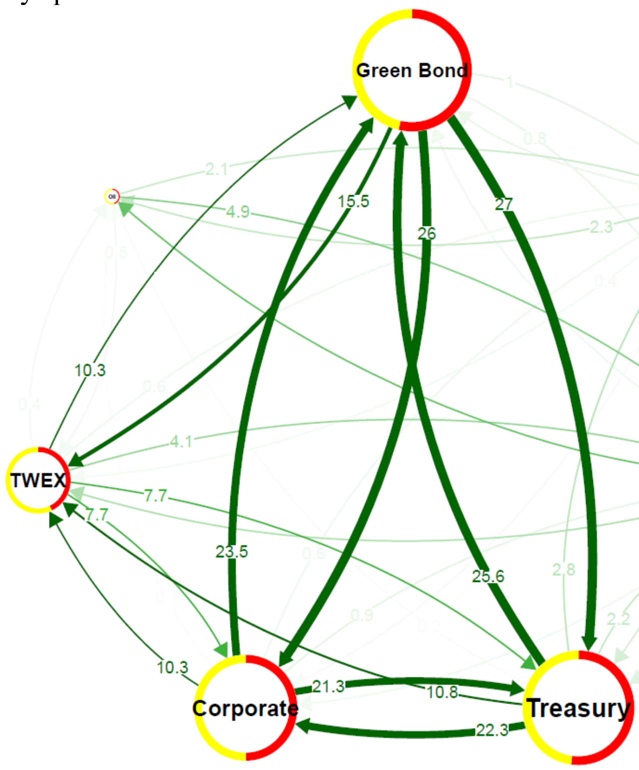
Note: This figure displays the time-frequency dynamics of total return connectedness (Plot A) and total volatility connectedness (Plot B) between green bond returns and the rest of asset classes over the full sample period using the connectedness methodology of Baruník and Křehlík (2018). The dotted lines show the magnitude of average total spillovers for each frequency band over the whole sample period. These dynamic total spillover indices are calculated using a rolling window size of 200 days. The red full line refers to the higher frequency band (until five days), while the blue dashed and black dotted lines account for the intermediate (6-22 days) and lower (more than 23 days) frequency bands, respectively.

Figure 3. Network graphs of directional spillovers based on the Diebold-Yilmaz approach

