Author(s): Naeem, Muhammad Abubakr; Karim, Sitara; Uddin, Gazi Salah; Junttila, Juha

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Small fish in big ponds: Connections of green finance assets to commodity and sectoral stock markets

Muhammad Abubakr Naeem [a,b], Sitara Karim [c], Gazi Salah Uddin [d,1], Juha Junttila [e,*]

[a] Accounting and Finance Department, United Arab Emirates University, P.O. Box 15551, Al-Ain, United Arab Emirates
[b] South Ural State University, Lenin Prospect 76, Chelyabinsk 454080, Russian Federation
[c] Nottingham University Business School, University of Nottingham Malaysia Campus, Semenyih, Malaysia
[d] Department of Management and Engineering, Linköping University, Linköping, Sweden
[e] University of Jyväskylä School of Business and Economics, Jyväskylä, Finland

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ABSTRACT

We analyze return and volatility connectedness of the rising green asset and the well-established US industry stock and commodity markets from September 2010 to July 2021. We find that the time-varying return and volatility connectedness have exhibited serious crisis jumps. Some individual assets of both the green and commodity markets are in connection to the US sectoral stock market returns, and the volatility connections are even more common than the return connections. Furthermore, some financial and economic uncertainty indicators manifest positive impacts from the volatility of some 'big pond' markets for e.g. commodities, whereas some others affect the connectedness negatively. Additional analysis of financial and economic uncertainty indicators manifests positive impacts from the volatility of some 'big pond' markets, e.g., commodities, while others negatively affect the connectedness.

1. Introduction

Sharing similar features with corporate treasury investments, green investments are new forms of financial intermediation whose proceeds are directly attributed toward environment-friendly and climate-oriented projects to reduce carbon emissions and encourage adaptation of renewable energy sources. In the future, there will be even more increasing attention of policymakers, regulation bodies, and investors concerning the magnified benefits of green markets as they are only weakly correlated with other markets (Pham & Huynh, 2020). Hence, from a practical point of view, they might also offer diversification benefits to the investors. At the first steps, introduced by the European Investment Bank in 2007, green investments were at the epicentre of financial regulators to channel the investments and assets to achieve sustainability and effectively tackle environmental challenges. Prior literature reveals green markets as an operative means to finance climate-oriented projects to achieve a low-carbon economy (Andersen, Bhattacharya, & Liu, 2020; Leitao, Ferreira, & Santibanez-Gonzalez, 2021). Since the enthusiasm about green investments has started to outperform nowadays that of traditional financial assets, several stock exchanges across the world are introducing specialized investments which fulfil the green objectives of the investors, and a sharp increase in the allocations to green investments has been already reported, going from $11 billion to $350 billion between 2013 and 2020 (Climate Bonds Initiative, H1–, 2020). The concentration of regulatory bodies on the COP26 accord and Paris Agreement from 2015 shows sustained pressure by governments to overcome climate degradation by reducing global warming below 2–1.5 degrees. Following this, green markets have exhibited >100% annual growth rate and they are expected to account for one-third of global assets by 2025. Hence, it is also evident that these markets might provide number of useful benefits in e.g., managing risk and reducing the losses on investments under extreme circumstances

* Corresponding author at: University of Jyväskylä School of Business and Economics, University of Jyväskylä, PO Box 35, FI-40014, Finland.
E-mail addresses: muhammad.naeem@uaeu.ac.ae (M.A. Naeem), Sitara.Karim@nottingham.edu.my (S. Karim), gazi.salah.uddin@liu.se (G.S. Uddin), juha-pekka.junttila@jyu.fi (J. Junttila).

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(Karim, Lucey, & Naeem, 2022; Karim, Lucey, Naeem, & Uddin, 2022; Karim & Naeem, 2021; Karim & Naeem, 2022; Naeem & Karim, 2021).

Based on this development, the relationships between green markets, US sectoral markets, and commodity markets are intuitively appealing as these market segments represent three different financial markets with unique underlying characteristics to absorb shocks and respond to the market uncertainties (Kilian & Zhou, 2018; Marshall, Nguyen, Nguyen, Visaltanachotin, & Young, 2021). Following the cross-market diversification perspective, Ngene (2021) has elaborated that industry-level diversification will dominate portfolio diversification in the stock markets in the long run, specifically in North America and Europe. Importantly, domestic investors overweigh the domestic investments compared to international investments and forgo the risk-adjusted diversification returns. As the US sectors are not sheltered from the market ups and downs, investors reallocate their investments during bullish and bearish market conditions to improve the risk-adjusted returns in times of economic recession. Similarly, the financialization of commodities provides an attractive hedging tool due to their risk mitigation ability during abrupt economic swings (Balli, Naeem, Shahzad, & de Bruin, 2019; Prokopczuk, Stancu, & Symeonidis, 2019). As the pricing mechanisms of commodities might differ from the conventional asset classes, for example, the traditional (spot/futures market) demand and supply shocks substantially determine the commodity prices. For example, the demand for commodities is associated with cumulative global aggregate demand conditions (Bakas & Triantafyllou, 2018), except for perhaps, e.g., precious metals as they have often been considered to provide hedging facilities in uncertain times.

Following this, volatility in the macroeconomic conditions and unexpected frequent downfalls might result in catastrophic consequences for risk-sensitive investments (Apostolakis, Floros, Gkillas, & Wohar, 2021; Wang, Xie, Zhao, & Jiang, 2018). Previous literature has postulated several uneven circumstances where growth in the financial markets, commodities, various sectors and industries is seized (Abakah, Addo, Gil-Alana, & Tiwari, 2021; Mensi, Nekhili, Vo, Suleman, & Kang, 2021; Naeem, Adekoya, & Oliyide, 2021; Naeem, Rabbani, Karim, & Billah, 2021). The most recent global outbreak resulted in a 5% decline in the US real GDP from the last quarter of 2019 to 2020 due to the pandemic's unprecedented havoc. Moreover, the unemployment rate erupted from 4.4% in March 2020 to 14.7% in April 2020. The crash of numerous stock and equity indices, and the fall in the valuation of banks and financial institutions by 39% in the US restricted traveling, and the increased loss exposure to the oil, energy and gas sector represents the extreme costs and damage caused by the COVID-19 pandemic (Shahzad, Bouri, Kristoufek, & Saeed, 2021). Meanwhile, financial markets experienced endangered susceptibility to the unexpected shocks propelled out of this world health emergency. Therefore, these shocks are central to the interconnectedness and volatility spillovers of financial assets, as more intensive risk spillovers spike the correlations among the markets (Kang, Hernandez, Sadorsky, & McIver, 2021). Given these turmoil periods, green investments seem to have remarkably sheltered the other investments from volatile and distressing episodes, accelerated the cross-market financialization, and provided noticeable evidence of diversification and hedging facilities (Arif, Hasan, Alawi, & Naeem, 2021; Naeem, Adekoya, & Oliyide, 2021; Naeem & Karim, 2021; Reboredo, Ugolini, & Aiube, 2020). Based on this practical observation, a thorough examination of the return and volatility connectedness between green and conventional assets presents a new dimension of analysis useful for the investors, policymakers, and strategists for designing their portfolios, devising useful policies and implementing them to reap the benefits of adding diversifiers in their asset-mix.

Theoretically, Modern Portfolio Theory (MPT) offers useful insights to choose among different market segments for risk mitigation and diversification objectives of the investors (Markowitz, 1952). In addition, we argue that several economic and financial factors influence the spillover network of the markets. This is consistent with market reaction hypothesis where investors not necessarily rely on all the available information, but rather their decisions are heterogenous and vary with the changing financial and economic circumstances (Naeem, Farid, Qureshi, & Taghizadeh-Hesary, 2022). Prior literature, for instance, Elsayed et al., (2022), Khalfaoui et al., (2022), Mensi et al., (2022), Tiwari et al., (2022), and Urom et al., (2021) present limited intuitions to the current body of knowledge by empirically testing the dependence of green markets from the other financial market segments using a multitude of econometric techniques. However, we differ from these studies by exhibiting unique return and volatility connectedness networks among green bonds (small fish), US sectors, and commodities (big ponds) based on employing diverse econometric techniques.

In light of this background, the current study contributes to the existing literature in many ways. First, this is the pioneer study that investigates the connectedness and spillover network among green markets (small fish), US sectors, and commodities (big ponds) to inspect their underlying relationships based on the utilized return and volatility connectedness measures. The rationale behind using both return and volatility connectedness measures implies that markets behave differently under the conditions of average returns and uncertain circumstances (Umar, Adekoya, Oliyide, & Gubareva, 2021). Thus, the focus on return and volatility connectedness provides a comprehensive outlook for assessing the variations in spillovers during stable and turbulent time periods. Second, we employed the time-frequency approaches of Diebold & Yilmaz (2012, Diebold and Yılmaz, 2014) and Baruník and Křehlík (2018) to compute the spillover network. The time-based connectedness approach of Diebold and Yilmaz (2012) addresses the network connectedness of markets, while the frequency-based approach sufficiently describes the spillovers given various time horizons.

Third, as additional evidence, the study further examines the impact of several economic and financial uncertainties on the return and volatility connectedness of green markets, US sectors, and commodities. Fourth, theoretically, the study embraces support from modern portfolio theory for indicating the investors' choices to offset risks of their investments and achieve diversification benefits. Moreover, to unveil the impact of several economic and financial uncertainties on the return and volatility spillovers, we posit that investors' reaction to various market conditions are heterogeneous. Thus, in line with market reaction hypothesis, we test the influence of financial and economic factors on the spillover networks. Finally, the study brings intriguing findings for policymakers, regulation authorities, financial market participants, investors, and portfolio managers to diversify their portfolios using green markets (small fish) and overcome the risk of other big ponds investments.

Our findings reveal complex intra-group and moderate inter-group return and volatility connectedness. The US stock market sectors reveal the strongest intra-group return and volatility connectedness. Alternatively, the system-wide connectedness for total, short- and long-term horizons indicates high spillover from green markets and commodities to the US sectors. Time-varying attributes of return and volatility connectedness exhibit that the markets have suffered from shocks during unexpected economic periods such as the European Debt Crisis, Shale oil crisis, Chinese stock market crash, and COVID-19 pandemic. Moreover, short-run return spillovers dominated the long-run spillovers, reflecting financial contagion during economically fragile times. Furthermore, time-varying NET return and volatility connectedness characterized the US sectors as the NET transmitters of spillovers, whereas the green markets and commodities are NET receivers of return and volatility spillovers with significant time-varying features.

Investigating the financial and economic drivers of connectedness among green markets, US stock market sectors, and commodity markets highlights the positive driving effect of implied volatilities of Russel Index and Gold and the negative driving effect of implied volatilities of exchange rates and bond markets. Moreover, we report a positive effect of the UK economic policy uncertainty and infectious disease tracker for the underlying connectedness in return and volatilities of green markets, US sectors, and commodities. Based on our results, we propose some new implications for policymakers, investors, financial market participants, and portfolio managers trying to diversify their portfolio risks and derive appropriate strategies from short and long-run perspectives.

The remaining parts of the paper are structured as follows: Section 2 reviews the earlier empirical studies; Section 3 elaborates methodology and data; Section 4 presents empirical results and discussion; and finally, Section 5 concludes the study with our main policy implications.

2. Literature review and theoretical background

2.1. Theoretical background

Modern portfolio theory (MPT) proposed by Markowitz (1952), offers strong theoretical underpinnings for the construction of diversified portfolios in order obtain the expected returns in connection to a certain level of market risk. At the same time, diversification cannot completely eliminate the risk of an investment, but rather, the diversification provides avenues for optimizing the investment streams and achieving higher expected returns. Hence, the essentials of MPT include the quantification of the risk-return relationship embraced from portfolio management theory (Omisore, Yusuf, & Christopher, 2012). MPT mathematically quantifies the diversification objectives of investors with the aim of selecting a set of investment avenues that bear relatively lower risk than an individual asset. Based on these ideas, we claim that nowadays the green markets, despite of begin still an emerging market segment in terms of their financial integration (funding) role, might offer greater diversification possibilities against other, more established financial market segments (Elsayed, Naifar, Nasreen, & Tiwari, 2022; Khalfaoui, Jabeur, & Dogan, 2022). Hence, we first hypothesize that:

H1. : Green markets offer new diversification benefits to mitigate the risk of US sectoral stock markets and commodity markets.