A) Total return spillovers



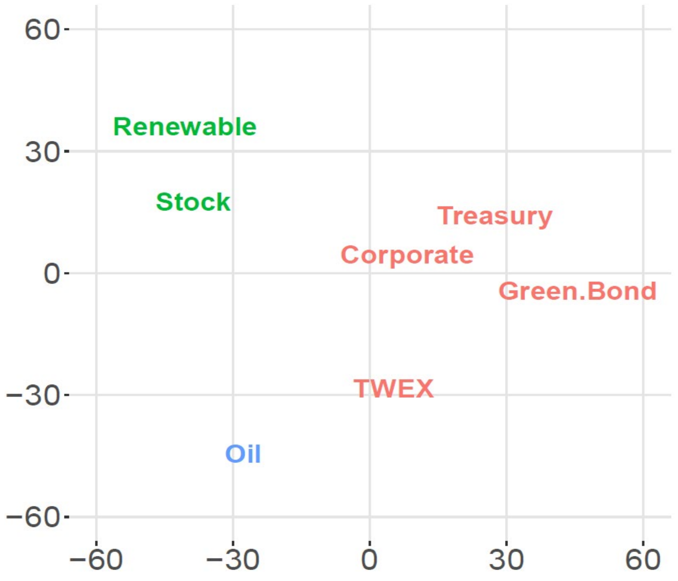
B) Total volatility spillovers



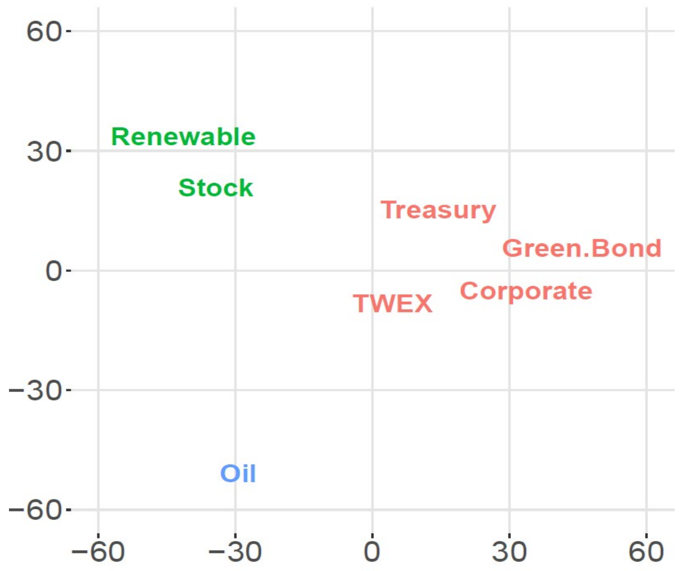
Note: This figure depicts the network graphs of average pairwise directional return (Plot A) and volatility (Plot B) spillovers based on the rolling window estimates of the Diebold-Yilmaz approach. The system of interest consists of global green bond returns (denoted by Green Bond) and returns of a set of conventional financial and energy markets, such as the global stock (Stock), Treasury bond (Treasury), investment-grade corporate bond (Corporate), renewable energy equity sector (Renewable), currency (TWEX) and crude oil (Oil) markets. The size of the node is proportional to the magnitude of contribution of each market to system-wide spillovers, while the node's border color indicate the direction of spillovers. Specifically, the red color reflects the extent to which the market of interest acts as a transmitter of spillovers to the rest of markets. In turn, the yellow color shows the degree to which that market is a net receiver of spillovers from the other markets. The color and thickness of edges connecting pairs of markets capture the strength of connectedness. The darker green the green color, the higher the pairwise connectedness. The edge label (at the start of each edge) indicates the magnitude of spillovers.

Figure 4. Hierarchical clustering of markets based on the Diebold-Yilmaz approach

A) Return spillovers



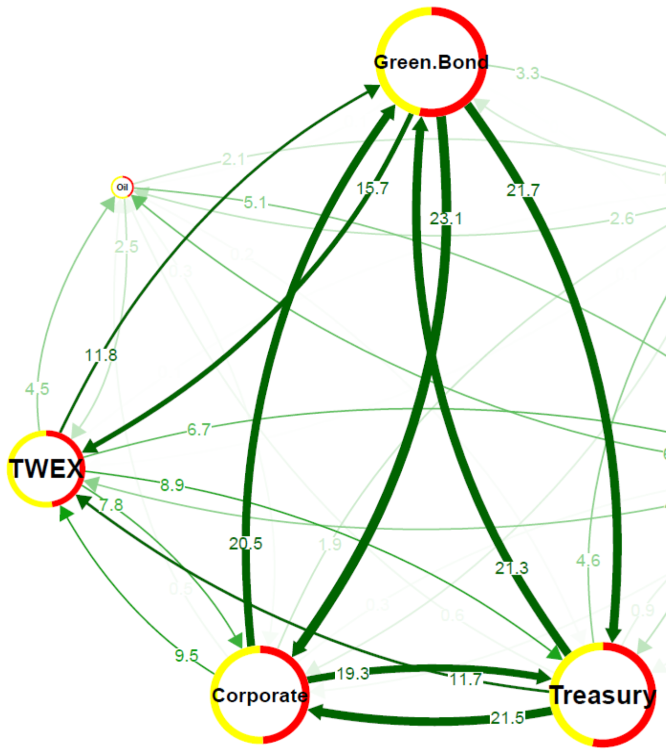
B) Volatility spillovers



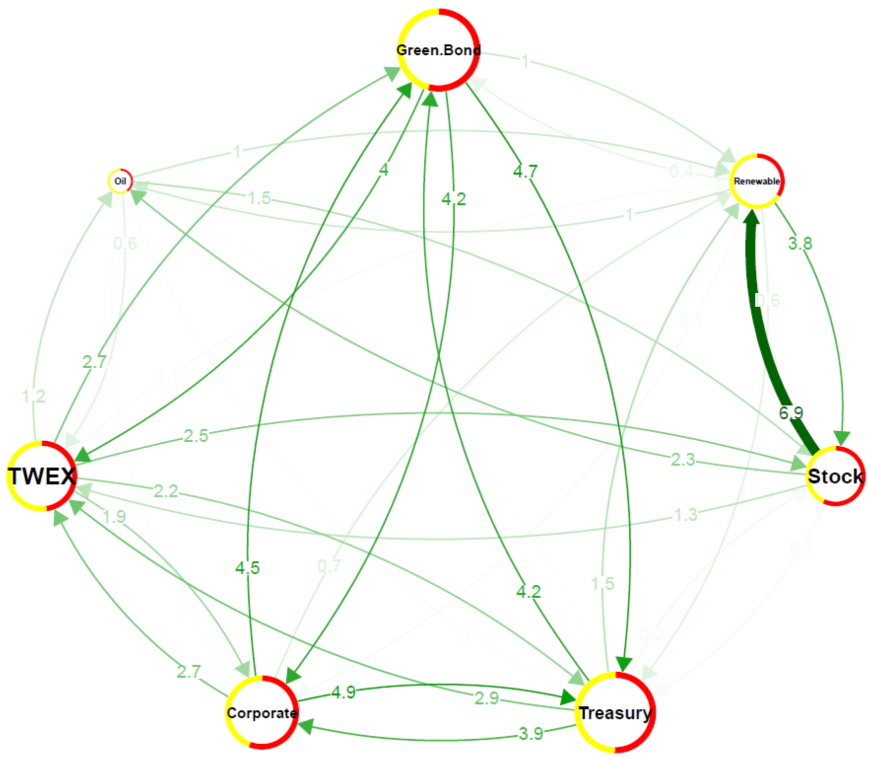
Note: The graphs in this figure depict the map of clusters across green bonds and the conventional financial and energy markets derived from the application of hierarchical clustering analysis on the spillover results of the approach of Diebold and Yilmaz (2012). Plot A refers to clusters constructed on the basis of return spillovers, while Plot B shows clusters based on volatility spillovers. The smaller the distance between two markets, the higher the similarity between them. Different colors (red, green and blue) are used to indicate different clusters.

Figure 5. Network graphs of directional return connectedness based on the Baruník-Křehlík framework

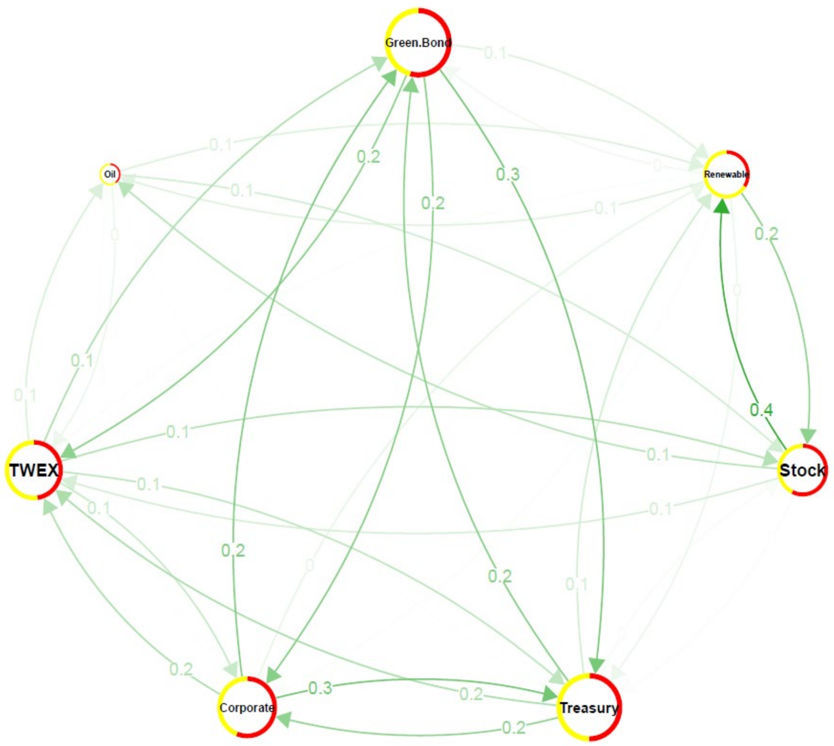
A. Short-term (up to 5 days) return connectedness