In addition, the market reaction hypothesis contends that investors, before making their investment decisions, do not always rely on the readily available information. Instead, their attitudes toward various investment streams determine the heterogenous responses across multiple financial markets (Naeem, Karim, Jamasb, & Nepal, 2022; Naeem, Pham, Senthilkumar, & Karim, 2022). In these circumstances, it is imperative to identify the impact of numerous financial and economic uncertainties on the spillover networks formed among green markets, US sectors, and commodities. We further extend our argumentation by suggesting that nonlinearities exist among financial markets embarked with structural variations. Therefore, investors must consider the impact of financial and economic uncertainties before reaching their investment decisions. Building on these arguments, we frame our second hypothesis in the form:

H2. : Financial and economic uncertainties significantly drive the spillover network of green markets, US sectors and commodities.

2.2. Earlier empirical literature

The existing strand of literature has most often focused on the advantages of *green bonds* for various investors, policymakers and regulatory authorities. Tang and Zhang (2020) reported that the issuance of green bonds has positively impacted the stock market indices. Likewise, Russo, Mariani, and Caragnano (2021) investigated the determinants of green bond performance for developing sustainable strategies. Another part of the literature has concentrated on the similar characteristics of green bonds and conventional markets with other financial assets (Ferrer, Shahzad, & Soriano, 2021). On the other hand, several studies have studied the hedge and safe haven characteristics of green bonds against several commodities, bonds, and other financial market segments (Arif, Naeem, Farid, Nepal, & Jamasb, 2021; Naeem, Adekoya, & Oliyide, 2021) and suggested that green bonds act as a potential diversifier during normal economic conditions, but they offer safe-haven attributes during the crisis periods. Meanwhile, several studies have reported mixed evidence for the connectedness structure of green bonds with other markets (Nguyen, Naeem, Balli, Balli, & Vo, 2020; Reboredo et al., 2020).

The previous literature presents evidence about the connections between green and conventional markets using various methodologies, such as comovement analysis based on wavelets (Mensi, Naeem, Vo, & Kang, 2022; Mensi, Rehman, & Vo, 2020; Nguyen et al., 2020), asymmetric time-frequency connectedness (Naeem, Adekoya, & Oliyide, 2021), quantile connectedness for estimating return connectedness of clean and dirty energy investments (Saeed, Bouri, & Alsulami, 2021; Tiwari, Abakah, Gabauer, & Dwumfour, 2022; Urom, Mzoughi, Abid, & Brahim, 2021), extreme quantile approach (Naeem, Rabbani, et al., 2021), time-varying optimal copula approach (Naeem & Karim, 2021), Diebold-Yilmaz framework (Bahloul & Khemakhem, 2021; Zhao, Umar, & Vo, 2021), and cross-quantilogram (Arif, Hasan, et al., 2021). However, the literature examining the determinants of a given or observed relationship is limited. For instance, Balli, Hasan, Ozer-Balli, and Gregory-Allen (2021) investigated the role of US uncertainty in driving spillovers of the global stock market. The authors reported that global factors, such as US uncertainties, substantially drive the US spillovers to global stock markets. Moreover, Abbas, Hammoudeh, Shahzad, Wang, and Wei (2019) reported that macroeconomic variables drive the connectedness of G7 markets.

Finally, from the funding perspective of firms in general, it is worth to mention here also that some of the papers in the most recent literature propose that actually the 'green finance certification' allows managers to signal firms' efficiency at addressing for example the energy transition activities. For example, the paper by Daubanes, Shema, and Rochet (2022) proposes that the firm-level green bond issuance signals firm's amplified incentives to decarbonize its production, too. Their theoretical model predicts that firms' managers are more inclined to issue green bonds when they are more interested in stock prices, and hence, the stock market valuation of their firm. They also test this prediction empirically by exploiting cross-industry differences in the stock-price sensitivity of managers' compensation and cross-country variations in effective carbon prices, finding that the effect of managers' incentives on green bond issuance increases with carbon penalties. This suggests that green bonds are complements to, rather than substitutes for, carbon pricing. Hence, based on this paper, from an investor's point of view, it is obviously relevant to analyze also the market level return and volatility connections of wider set of green assets (than just green bonds) on the US sectoral stock markets, and also some relevant green transition related commodity markets. This is the focus of our empirical analysis, and next we describe the contents of it in more details.

3. Methodology and data

This study investigates the return and volatility connectedness of green asset markets, US stock market sectors, and commodity markets. First of all, for estimation purposes, all the analyzed asset price series (P) are converted into log returns (R, in %) based on the first differences of prices:

$$R_t = ln(P_t - P_{t-1}) \times 100 \quad (1)$$

where t refers to the time period of observation.

3.1. Volatility estimation

For computing volatility, the individual time series of returns belonging to the vector of return series $R_t = [R_{1t}, \ldots\ldots, R_{nt}]'$ is supposed to be given as an AR(1) process as follows:

$$R_t = \mu_t + \gamma R_{t-1} + \varepsilon_t \quad (2)$$

The vector of constant terms is denoted by $\boldsymbol{\mu}$, whereas $\boldsymbol{\varepsilon}_t$ = [e_{1t},

……, ε_{nt}] illustrates the vector of error terms. In addition, the conditional volatilities h_{it}^2 (for each asset i) are based on estimating the univariate GARCH (1,1) models[2] for each of them given as:

$$h_{it}^2 = \omega + a\varepsilon_{it-1}^2 + \beta h_{it-1}^2 \quad (3)$$

where $\omega > 0$, $\alpha \geq 0$, *and* $\beta \geq 0$, *and* $\alpha + \beta < 1$.

3.2. Connectedness approach

Based on Diebold and Yılmaz (2014), this study employs a unique connectedness measure derived from the variance decomposition matrix of the vector autoregressive (VAR) technique. The stationary N-variable vector is denoted as VAR(p), so for each component of the N-variable vector we have $y_t = \sum_{i=1}^{p} \omega_i y_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$ whereas the moving average representation is given by $y_t = \sum_{i=0}^{\infty} \varnothing_i \varepsilon_{t-1}$and $\varnothing_i$ is the combination of $N \times N$ coefficient matrices obeying the recursion $\varnothing_i = \omega_i \varnothing_{i-1} + \omega_i \varnothing_{i-2} + \ldots + \omega_p \varnothing_{p-1}$ and $\varnothing_0$ represents identity matrix where $\varnothing_i = 0$ *and* $i \ll 0$. In this way, moving averages facilitate understanding the dynamics. For this reason, variance decompositions are employed to obtain the transformations through moving averages. It also splits variable error variances into parts through H-step-ahead forecast, denoted as various shocks in the system.

Orthogonality in the variables is attained using the Cholesky factorization, which ascertains the ordering of the variables. Following Pesaran and Shin (1998), the generalized approach is employed, allowing appropriate treatment of the correlated shocks. Thus, entries of the connectedness table are denoted as $c_{ij}^{g(H)}$ which measure the contribution of variable j to H-step-ahead generalized forecast error variance of variable i given as:

$$c_{ij}^{g(H)} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \varnothing_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \varnothing_h \sum \varnothing_h' e_j\right)^2} \quad (4)$$

Here the non-orthogonalized VAR representation of the covariance matrix is represented by Σ. Furthermore, σ_{jj} is the standard deviation of the j-th diagonal component. For the i-th component, the selection vector e_i has value of 1 and 0 otherwise. $\varnothing_h$ represents the coefficient matrix of non-orthogonalized VAR model, which multiplies h-lagged errors in infinite moving averages.

In the connectedness table, $c_{ij}^{g(H)}$ estimated pairwise directional connectedness from j to i are calculated based on

$$C_{i \leftarrow j}^{H} = c_{ij}^{g(H)} \quad (5)$$

On the other hand, the total directional connectedness from others to i in the off-diagonal sum of rows is represented as:

$$C_{i \leftarrow \bullet}^{H} = \sum_{\substack{j=1 \\ j \neq i}}^{N} c_{ij}^{g(H)} \quad (6)$$

However, the total directional connectedness to others from j in the off-diagonal sum of columns is represented as:

$$C_{\bullet \leftarrow j}^{H} = \sum_{\substack{i=1 \\ i \neq j}}^{N} c_{ij}^{g(H)} \quad (7)$$

Finally, the system-wide total connectedness is obtained by summing the to-others and from-others elements of variance decompositions matrix given as:

$$C^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} c_{ij}^{g(H)} \quad (8)$$

The structural connectedness table is graphically visualized so that the individual markets such as green markets, US stock market sectors and commodity markets represent nodes and the arrows present pairwise connectedness among these markets.

3.3. Decomposing frequency connectedness

In this step, frequency connectedness is decomposed into short- and long-run frequencies by taking into account several spectral representations of variance decompositions. Apart from shock impulses, these decompositions are based on frequency responses to shocks. Thus, the frequency response function is denoted as $\aleph(e^{-i\omega g}) = \sum_g e^{-i\omega g} \aleph_g$, obtained as Fourier transform of the coefficients $\aleph_g$ with $i = \sqrt{-1}$. In this way, the Fourier transform for moving averages MA(∞) for spectral density of UV_t at frequency ω is filtered as:

$$S_{UV}(\omega) = \sum_{g=-\infty}^{\infty} E\left(UV_t UV'_{t-g}\right) e^{-iwg} = \aleph\left(e^{-iw}\right) \sum \aleph'\left(e^{+iw}\right) \quad (9)$$

Here $S_{UV}(\omega)$ denotes the key quantity power spectrum and frequency dynamics rely on this function as it describes the distribution of variance over frequency components ω. Nonetheless, the frequency domains are explained by the spectral decomposition of covariance in the form of $E(UV_t UV_{t-g}') = \int_{-\varphi}^{\varphi} S_\gamma(\omega) e^{i\omega g} d\omega$. Baruník and Křehlík (2018) explained the comprehensive derivation of quantities, whereas we describe the connectedness of markets at varying frequencies. Therefore, spectral quantities are transformed by standard Fourier transforms across interval's cross-spectral density $d = (a,b) : a, b \ \epsilon \ (-\varphi, \varphi)$, $a \ll b$ as:

$$\sum_{\omega} \widehat{\aleph}(\omega) \sum \widehat{\aleph}'(\omega) \quad (10)$$

For $\omega \in \left\{ \left| aG/_{2\pi} \right|, \ldots, \left| bG/_{2\pi} \right| \right\}$ where

$$\widehat{\aleph}(\omega) = \sum_{g=0}^{G-1} \widehat{\aleph}_g e^{-2i\varphi\omega/G} \quad (11)$$

And $\sum \widehat{\varepsilon}' \widehat{\varepsilon} /_{(T-x)}$ where x is the correction for loss of degrees of freedom and it solely depends on VAR specifications.

The impulse response decomposition function is measured at a frequency given by the band $\widehat{\aleph}(d) = \sum_{\omega} \widehat{\aleph}(\omega)$. In this way, the desired frequency band for generalized decompositions of variance is estimated as:

$$\left(\widehat{\partial}_d\right)_{j,l} = \sum_{\omega} \widehat{\rho}_j(\omega) \left(\widehat{f}(\omega)\right)_{j,l} \quad (12)$$

Here $\left(\widehat{f}(\omega)\right)_{j,l} = \widehat{\delta}_{ll}^{-1} \left(\left(\widehat{\aleph}(\omega) \sum\right)_{jl} \right)^2 / \left(\widehat{\aleph}(\omega) \sum \widehat{\aleph}'(\omega)\right)_{jj}$ is the generalized causation spectrum and $\widehat{\rho}_j(\omega) = \left(\widehat{\aleph}(\omega) \sum \widehat{\aleph}'(\omega)\right)_{j,j} / (\varnothing)_{j,j}$ is the weighted fraction and $\varnothing = \sum_{\omega} \aleph(\omega) \sum \widehat{\aleph}'(\omega)$. Thus, the measure of connectedness at a given desired frequency band is derived by substituting $\left(\widehat{\partial}_d\right)_{j,l}$ into traditional measures.