B. Medium-term (from 6 to 22 days) return connectedness



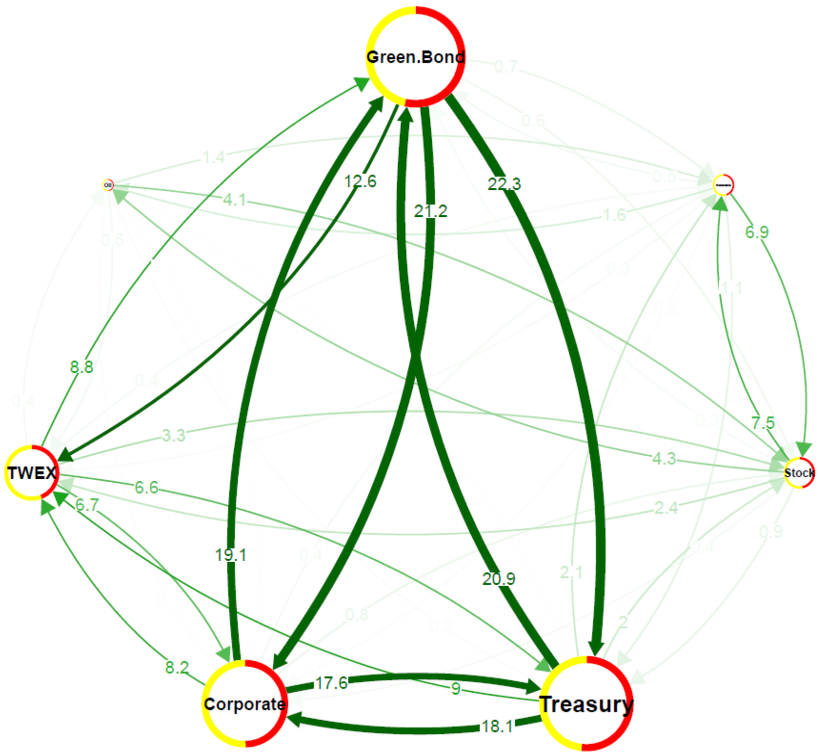
C. Long-term (from 23 to 200 days) return connectedness



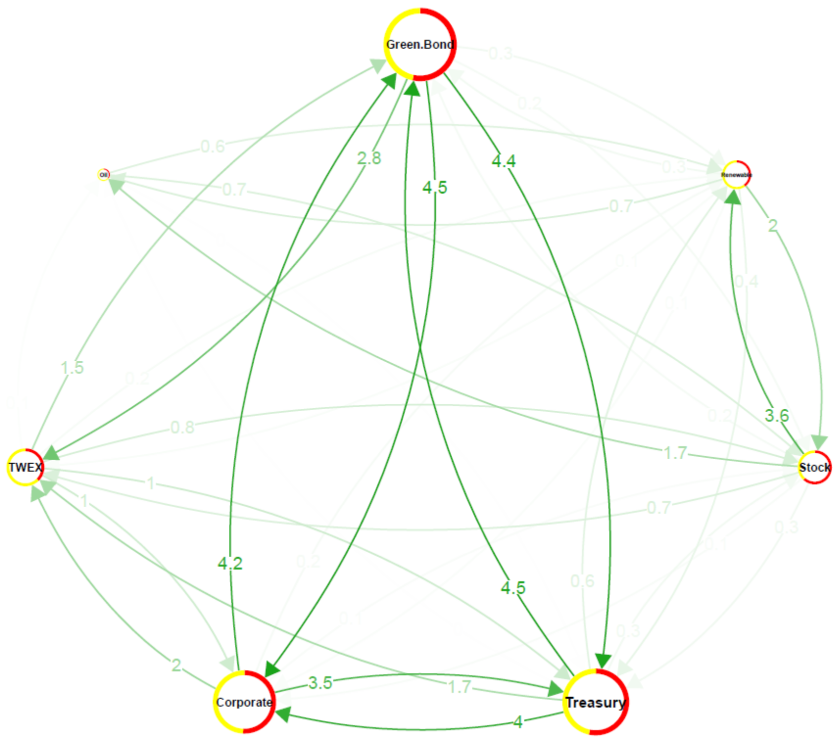
Note: This figure displays the network graphs of average pairwise directional return connectedness for different frequency bands based on the methodology of Baruník and Křehlík (2018). In particular, Plot A refers to return connectedness in the short-term (up to 5 days), while Plots B and C reflect return connectedness in the medium- (from 5 to 22 days) and long-term (from 23 to 200 days). The system of interest consists of global green bond returns (denoted by Green Bond) and returns of a set of conventional financial and energy markets, such as the global stock (Stock), Treasury bond (Treasury), investment-grade corporate bond (Corporate), renewable energy equity sector (Renewable), currency (TWEX) and crude oil (Oil) markets. The size of the node is proportional to the magnitude of contribution of each market to system-wide return connectedness, while the node's border color indicates the direction of connectedness. Specifically, the red color reflects the extent to which the market of interest acts as a transmitter of connectedness to the rest of markets. In turn, the yellow color shows the degree to which that market is a net receiver of connectedness from the other markets. The darker green the green color, the higher the pairwise connectedness. The edge label (at the start of each edge) indicates the magnitude of connectedness.

Figure 6. Network graphs of directional volatility connectedness based on the Baruník-Křehlík framework

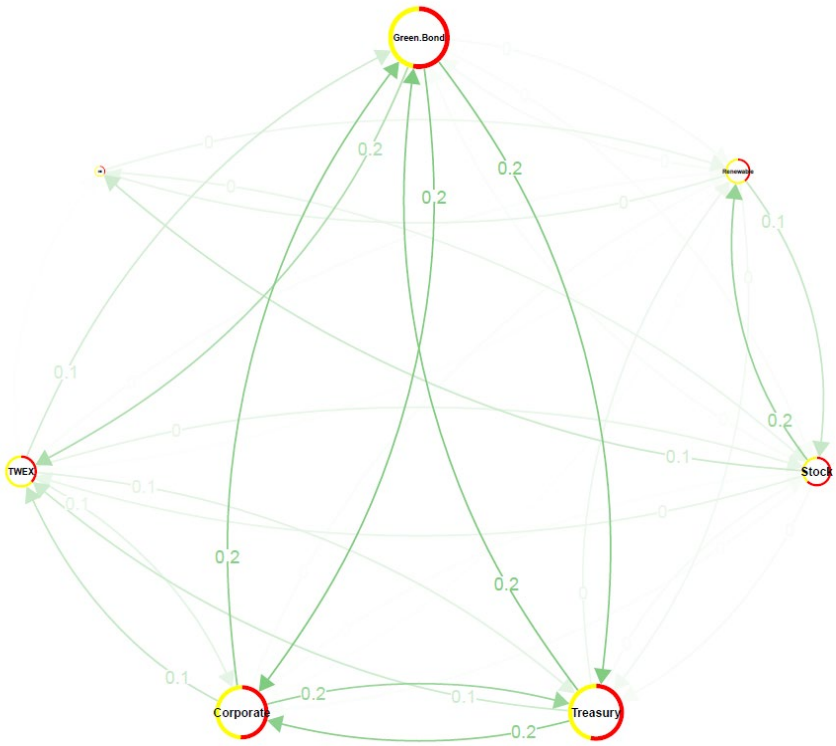
A. Short-term (up to 5 days) volatility connectedness



B. Medium-term (from 6 to 22 days) volatility connectedness



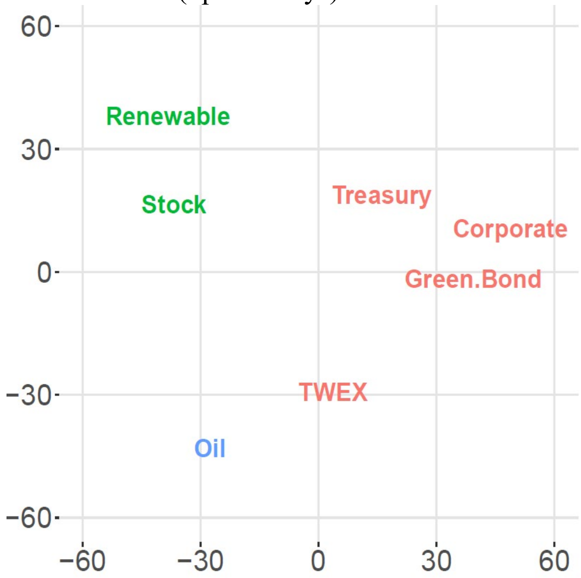
C. Long-term (from 23 to 200 days) volatility connectedness



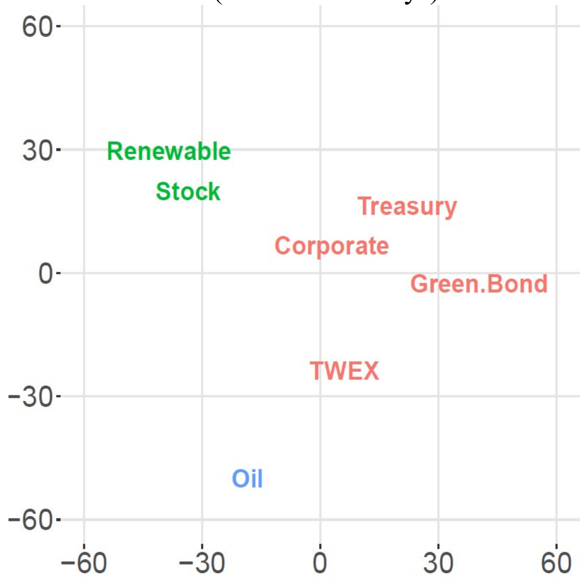
Note: This figure displays the network graphs of average pairwise directional volatility connectedness for different frequency bands based on the methodology of Baruník and Křehlík (2018). In particular, Plot A refers to volatility connectedness in the short-term (up to 5 days), while Plots B and C reflect volatility connectedness in the medium- (from 5 to 22 days) and long-term (from 23 to 200 days). The system of interest consists of global green bond returns (denoted by Green Bond) and returns of a set of conventional financial and energy markets, such as the global stock (Stock), Treasury bond (Treasury), investment-grade corporate bond (Corporate), renewable energy equity sector (Renewable), currency (TWEX) and crude oil (Oil) markets. The size of the node is proportional to the magnitude of contribution of each market to system-wide volatility connectedness, while the node's border color indicates the direction of volatility connectedness. Specifically, the red color reflects the extent to which the market of interest acts as a transmitter of volatility connectedness to the rest of markets. In turn, the yellow color shows the degree to which that market is a net receiver of connectedness from the other markets. The darker green the green color, the higher the pairwise connectedness. The edge label (at the start of each edge) indicates the magnitude of connectedness.