3.4. Determinants of connectedness

We used some generally focused financial and economic uncertainty indicators to determine green markets' return and volatility connectedness with respect to the US stock market sectors and commodity

[2] Note that in the empirical analysis, in addition to the standard GARCH(1,1)-model, the conditional volatility was modeled also based on an asymmetric representation of the data in the form of Glosten, Jagannathan, and Runkle (1993) GJR-GARCH-model, but this specification had no qualitative effect on our main results.

markets. The financial uncertainty indicators[3] used for the regression analysis are VIX, RUS, GVZ, EXG, EMR, and MOVE, whereas the economic uncertainty indicators[4] employed for the multivariate regressions are USEPU, UKEPU, USEQU, and INFD. The regression equation is given as follows:

$$TC_{it} = \beta_0 + \beta_1 \sum Financial_{it} + \beta_2 \sum Economic_{it} + \varepsilon_{it} \quad (13)$$

where TC_{it} denotes total return and volatility connectedness of market i at time t. β_0 is the intercept, whereas ε_{it} is the error term. The component $\sum Financial_{it}$ represents the proxies of six financial variables employed in the study, while $\sum Economic_{it}$ reflects the four proxies of economic (and pandemic) uncertainty variables.

3.5. Data and descriptive statistics

For investigating the return and volatility spillovers of green (financial) markets, US stock market sectors and commodity markets. For this purpose, we utilized the data from green markets in the form of S&P Green Bond Index (SPGB), Wilderhill Clean Energy Index (WHCL), World Renewable Energy Index (RENX), MSCI Global Green Building Index (MSGB), S&P Global Clean Energy Index (SPCL), MSCI ACWI Water Utility Index (MSWT), and EEX-EU CO_2 Emissions Index (EUCO). As representing the US stock market sectors we utilize the industry indexes from the healthcare (HLTH), consumer discretionary (CODC), energy (ENER), financials (FINL), industrials (INDS), communication services (COSV), materials (MATR), consumer staples (COST), information technology (TECH), and utilities (UTIL). Additionally, the commodity market indexes included in the study are from the crude oil (CWTI), heating oil (HTOL), natural gas (NTGS), gold (GOLD), silver (SLVR), copper (COPR), and wheat (WHET) spot markets. The daily data are taken from the Refinitiv/EIKON/Datastream, spanning observations form September 2010 to July 2021.

Table 1 presents the descriptive statistics of return series (based on the natural log difference of the price/index series) where the highest average return from the green markets is reported by EUCO, followed by MSWT, RENX, MSGB, WHCL, and SPCL. Interestingly, SPGB, i.e., the S&P green bond index markets, showed zero average return for the sample period. TECH yields the highest mean return among US stock market sectors, followed by CODC and HLTH. Moderate mean returns are exhibited by INDS, FINL, MATR, COST, COSV, and UTIL. However, ENER showed negative average returns. Commodities like CWTI and GOLD revealed the highest mean returns, followed by COPR and SLVR. The lowest average returns are obtained from HTOL, NTGS, and WHET. Similar to the mean values, the variability of return series showed the highest value for the EUCO market, followed by RENX, WHCL, SPCL, and MSGB, whereas SPGB has the lowest variability. The US stock sectors with the highest variability in returns are ENER, FINL, MATR, INDS, and TECH. The other US sectors revealed moderate to low variability in the returns, such as CODC, COSV, UTIL, HLTH, and COST. Out of commodity market returns, the strongest variability is denoted in the cases of NTGS, CWTI, and HTOL, whereas the rest of the commodity markets showed moderate variability. Slightly negative skewness values indicate that green markets, US sectoral returns, and commodity markets have experienced substantial losses under unfavorable market conditions. The Jarque-Bera test reveals abnormal values in all series, pointing to the non-normal distribution of return series.

Table 2 illustrates the descriptive statistics of the volatility series where EUCO yields the highest average volatility among the green asset markets, followed by WHCL and RENX. SPCL, MSWT, and MSGB experience moderate volatility, whereas SPGB marked has the lowest average volatility for the sample period. ENER sector, among US sectors, showed the highest average volatility, followed by FINL, MATR, TECH, INDS, and COSV. Conversely, CODC, UTIL, HLTH, and COST exhibited the lowest volatilities in average terms. NTGS and CWTI reported the highest mean volatilities among the commodity market assets, followed by SLVR, HTOL, WHET, and COPR, with GOLD indicating the lowest volatility. The volatility statistics reflect the highest variation in the RENX and EUCO green markets, followed by WHCL, SPCL, and MSGB. However, SPGB revealed the lowest variability in terms of average volatility. The US sectoral volatility series show comparable values confirming that these sectors are subject to volatile economic periods. Nevertheless, the commodity markets are denoted to experience the highest variability in the volatility for CWTI, while the remaining commodities have moderate to low variability in the volatilities. The positive values of (excess) skewness coefficients validate the existence of potential shocks, so the markets seem to have also been exposed to uncertainties. In addition, the Jarque-Bera test shows abnormally large values indicating that volatilities are not normally distributed.

Fig. 1 presents the correlation heat maps between the green markets, US sectoral stocks, and commodities for both the return and volatility analyses, where the warm colour (orange) denotes the highest correlation whereas the cool colour (yellow) manifests low correlation. It is indicated in Fig. (1a) that WHCL and SPCL are highly correlated with the US stock market sectors, whereas slight correlation relationships are identified between the green markets and commodities. Correspondingly, US stock market sectors demonstrate high intercorrelations, whereas zero correlations are reported with commodities. Similarly, commodities also depict high correlations with the other commodities while no correlations are reported with green markets and US stock market sectors. Fig. (1b) presents the correlation heat-maps of volatility connectedness where some fragments of correlations are evident, reflecting within asset class high correlations and moderate to low correlations with other types of markets. Almost all green markets except SPGB, RENX, and EUCO reveal high correlations with the US stock market sectors and commodities. A larger fragment of high pairwise correlations among the US stock market sectors is presented, reiterating stronger correlations among similar classes of assets. Concurrently, commodities showcase sound correlations with other commodity classes and moderate to low correlations are reported with green markets and US sectors.

4. Empirical results

4.1. Return and volatility connectedness

Fig. 2 illustrates more detailed results about the characteristics of the return connectedness of green markets with the US stock market sectors, and commodity markets, in terms of total connectedness (Fig. 2A) using the Diebold and Yilmaz (2012) spillover procedure, and short-run connectedness (Fig. 2B), and long-run connectedness measures (Fig. 2C) based on the Baruník and Křehlík (2018) approach. The total returns' connectedness in Fig. 2A reveals pronounced intra-group connectedness among the US stock market sectors, whereas the green and commodity markets show low intra-group connectedness. The green markets consisting of WHCL, SPCL, and RENX indexes seem to form a distinct group within the same category market, while the other green markets show intra-group disconnection. Forming a separate cluster within the same category of green markets highlights the strong interconnectedness among the markets having similar features. For instance, WHCL, SPCL, and RENX share similar characteristics; therefore, their interconnectedness is significant. The high connectedness of green

[3] VIX represents CBOE SPX Volatility Index, RUS denotes CBOE RUSSELL 2000 Volatility Index, GVZ is CBOE Gold Volatility Index, EXG is CBOE exchange index, EMR reflects CBOE Emerging Markets Volatility Index, and MOVE indicates ML MOVE 1 M Bond Volatility Index. All these implied volatilities are price indexes.

[4] USEPU denotes US Economic Policy Uncertainty Index, UKEPU is UK Economic Policy Uncertainty Index, USEQU is US Equity related Economic Uncertainty, and INFD is the Infectious Disease EMV Tracker. All variables are economic series.

Table 1
Preliminary statistics for the return series.

Group	Symbol	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
	SPGB	0.000	2.557	−3.091	0.390	−0.354	9.219	4645.526***
	WHCL	0.024	13.399	−16.239	1.951	−0.513	9.678	5412.619***
	SPCL	0.013	11.035	−12.498	1.459	−0.615	11.361	8468.35***
Green Markets	RENX	0.035	42.217	−41.627	2.302	−0.519	129.948	1911188***
	MSGB	0.031	9.089	−11.740	1.029	−1.453	24.441	55,515.12***
	MSWT	0.036	9.750	−9.411	1.030	−0.363	15.581	18,831.460***
	EUCO	0.044	21.060	−44.655	3.153	−1.004	21.194	39,729.96***
	HLTH	0.055	7.314	−10.528	1.034	−0.455	13.213	12,467.71***
	CODC	0.064	8.286	−12.877	1.134	−0.978	15.944	20,320.99***
	ENER	−0.001	15.111	−22.417	1.715	−0.978	23.975	52,622.52***
	FINL	0.042	12.425	−15.071	1.429	−0.612	18.273	27,840.03***
US Sectors	INDS	0.045	12.001	−12.155	1.226	−0.676	17.069	23,687.51***
	COSV	0.032	8.802	−11.030	1.111	−0.540	12.528	10,904.09***
	MATR	0.036	11.003	−12.147	1.303	−0.603	12.842	11,659.36***
	COST	0.035	8.075	−9.690	0.861	−0.427	20.435	36,132.09***
	TECH	0.074	11.300	−14.983	1.297	−0.613	16.989	23,385.67***
	UTIL	0.027	12.320	−12.265	1.096	−0.329	25.549	60,345.49***
	CWTI	0.015	22.394	−28.221	2.573	−0.307	28.210	75,407.24***
	HTOL	0.003	18.196	−19.996	2.011	−0.589	17.197	24,066.48***
	NTGS	0.002	26.749	−18.055	2.920	0.416	8.684	3913.353***
Commodities	GOLD	0.013	5.775	−9.821	1.015	−0.653	10.250	6435.749***
	SLVR	0.009	8.948	−19.518	1.937	−0.998	11.392	8823.807***
	COPR	0.010	6.810	−7.591	1.336	−0.144	5.452	723.0313***
	WHET	0.002	12.929	−9.223	1.830	0.423	5.817	1026.071***

Note: *** indicates significance at 1%.

Table 2
Preliminary statistics for volatility series.

Group	Symbol	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
	SPGB	0.356	1.092	0.168	0.154	1.803	6.891	3337.819***
	WHCL	1.775	7.731	0.947	0.792	2.837	15.153	21,330.25***
	SPCL	1.302	6.706	0.613	0.643	3.271	19.669	38,025.42***
Green Markets	RENX	1.764	31.417	1.042	1.508	10.497	148.007	2545725***
	MSGB	0.867	5.533	0.432	0.515	4.089	26.796	75,075.67***
	MSWT	0.912	5.244	0.602	0.385	6.910	65.360	483,797.6***
	EUCO	2.941	15.890	1.143	1.435	2.605	15.951	23,109.54***
	HLTH	0.922	5.224	0.509	0.433	4.405	32.411	111,779.1***
	CODC	1.000	6.776	0.528	0.514	4.178	31.678	105,804.1***
	ENER	1.474	8.943	0.651	0.878	3.998	26.162	71,200.36***
	FINL	1.216	8.930	0.639	0.692	4.643	34.956	131,316.3***
US Sectors	INDS	1.065	6.924	0.557	0.575	4.707	35.858	138,536.6***
	COSV	1.024	5.537	0.694	0.356	5.300	46.790	240,716.2***
	MATR	1.166	6.463	0.598	0.570	4.012	27.271	77,492.92***
	COST	0.747	5.626	0.437	0.379	6.450	63.298	450,889.5***
	TECH	1.144	8.126	0.576	0.591	4.513	36.567	143,268.4***
	UTIL	0.927	6.360	0.540	0.510	6.524	56.460	359,092.9***
	CWTI	2.184	14.036	1.000	1.359	4.503	29.119	90,517.12***
	HTOL	1.804	8.587	0.919	0.864	3.348	18.070	32,244.93***
	NTGS	2.779	9.042	1.575	0.895	1.850	8.332	4993.389***
Commodities	GOLD	0.976	2.061	0.617	0.262	1.454	5.221	1586.948***
	SLVR	1.828	5.019	1.032	0.645	1.391	5.121	1450.875***
	COPR	1.314	2.987	0.854	0.267	2.051	10.581	8811.059***
	WHET	1.794	3.198	1.089	0.364	0.765	3.485	305.1684***

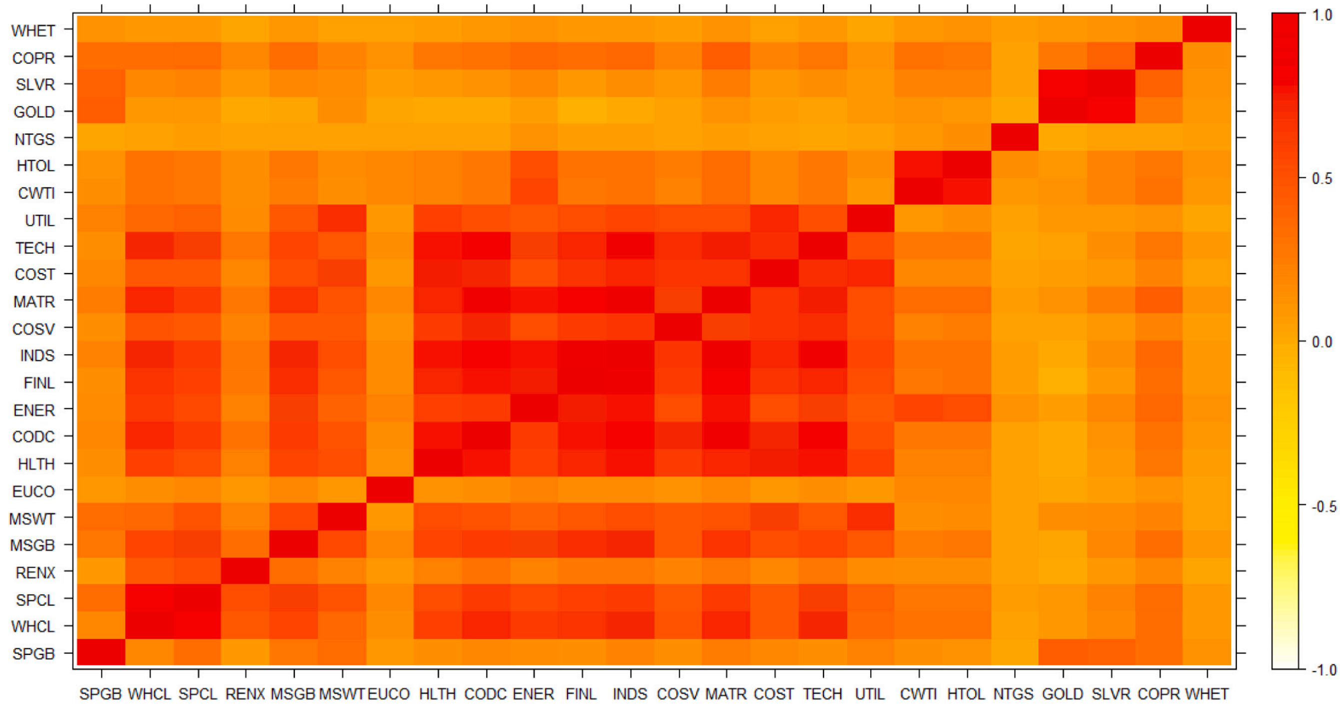
Note: *** indicates significance at 1%.

markets corroborates with the results of Naeem et al. (Naeem, Adekoya, & Oliyide, 2021; Naeem, Rabbani, et al., 2021), who also reported strong interconnection among the green market segments. However, our findings are against Elsayed, Nasreen, and Tiwari (2020), who reported similar results where green markets are lowly connected with various markets. However, the strong disconnection of remaining green markets highlights their diversification potential for several risky investments consistent with with Reboredo et al. (2020) and Arif, Hasan, et al. (2021), who also report strong diversification benefits of green markets.

The US stock market sectors show strong intra-market connectedness demonstrating higher dependence of US sectors with frequent bidirectional spillovers. INDS is receiving spillovers from ENER, FINL, COSV, COOC, and HLTH, indicating in general that INDS is an aggressive industry that receives surmounted spillovers from others (see also Ngene, 2021). The commodity markets form two clusters where the precious metals are strongly interconnected, and heating and crude oil form another cluster among the commodity markets, whereas the rest of the commodities are disconnected from the network. The clustering of commodities aligns with the studies of Caporin et al. (2021) and Balli et al. (2019), where similar commodities were found to be clustered into distinct groups due to their comparable features.

Notably, there is weak inter-group connectedness between the green markets, US stock market sectors, and commodities, where UTIL and MSWT experience bidirectional spillovers and concur the findings of Diebold, Liu, and Yilmaz (2017). This contends that inherent parallel characteristics of markets are more connected as compared to those with

a) Returns



b) Volatility

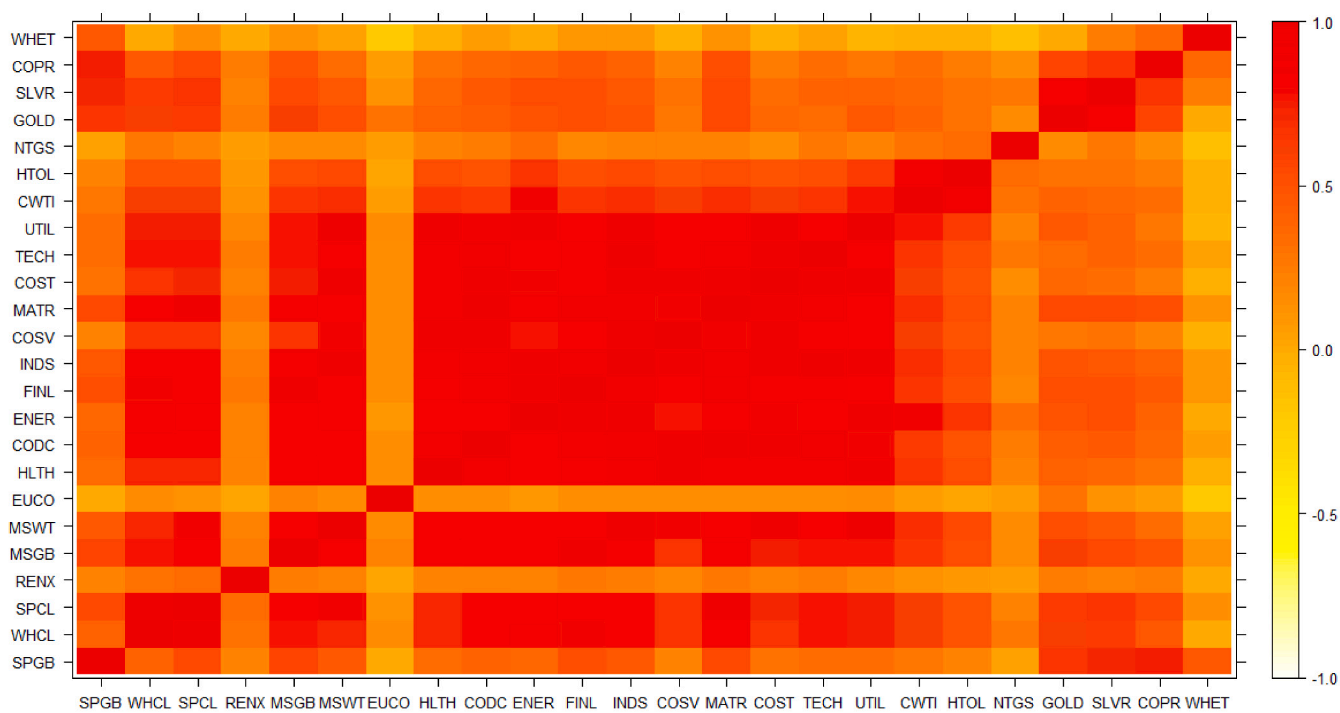


Fig. 1. Correlation heat-maps.
Note: This figure shows the correlation heat-maps among Green Markets, US Sectors and Commodities. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

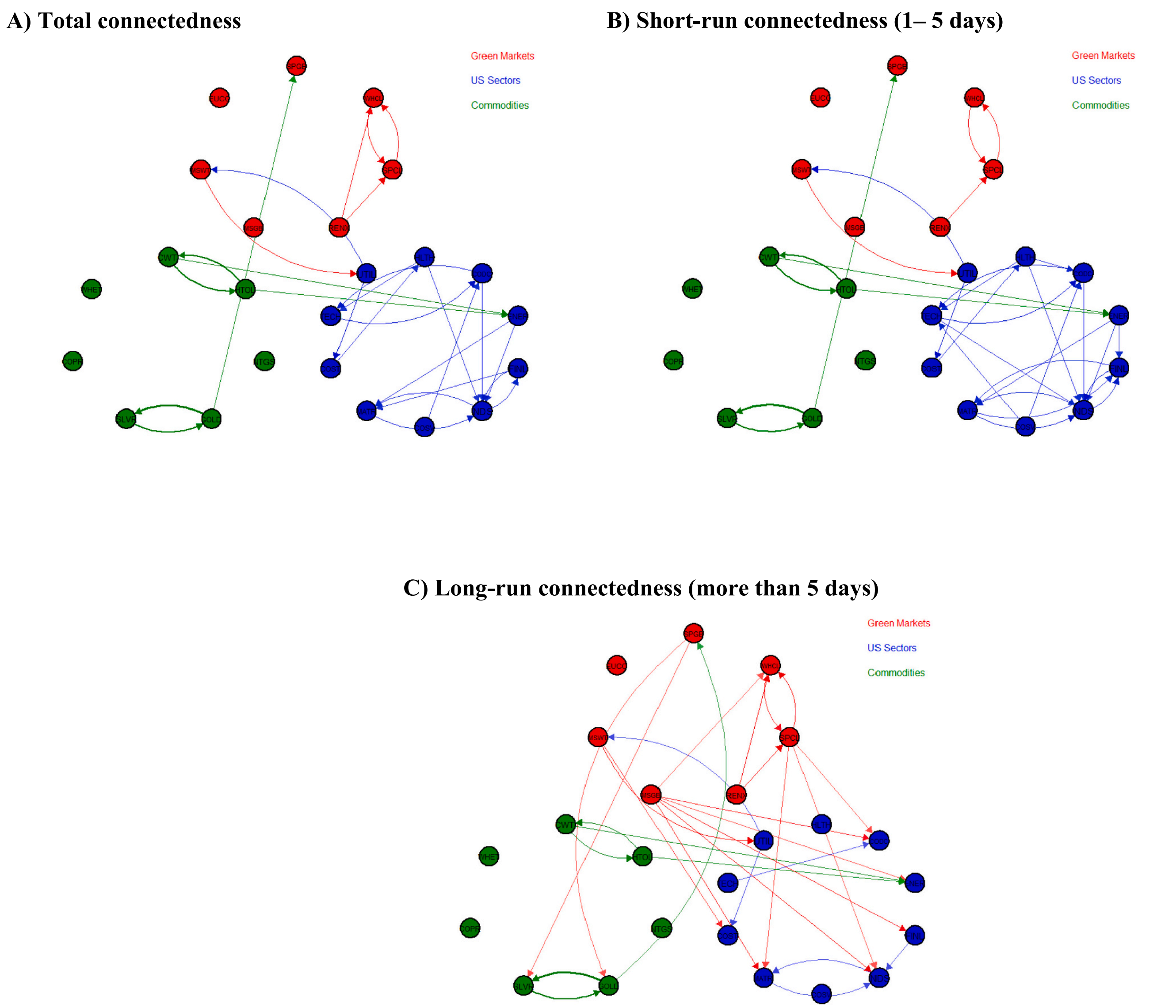


Fig. 2. Return connectedness network among green asset markets, US stock market sectors and commodity markets.
Note: This Figure shows the return connectedness among green asset markets, US stock market sectors and commodity markets. Total connectedness network is estimated using the Diebold and Yilmaz (2012) procedure, whereas short-run and long-run connectedness networks are estimated using the Barunik and Krehlik (2018) approach. Each group is represented by a colour. We only report the values larger than the average of the 100 largest individual pairwise connectedness measures. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