Figure 7. Hierarchical clustering of markets based on return connectedness using the Baruník-Křehlík framework

A. Short-term (up to 5 days)



B. Medium-term (from 6 to 22 days)

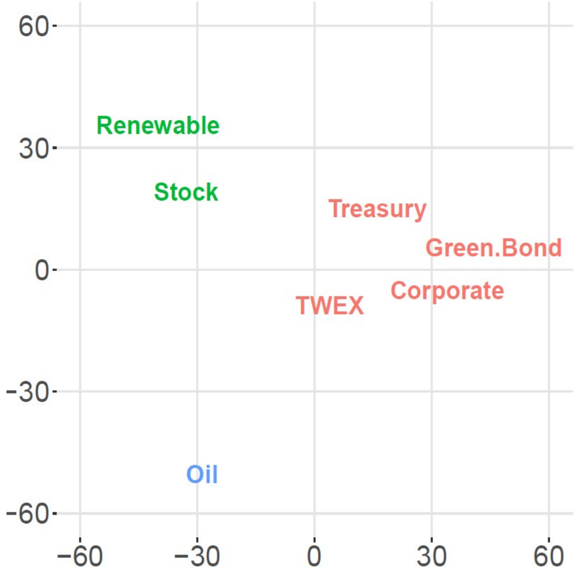


C. Long-term (from 23 to 200 days)

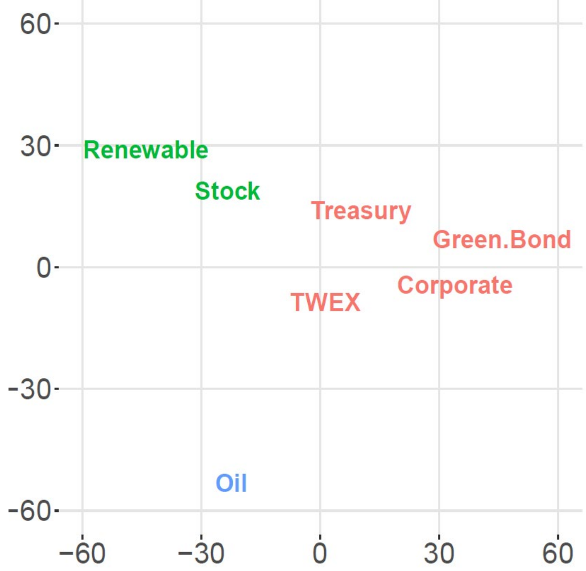
Note: The graphs in this figure depict the map of clusters across green bonds and conventional financial and energy markets derived from the application of hierarchical clustering analysis on the return connectedness results of the methodology of Baruník and Křehlík (2018). Plot A refers to clusters based on return connectedness in the short-term (up to 5 days), while Plots B and C show clusters based on return connectedness in the medium- (from 6 to 22 days) and long-term (more than 22 days). The smaller the distance between two markets, the higher the similarity between them. Different colours (red, green and blue) are used to indicate different clusters.

Figure 8. Hierarchical clustering of markets based on volatility connectedness using the Baruník-Křehlík framework