dissimilar features. Gold has a unidirectional spillover with SPGB, whereas CWTI and HTOL experience unidirectional connectedness with ENER. A closer look at Fig. 2B manifesting the short-run connectedness of green markets, US sectors, and commodities, following the Baruník and Křehlík (2018) approach, reveals a parallel connectedness pattern as depicted by the total connectedness. However, the connectedness pattern in the long-run (Fig. 2C) shows strong inter-group connectedness and weak intra-group spillovers. The strong inter-group connectedness among markets concurs with the results of Zhao et al. (2021), documenting strong spillovers in the long-run. Moreover, spillovers are significant for green markets highlighting their net transmitting role in influencing the network spillovers. These findings align with the results of Arif et al. (Arif, Hasan, et al., 2021; Arif, Naeem, et al., 2021) and Naeem, Nguyen, Nepal, Ngo, and Taghizadeh-Hesary (2021), where the green markets exhibit strong spillovers with respect to other markets.

Fig. 3 illustrates the volatility connectedness of green markets, US stock market sectors, and commodities, where the system-wide connectedness indicates high inter-group spillovers transmitting from green markets to US sectors and moderate spillovers from commodities to the stock market sectors. Hence, the green and commodity markets are net transmitters in the total connectedness, whereas the US stock market sectors are net recipients of volatility spillovers. Meanwhile, the intra-group volatility connectedness is significant in the US sectors, and modest to low intra-group volatilities are observed in the green markets and commodities. Interestingly, the volatility connectedness in the short-run (Fig. 3B) is prominent in the US stock market sectors, whereas mild spillovers are evident in the green markets and commodities. In our data, the volatility connectedness in the long-run (Fig. 3C) exhibits similar spillover patterns as shown in Fig. 3A, where the green markets and commodities are transmitting spillovers to various US stock market sectors, which indicates their outperformance during volatile times.

In contrast, strong intra-group volatility connectedness of the US stock market sectors and the net recipient characteristics of volatility spillovers highlight their extreme exposure to the uncertainties of the economic environment. In line with Mensi et al. (2021), our findings confirm that the US sectoral returns exhibit intense spillovers possibly

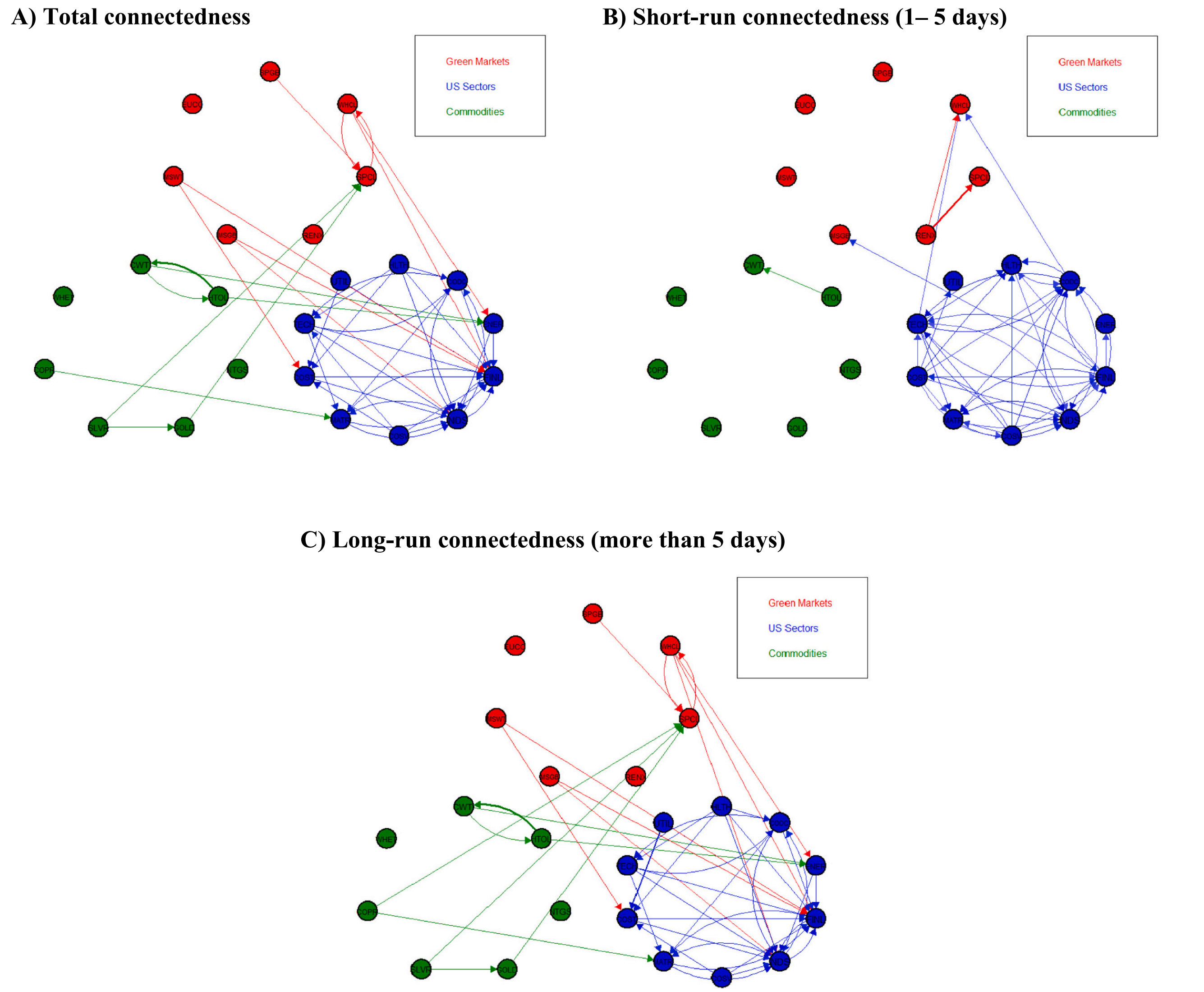


Fig. 3. Volatility connectedness network among green asset markets, US stock market sectors and commodity markets.
Note: This Figure shows the volatility connectedness among green asset markets, US stock market sectors and commodity markets. Total connectedness network is estimated using the Diebold and Yilmaz (2012) procedure, whereas short-run and long-run connectedness networks are estimated using the Barunik and Krehlik (2018) approach. Each group is represented by a colour. We only report the values larger than the average of the 100 largest individual pairwise connectedness measures. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

due to varying economic, financial, and geopolitical events. However, the role of net transmitters such as the green markets and commodities in the system-wide volatility connectedness highlights also their ability to rescue the profitability of investments during uncertain market conditions. As explained by Naeem, Nguyen, et al. (2021), Caporin et al. (2021) and Bahloul and Khemakhem (2021), the green asset markets and commodity markets transmit spillovers to other markets due to their risk-absorbance potential in times of high volatility. These findings imply that the green asset and commodity markets can provide flight-to-safety to investors during distressed periods.

Overall, there are many interconnections among the US sectoral stock market volatilities, but the spillovers of US sectoral stock market return volatilities from the commodity, and even more importantly, especially the green market return volatilities seem to be much more infrequent. Furthermore, in cases where we find connectedness, we have good economic reasons for the findings, based on supply chain connections of, e.g., the commodities relevant to the firms' production processes that seem to be affected by the individual commodity or green market developments.

4.2. *Time-varying connectedness*

Fig. 4 displays the trends in terms of market ups and downs with different time periods framing connectedness of green asset markets, US stock market sectors, and commodity markets where panel (A) presents the total connectedness based on the Diebold and Yilmaz (2012) model. The time-varying attributes of this approach manifest various spikes and troughs in the graph where the spikes denote a distressing occasion whereas subsequent trough indicates recovery to normal market conditions (Kang et al., 2021). The initial jump in the graph points toward the European Debt Crisis (2010–2012), where the European economy experienced a downturn due to the Greek government's balance sheet inaccuracies that eventually embarked the high spillovers among markets. The anti-inflation mechanism of the central banks restricted the outbound of resources (Blundell-Wignall, 2012), which resulted in intense risk spillovers. Following this time period, intense risk spillovers among markets were spotted revealing various risk attitudes of investors in the face of uneven market situations (Rufino, 2018).

The sequential jumps in the plot around 2014–2016 mirror two major incidents namely, the Shale oil revolution (SOR) and the crash of

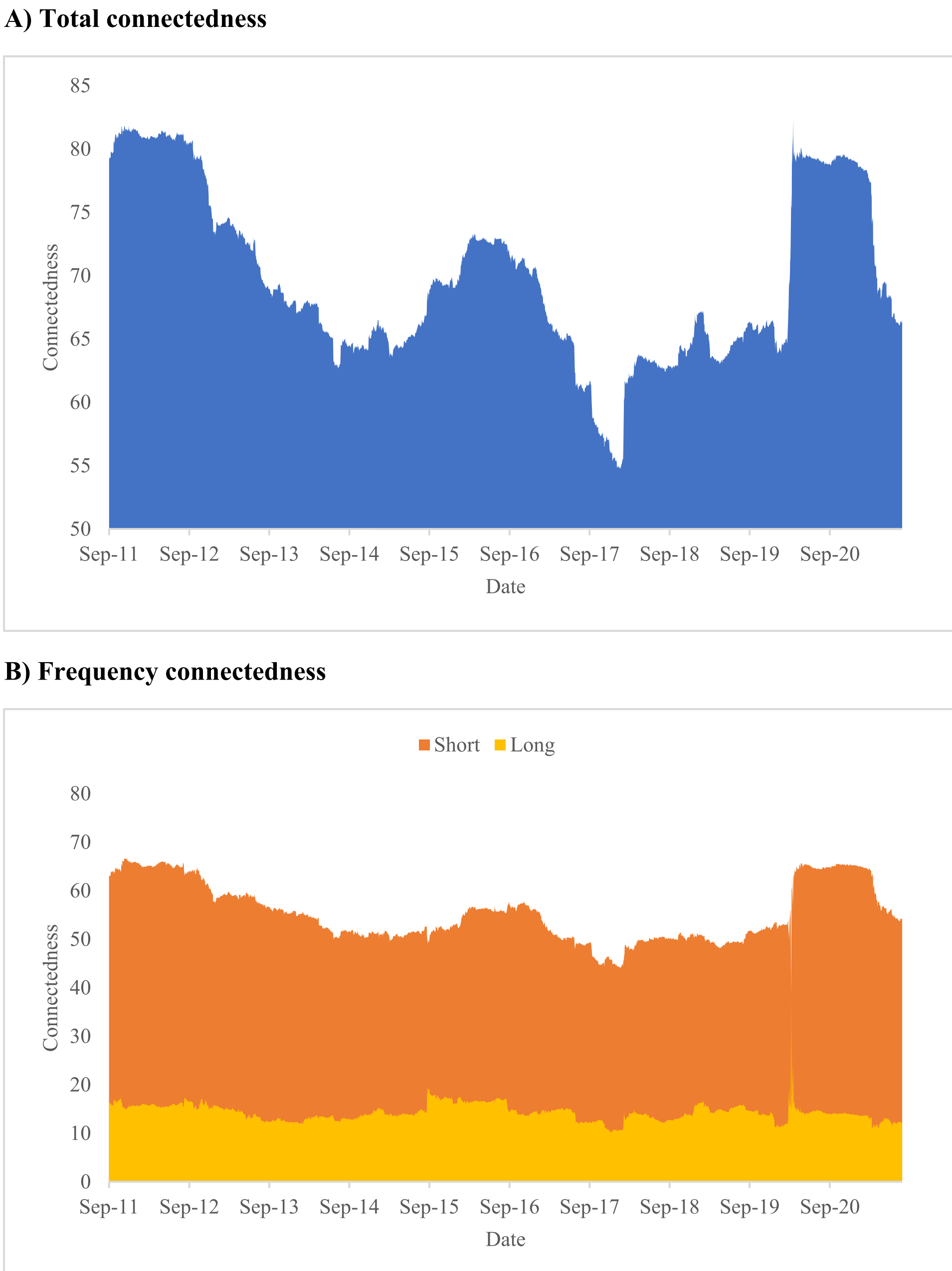


Fig. 4. Time-varying return connectedness among green asset markets, US stock market sectors and commodity markets.
Note: This Figure shows the time and frequency return connectedness among green asset markets, US stock market sectors and commodities. Total connectedness network is estimated using the Diebold and Yilmaz (2012) procedure, whereas short-run and long-run connectedness networks are estimated using the Barunik and Krehlik (2018) approach. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Chinese exchange market in a single day. The former represents the volatility transmission of energy markets (Arif, Hasan, et al., 2021), and the latter signifies how Chinese stock exchange crashed all of the sudden (Womack, 2017). The higher connectedness during this period reflects markets operating around the globe experienced severe price and volatility jumps that formed intense spillovers in the meantime (Nguyen et al., 2020). Similarly, the years 2017–2018 point toward the escalated spillovers due to pronounced interest rates announced by the government of USA (Elsayed et al., 2020; Kang et al., 2021). Finally, a sharp incline in the spillovers during the year 2019–2020 signals the catastrophic impacts of the recent global pandemic of COVID-19 where a health crisis leads the markets toward a financial and economic pandemic (Karim, Lucey, & Naeem, 2022; Karim, Lucey, Naeem, & Uddin, 2022). Bouri, Cepni, Gabauer, and Gupta (2021) resonated this finding as a financial contagion that influenced the operations of global markets forming high spillovers. In summary, the finding of time-varying dynamics indicates that markets around the globe are not insensitive rather they are reactive to the ongoing economic pressures. In the meantime, the connectedness of the whole system raises following the unstable external conditions of markets whereas when circumstances become stable, the connectedness returns to normal less connected spillovers.

Panel (B) displays the frequency connectedness where spillovers are divided into short- and long-run components over the sample period. Analogously to the results from panel (A), the short-run connectedness detects successive ups and downs in the graph featuring stressful events. Again, the initial spike during 2010–2012 denotes the European Debt Crisis (Mensi et al., 2020), whereas the jump in the graph during 2014–2016 illustrates two significant crises, i.e., the Shale oil crisis (Naeem, Hasan, Arif, Balli, & Shahzad, 2020) and Chinese market crash (Zhao et al., 2021). The final peak in the graph characterizes the ongoing COVID-19 pandemic, where intense spillovers have been detected due to the global emergency states and unexpected market conditions (Arif, Naeem, et al., 2021; Bahloul & Khemakhem, 2021; Naeem, Adekoya, &

Oliyide, 2021; Shahzad et al., 2021). On the other hand, spillovers in the long-run exhibit that short-run spillovers dominated the long-run spillovers, and according to Naeem et al. (2020), daily returns have higher connectedness in the short-run than in the long-run due to uncertainty and abrupt variation in the economic conditions. From the investors' point of view, reactions to unexpected incidents are more prompt than in the usual circumstances driving the markets' connectedness. In this way, the short-run spillovers, followed by stressed periods, are prevalent in the graph compared to the long-run, given the uncertainty of the markets (Kang et al., 2021).

Fig. 5 portrays the time-varying volatility connectedness of green asset markets, US sectoral stock returns, and commodity market returns for the given sample period. The trajectory of total volatility spillovers indicates time-varying attributes, implying several portfolio ramifications for the investors. In panel (A), we observe that the volatility spillovers varied from 80% in 2010 to 92% in 2020. The fluctuations in the volatility spillovers were intense during economic and political events, where the highest volatility spillovers were observed in 2019, corresponding to the period leading to the COVID-19 pandemic. The alarming worldwide health and economic crisis led to the increasing market volatility of up to 92%. To further detail our analysis, we differentiate the short- and long-run volatilities in Panel (B) and observe that the long-run volatilities dominate the short-run volatilities in line with Abbas et al. (2019), who argue that there are more noticeable volatilities among the markets in the long-run than in the short-run. Mensi et al. (2021) also supported this argument by claiming that the volatility is more a phenomenon of the long-run than short-run, which manifests significant pointed spikes in the long time-horizons. Thus, these results are useful for investors and fund managers in allocating their resources for structuring their portfolios based on understanding the time-varying volatility dynamics between the green asset markets, US stock market sectors, and commodity markets.

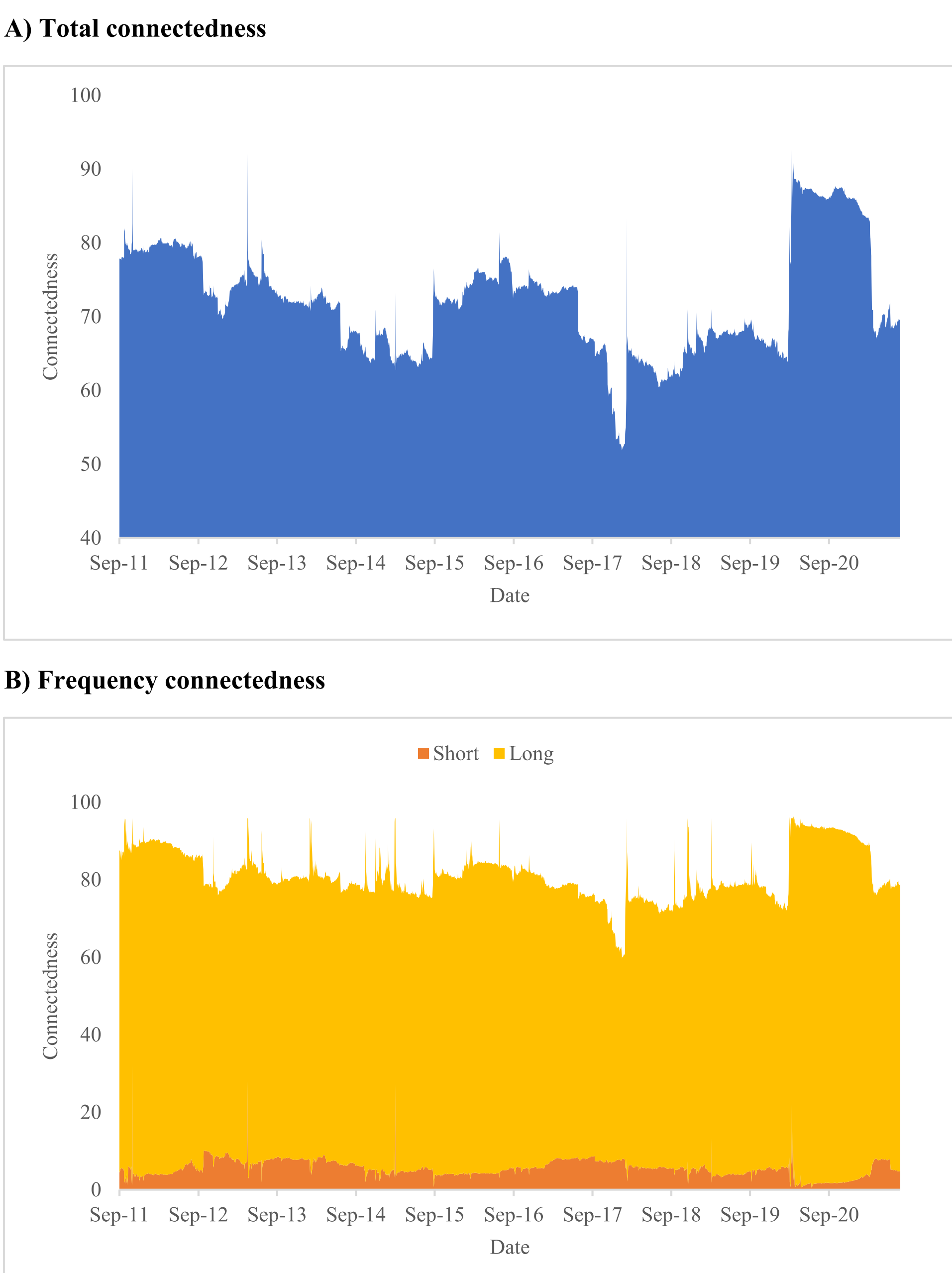


Fig. 5. Time-varying volatility connectedness among green asset markets, US stoc amrket sectors and commodity markets.
Note: This Figure shows the time and frequency volatility connectedness among green asset markets, US stock market sectors and commodity markets. Total connectedness network is estimated using the Diebold and Yilmaz (2012) procedure, whereas short-run and long-run connectedness networks are estimated using the Barunik and Krehlik (2018) approach. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.3. Time-varying NET connectedness

Fig. 6 depicts the time-varying NET return connectedness of the analyzed markets in terms of total connectedness (Panel A), short-run connectedness (Panel B), and long-run connectedness (Panel C). The time-varying NET return connectedness in Panel A reveals that the US stock market sectors configure positive spillovers. In contrast, the green asset markets and commodity markets have negative spillovers indicating that the US sectors are NET transmitters, whereas the green asset markets and commodity markets are recipients of spillovers. The NET transmitter role of US sectors is in line with Mensi et al. (2021), who also detected asymmetric volatility connectedness among the US stock market sectors. In line with Naeem et al. (Naeem, Adekoya, & Oliyide, 2021,Naeem, Nguyen, et al., 2021) and Arif, Hasan, et al. (2021), the green asset and commodity markets offer significant diversification potential to hedge investors' investments against unexpected losses. Furthermore, the time-varying dynamics of green asset markets, US sectors, and commodities emphasize that the spillovers vary over time, and markets tend to experience strong connectedness during the crisis periods. The prominent spillovers during the COVID-19 outbreak are in line with Ahmad, Hernandez, Saini, and Mishra (2021), who reported strengthened spillovers during the pandemic. Similarly, Shahzad et al. (2021) endorsed the findings of Ahmad et al. (2021) by reporting stronger spillovers during periods of economic fragility.

The short-run analysis (Panel B) reveals the role of US stock market sectors as the NET transmitter of spillovers while the green asset markets and commodity markets are NET recipients. However, the time-varying dynamics assert significant collision of spillovers, particularly during the COVID-19 pandemic, where harsh economic conditions due to worldwide lockdowns, trade and travel restrictions, and closure of business operations intensified the spillovers. In contrast, in the long-run (Panel C), the green asset markets and commodity markets received spillovers from the US stock market sectors. The sharp increase (decline) in the spillovers of US stock market sectors (commodities) during the global COVID-19 pandemic highlights the diversification feature of commodity markets when the economic circumstances are unfavorable (Naeem, Karim, et al., 2022).