A. Short-term (up to 5 days)



B. Medium-term (from 6 to 22 days)



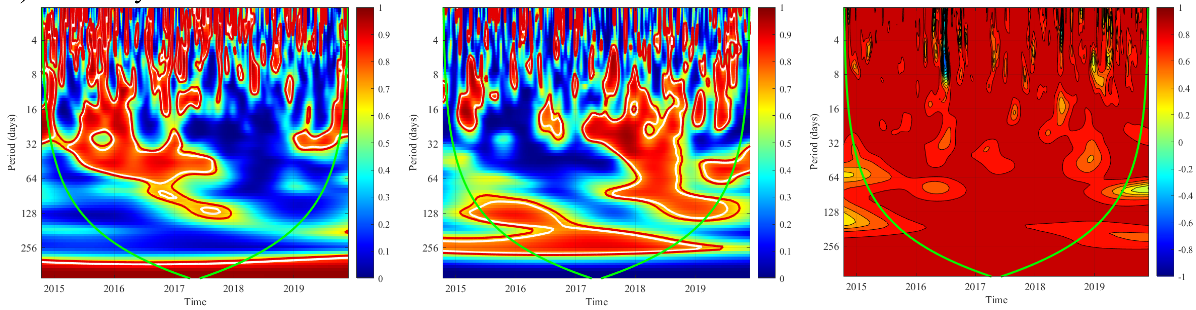
C. Long-term (from 23 to 200 days)

Note: The graphs in this figure depict the map of clusters across green bonds and conventional financial and energy markets derived from the application of hierarchical clustering analysis on the volatility connectedness results of the methodology of Baruník and Křehlík (2018). Plot A refers to clusters based on volatility connectedness in the short-term (up to 5 days), while Plots B and C show clusters based on volatility connectedness in the medium- (from 6 to 22 days) and long-term (more than 22 days). The smaller the distance between two markets, the higher the similarity between them. Different colours (red, green and blue) are used to indicate different clusters.

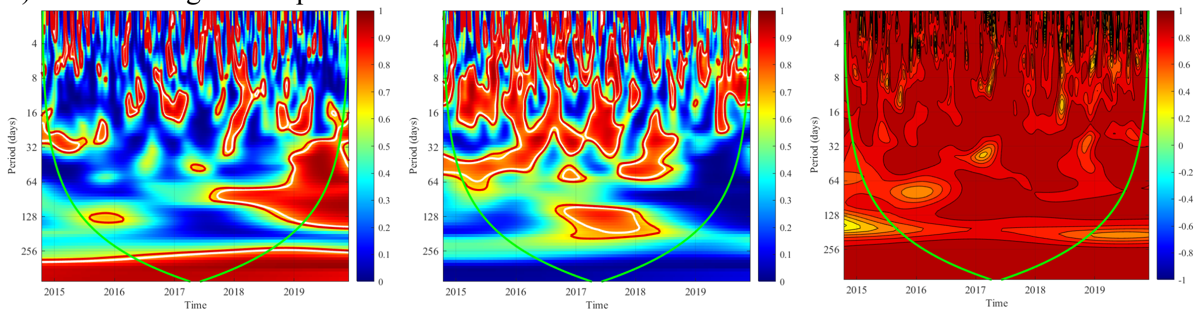
Figure 9. Wavelet correlation and wavelet-based Granger causality test

Panel A. Causality from green bonds | Panel B. Causality To green bonds | Panel C. Wavelet correlation