Next, we examine the time-varying NET volatility connectedness (Fig. 7) of the green assets, US stock market sectors, and commodity markets in terms of the total NET connectedness (Panel A), short-run NET connectedness (Panel B), and long-run NET connectedness (Panel C). As indicated in the plot, the US sectors mainly transmitted spillovers to the green asset markets and commodities. Meanwhile, the spikes in the volatility spillovers of green markets, US sectors, and commodities during 2010–2012 manifest the European Debt Crisis, where the US sectors received volatility spillovers from commodities which elucidate the safe-haven characteristics of commodities against US sectors. Similarly, during the shale oil crisis (2014–2015), volatility spillovers were transmitted by commodities, whereas the US sectors received volatility spillovers, which mirrored the safe-haven and diversification features of commodities against the US sectors (Farid, Kayani, Naeem, & Shahzad, 2021; Naeem et al., 2020). Notably, the US sectors and green asset markets received spillovers from the commodity markets during the COVID-19 crisis, which manifests the safe-haven characteristics of commodities in the crisis period (Karim, Khan, Mirza, Alawi, & Taghizadeh-Hesary, 2022; Salisu, Raheem, & Vo, 2021).

Interestingly, the short-run NET volatility connectedness (Panel B) mainly remained near zero in the plot tracking few exceptions during the European Debt Crisis (2010–2012), Shale oil crisis (2014–2015), and COVID-19 outbreak, reiterating our results reported in Panel A. In addition, the long-run NET volatility connectedness (Panel C) unveils numerous patterns with sharp upward (positive) and downward (negative) volatilities. The pattern reflects that the US stock market sectors predominantly transmitted spillovers to green asset markets and commodity markets during EDC, SOC and COVID-19 pandemic crises, indicating the diversification and safe-haven features of green asset and commodity markets, supporting the findings of Wang, Chen, Li, Yu, and Zhong (2020) who narrated the US stock market sectors as being the NET transmitter of spillovers. Moreover, green assets and commodity markets regain their diversification traits and safe-haven characteristics in an orderly manner when the financial markets are experiencing extreme economic conditions. With these findings, we intuitively outline potential implications for investors, policymakers, financial market participants and regulatory authorities to keenly explore investment potentials with risk-mitigation features and sheltering facilities when economic circumstances are underlining serious shocks.

4.4. Impact of financial and economic uncertainty indicators on time-frequency connectedness

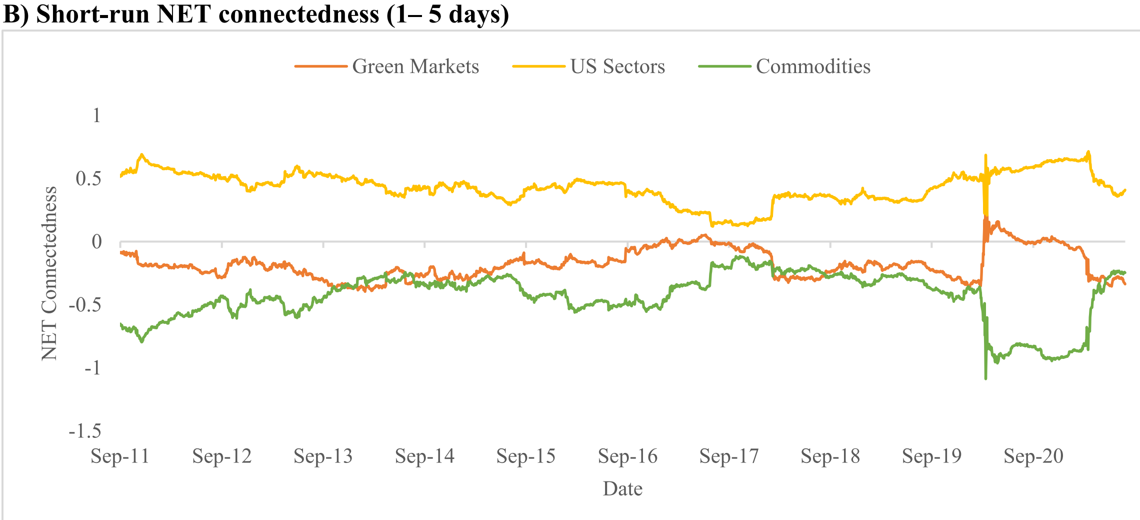
One of the most important contributions in this study is to investigate further the driving factors of return and volatility connectedness of the scrutinized markets by explicitly employing financial and economic uncertainty indicators to analyze the time-frequency connectedness between the considered market segments. Table 3 presents the impact of financial and economic uncertainty indicators on the time-frequency return connectedness.[5] The best fits of the model are obtained for the total and short-run connectedness (adjusted R^2 = 0.746 and 0.777, respectively), whereas the lowest fit is for the long-run connectedness, with adjusted $R^2 = 0.342$. The financial uncertainty indicators, such as VIX and MOVE, drive negatively the total and short-run return connectedness, whereas both VIX and MOVE drive positively the long-run return connectedness. These findings imply that increases in the volatilities of stock and bond markets decrease the connectedness for the complete sample period and in the short-run. However, the connectedness becomes stronger in the long-run. Conversely, RUS and GVZ are positive determinants of connectedness in the total and short-run analyses, whereas they have a negative effect on the long-run connectedness, implying that with the increase in the volatility of Russel index and gold markets, the connectedness increases in the total and short-run time horizons and vice versa for the long-run case. EXG shows consistent negative effects on the total, short- and long-run return connectedness, implying that an increase in the EXG reduces the connectedness in every respect. EMR does not drive the underlying connectedness, entailing an insignificant impact on the connectedness of the markets. Furthermore, the economic uncertainty seems to be a driving force of INFD in the total and short-run connectedness, whereas the other uncertainty indicators seem to be less significant determining factors. We can again intuitively propose that, in line with Zhao et al. (2021), Mensi et al. (2021), and Naeem et al. (2020), the return connectedness is prevalent in the total and short-run perspective and some markets seem to experience the potential to serve as diversifiers, hedges, and safe-havens, and co-move with the general financial uncertainty indicators under different circumstances.

Table 4 illustrates the impact of financial and economic uncertainty indicators on the time-frequency volatility connectedness where the best fits of the model are obtained for the total and long-run connectedness, with Adjusted $R^2 = 0.635$ and 0.549, respectively. Now the poorest fit of the model is reported for the short-run effects, where the adjusted $R^2 =$ 0.234. A closer look at the table manifests a negative effect of VIX for the total volatility connectedness, suggesting a decreasing connectedness of markets with the increase in the VIX. RUS and GVZ are significant and positive determinants of total and long-run connectedness, reflecting an increase in the connectedness with the increase in the Russell and gold implied volatilities. EXG affects negatively the connectedness for all time horizons implying declining connectedness with the increase in the

[5] Note that analogously to the measures for the green finance, commodity and sectoral stock market performance, we use the log differenced values of each of the economic and financial market uncertainty indicators at this final stage of our empirical analyses.

A) Total NET connectedness

B) Short-run NET connectedness (1– 5 days)



C) Long-run NET connectedness (more than 5 days)

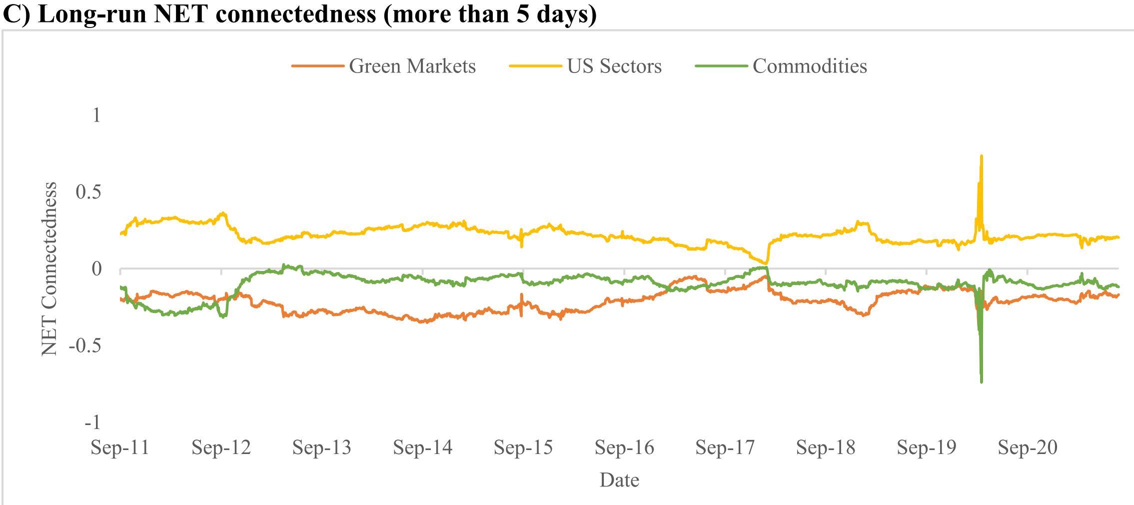
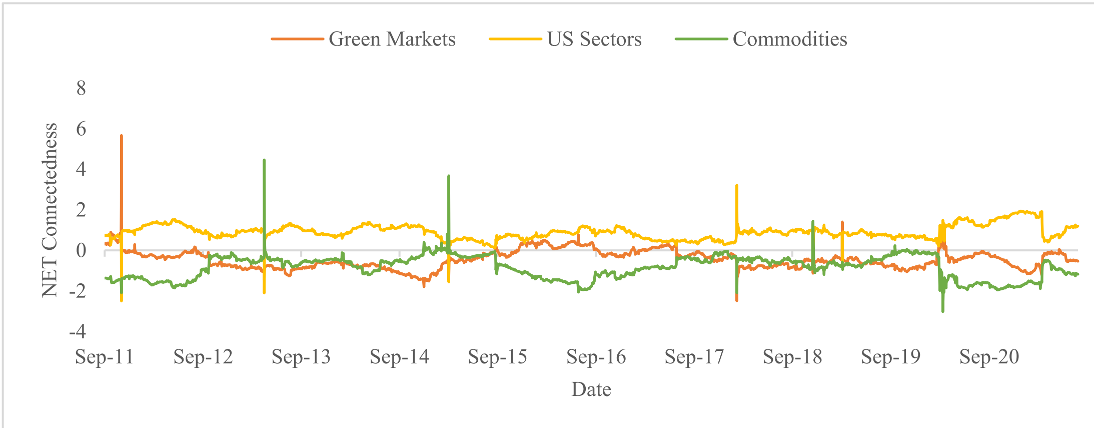
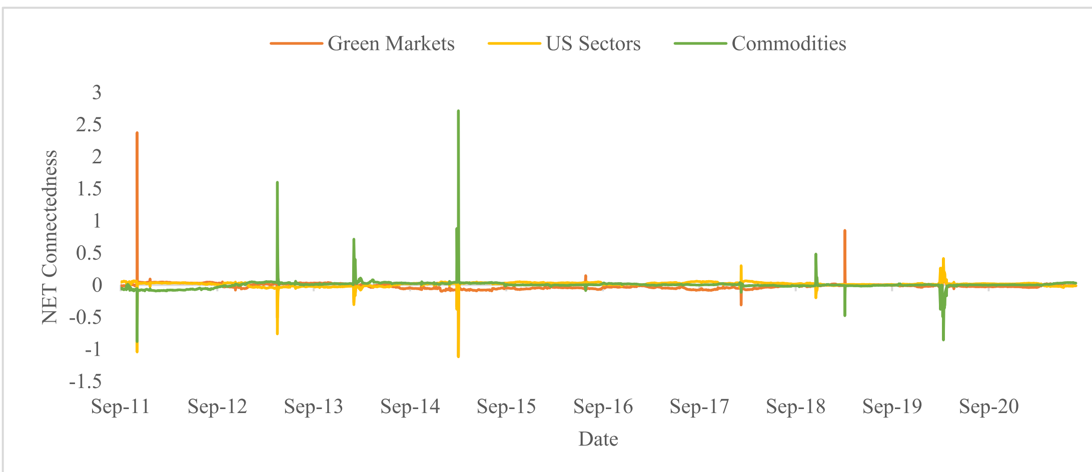


Fig. 6. Time-varying NET return connectedness.
Note: This Figure shows the time-varying NET connectedness of green asset markets, US stock market sectors and commodity markets. Total connectedness network is estimated using the Diebold and Yilmaz (2012) procedure, whereas short-run and long-run connectedness networks are estimated using Barunik and Krehlik (2018) approach. Each group is represented by a colour. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

A) Total NET connectedness



B) Short-run NET connectedness (1– 5 days)



C) Long-run NET connectedness (more than 5 days)

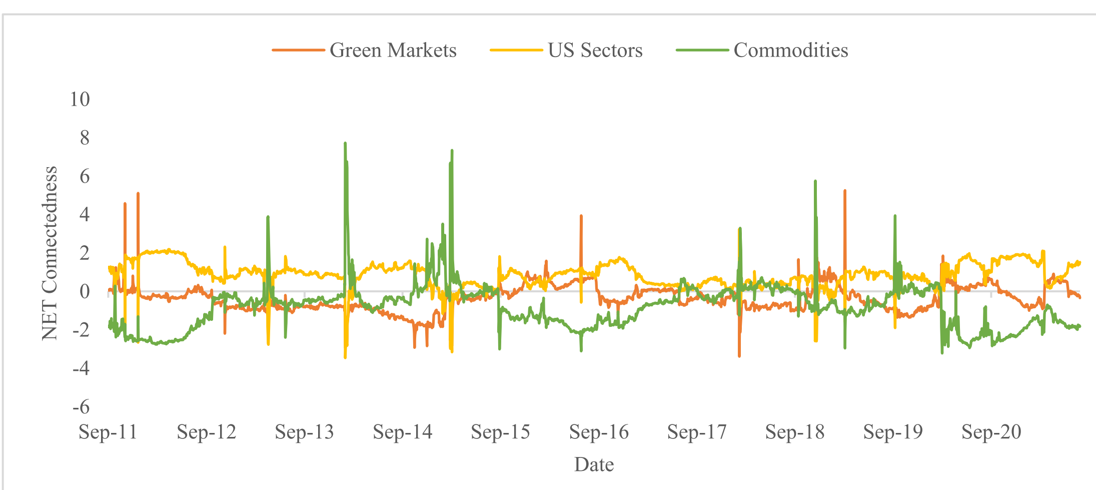


Fig. 7. Time-varying NET volatility connectedness.
Note: This Figure shows the time-varying NET connectedness of green asset markets, US stock market sectors and commodity markets. Total connectedness network is estimated using the Diebold and Yilmaz (2012) procedure, whereas short-run and long-run connectedness networks are estimated using the Barunik and Krehlik (2018) approach. Each group is represented by a colour. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Impact of financial and economic uncertainty indicators on time and frequency return connectedness.

	Indicator	Total	Short	Long
Financial	C	87.812***	72.458***	15.348***
		(1.759)	(1.499)	(0.625)
	VIX	−0.173*	−0.402***	0.229***
		(0.095)	(0.084)	(0.042)
	RUS	0.298***	0.422***	−0.124***
		(0.091)	(0.078)	(0.034)
	GVZ	0.414***	0.450***	−0.035*
		(0.058)	(0.055)	(0.020)
	EXG	−0.199***	−0.173***	−0.025***
		(0.009)	(0.007)	(0.003)
	EMR	−0.057	−0.051	−0.007
		(0.060)	(0.054)	(0.022)
	MOVE	−0.039***	−0.064***	0.025***
		(0.014)	(0.014)	(0.006)
Economic	USEPU	0.002	0.004*	−0.002**
		(0.002)	(0.002)	(0.001)
	UKEPU	0.002**	0.001	0.001***
		(0.001)	(0.001)	(0.000)
	USEQU	−0.002	−0.003**	0.001
		(0.002)	(0.001)	(0.001)
	INFD	0.180***	0.201***	−0.021
		(0.046)	(0.043)	(0.013)
	R^2	0.747	0.778	0.344
	Adjusted R^2	0.746	0.777	0.342

Note: This regression is based on HAC (Newey-West) heteroscedasticity-consistent standard errors & covariance. The table presents the results for the role of financial and economic uncertainty indicators, based on using log changes of the indexes for the US stock market volatility (VIX), UK stock market volatility (RUS), Gold market volatility (GVZ), CBOE Exchange Index (EXG), Emerging markets volatility (EMR), Treasury market volatility (MOVE), US Economic Policy Uncertainty (USEPU), UK Economic Policy Uncertainty (UKEPU), US Equity related Uncertainty (USEQU), and the Infectious Diseases Tracker (INFD), respectively. The values in () are standard errors. C refers to the constant term in the regression equation. The asterisks *, ** and *** stand for the 10, 5 and 1% risk levels of significance, respectively.

Table 4
Impact of financial and economic uncertainty indicators on time and frequency volatility connectedness.

	Indicator	Total	Short	Long
Financial	C	73.452***	11.431***	67.103***
		(2.202)	(1.201)	(3.204)
	VIX	−0.358***	−0.068	−0.017
		(0.126)	(0.061)	(0.162)
	RUS	0.479***	−0.170**	0.597***
		(0.116)	(0.071)	(0.165)
	GVZ	0.640***	−0.004	0.558***
		(0.075)	(0.035)	(0.086)
	EXG	−0.087***	−0.025***	−0.038**
		(0.011)	(0.007)	(0.018)
	EMR	−0.082	0.078**	−0.248***
		(0.079)	(0.037)	(0.096)
	MOVE	−0.083***	0.006	−0.048**
		(0.019)	(0.010)	(0.021)
Economic	USEPU	0.002	−0.002	−0.001
		(0.003)	(0.002)	(0.004)
	UKEPU	0.004***	0.000	0.001
		(0.001)	(0.000)	(0.001)
	USEQU	0.001	0.003**	−0.005*
		(0.002)	(0.002)	(0.003)
	INFD	0.202***	0.057	0.043
		(0.051)	(0.041)	(0.075)
	R^2	0.637	0.237	0.550
	Adjusted R^2	0.635	0.234	0.549

Note: This regression is based on HAC (Newey-West) heteroscedasticity-consistent standard errors & covariance. The table presents the results for the role of financial and economic uncertainty indicators, based on using log changes of the indexes for the US stock market volatility (VIX), UK stock market volatility (RUS), Gold market volatility (GVZ), CBOE Exchange Index (EXG), Emerging markets volatility (EMR), Treasury market volatility (MOVE), US Economic Policy Uncertainty (USEPU), UK Economic Policy Uncertainty (UKEPU), US Equity related Uncertainty (USEQU), and the Infectious Diseases Tracker (INFD), respectively. The values in () are standard errors. C refers to the constant term in the regression equation. The asterisks *, ** and *** stand for the 10, 5 and 1% risk levels of significance, respectively.

volatilities of exchange rates. EMR drives negatively the connectedness of the markets in the long-run, implying that the connectedness becomes weaker when the EMR upsurges. In the case of MOVE, the increase in the bond market volatility reduces the volatility connectedness of markets in view of the total and long-run perspectives. Concerning the general economic uncertainty effects, only UKEPU and INFD show up as determinants of the total volatility connectedness, suggesting an increase in the UKEPU and INFD enhances the volatility connectedness of the markets. Given this, we report that the financial indicators drive substantially, whereas the economic indicators drive more modestly the connectedness between green asset markets, US stock market sectors, and commodity markets.

5. Conclusions and policy implications

We aimed to investigate the time-frequency return and volatility connectedness of green markets, US sectors, and commodity markets using daily data from September 2010 to July 2021. We utilize the GARCH (1,1) model to estimate the conditional volatility of the sample of all the analyzed return series. Using the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) methods, we analyzed the time-frequency connectedness of the markets given their return and volatility connections. Furthermore, we analyzed the role of some relevant financial and economic uncertainty indicators prominently underlining the connectedness. Our study embraced support from modern portfolio theory for diversifying the risk of financial markets. On the other hand, the market reaction hypothesis posits that various financial and economic uncertainties drive the underlying spillover network of markets echoing the heterogenous response of investors toward these factors. Our results indicate complex intra-group return connectedness and mild inter-group return connectedness. The US stock market sectors revealed strong intra-group spillovers for the part of both the time and frequency return connectedness. On the other hand, the finding of system-wide volatility connectedness regarding the total, short- and long-term relationships indicates a high transmission of spillovers from the green asset markets and commodity markets to the US stock market sectors and strong intra-group connectedness among the US sectors.

Based on our results, we propose the following implications for the policymakers and investors or portfolio managers regarding their asset allocation, risk mitigation, and other financial market actions. First of all, the time-varying attributes of return and volatility connectedness exhibit that the analyzed markets have suffered from strong shocks during unexpected economic periods such as the European Debt Crisis, Shale oil crisis, Chinese stock market crash, and COVID-19 pandemic. Spillovers between the markets intensify when the markets experience stressful times, whereas the troughs in the connectedness graphs are in connection to the stable market conditions. Moreover, the short-run return spillovers seem to dominate the long-run spillovers reflecting the emergence of financial contagion during economically most fragile times. However, the time-varying results of volatility connectedness stress our finding that higher volatility is associated with long-term developments, with several significant events affecting the market spillovers. Hence, the long-run volatility spillovers dominate the short-run spillovers based on our results. Furthermore, time-varying NET return and volatility connectedness results characterize the US stock market sectors as the NET transmitters of spillovers. In contrast, the green asset markets and commodity markets can be denoted as NET receivers of return and volatility spillovers with significant time variations. While assessing the driving forces of financial and economic uncertainty indicators underscoring the connectedness, we found a positive driving influence of Russell Index and Gold, but a negative effect of currency and bond markets on the return and volatility connectedness of the markets focused. We report that the UK economic policy uncertainty and infectious disease tracker positively affect the return and volatility connectedness of markets for the part of general economic uncertainty factors.

These findings are crucial for policymakers for developing and assessing their future policies, particularly when investors have serious concerns about economic and financial stability in the face of an economic downturn. Moreover, a clear picture is provided to the policymakers through a nuanced approach of time and frequency connectedness for the return and volatilities, independently. The findings can set a benchmark for the policymakers in restructuring and revisiting their outdated policies about the stability of the financial and commodity markets. For investors, the results are vital for risk mitigation and streamlining their portfolios as this study would also help intuitive decision-making when predicting the future returns and trying to offset the portfolio risks by adding diversifiers in their portfolios. For example, for the green asset market investors, the findings are appealing because they give a clearer picture of the connections between the green asset markets and other relevant financial market sectors, both in terms of return and volatility connections.

Finally, the last step of our empirical analysis revealed that the spillovers seem to shift based on market ups and downs during unexpected financial and economic stress conditions. Hence, investors have to clearly distinguish between the short- and long-run spillovers, both with respect to the return and volatility connectedness. This should also help the policymakers in revealing the risk-adjusted potential of the small fish (green markets) in mitigating the risks of other big ponds (US stock market sectors and commodities) markets.

Considering the determinants of return and volatility connectedness in various financial and economic uncertainty indicators, our findings can potentially benefit investors and policymakers for risk and return predictability during unfavorable financial markets and aggregate economic circumstances. Investors and financial market participants can consider these driving forces for their portfolio management, risk management, and asset allocation decisions. In addition, our time-varying analysis revealed that it is essential for the traders and portfolio managers to make adjustments in their existing investment positions during varying market conditions. Our detailed analysis of the spillover structure provides significant insights to the macro-prudential regulators to protect the most fragile markets and select the appropriate policies and regulatory attempts to preserve the interests of investors during unexpected financial and economic conditions.

CRediT authorship contribution statement

Muhammad Abubakr Naeem: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – review & editing. **Sitara Karim:** Conceptualization, Writing – original draft, Writing – review & editing. **Gazi Salah Uddin:** Conceptualization, Data curation, Writing – review & editing, Project administration. **Juha Junttila:** Writing – original draft, Writing – review & editing, Supervision, Funding acquisition.

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