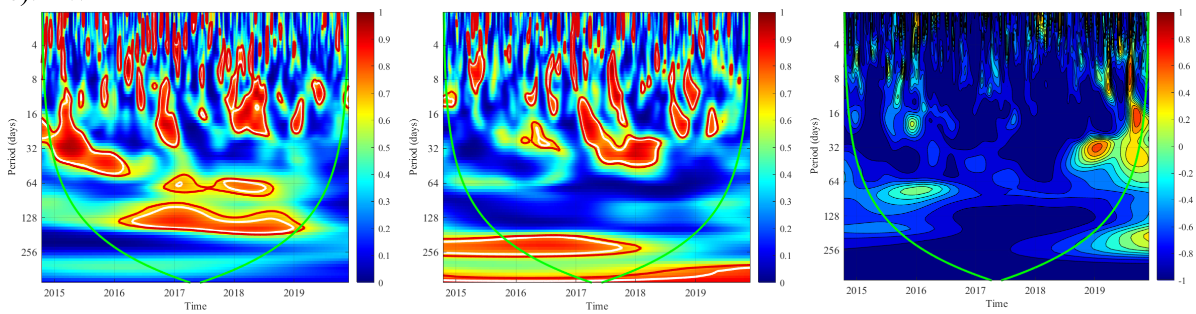
a). Treasury bonds



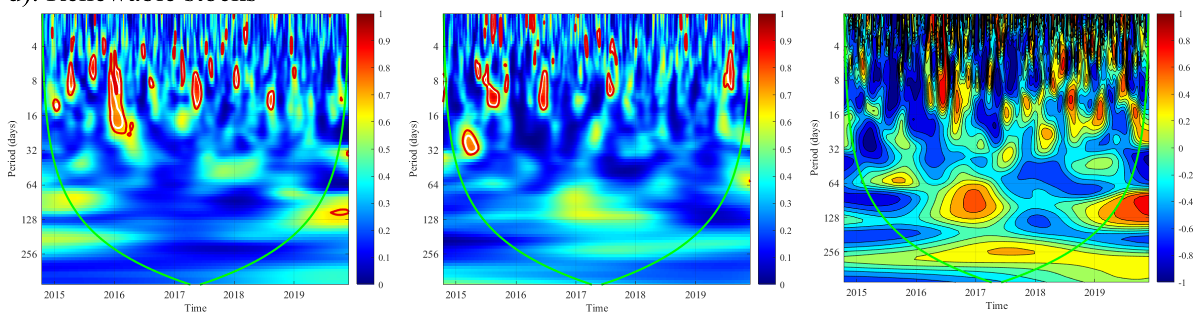
b). Investment-grade corporate bonds



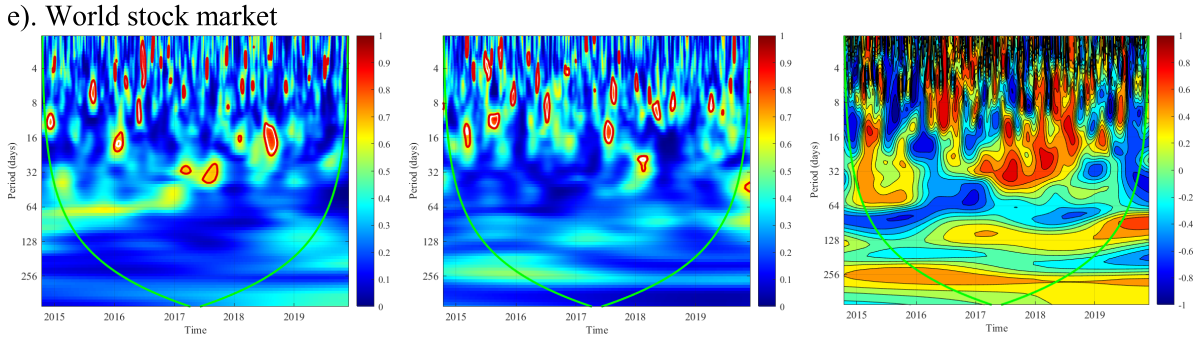
c). TWEX



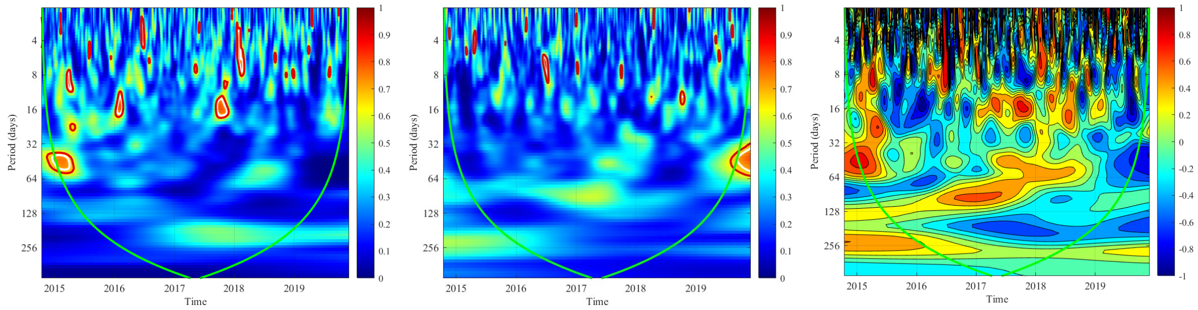
d). Renewable stocks



e). World stock market



f). Crude oil



Note: This figure shows the plots of the wavelet-based Granger causality test of Olayeni (2016) and the wavelet correlation measure of Rua (2010) between green bonds and each conventional financial and energy market. Panel A refers to the causal links from green bonds to the rest of mainstream markets, while Panel B reflects the causal flows from each mainstream market to green bonds. In turn, Panel C reports the magnitude of the wavelet correlation measure. Time and frequency or period (in days) are represented on the horizontal and vertical axes, respectively. A color code shows the strength of the wavelet correlation and the wavelet-based causal relations. Dark blue color means no causal links and strong negative wavelet correlation, while dark red color implies strong causal links and strong positive wavelet correlation. The red and white contours indicate statistical significance at the 10% and 5% levels, respectively. The significance levels are computed based on 1,000 Markov bootstrapped series. The cone of influence (COI) that delimits the areas affected by edge effects is highlighted by a green bold line.