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Time and frequency connectedness of green equity indices: Uncovering a socially important link to Bitcoin

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ABSTRACT

Green investment funds continue to interest as a sustainable non-conventional asset class. We examine their interconnectedness, using network and wavelet analyses, with both traditional and non-traditional financial assets. Results indicate that global stock market performance, along with the returns of emerging markets, commodity markets, and FinTech are strongly correlated with green indices. However, in comparison, Bitcoin is found to be isolated, as confirmed by wavelet analyses. When considering the evolution of green investment indices, their role as diversifiers to Bitcoin is especially interesting, suggesting many potential benefits for investors and policymakers. Perhaps the most prominent application of our results is for Bitcoin investors to consider more closely investing in green funds as an offset to concerns about the negative environmental consequences of investing in proof-of-work cryptocurrencies.

1. Introduction

As governments and policymakers promote sustainable projects towards ensuring low carbon emissions and environmental sustainability, world economies are in turn gravitating towards projects and investments that are in line with social goals (Barbier, 2010). As, for example, the World Economic Agenda 2030 for sustainable development and other organisations advocate towards sustainable projects, there is concomitantly enthusiasm for green assets. During the last decade, the demand for green investments has shown unprecedented growth (Bourcet, 2020; Koellner, Weber, Fenchel, & Scholz, 2005). Investors are also moving towards sustainable-fund investments in part because of increased positive flows of financing (Naqvi et al., 2021). Moreover, the financialization of the energy market has diverted investments from conventional, or more traditional funds, to energy funds (Gagnon, Manseau, & Power, 2020). This is reflected in the influx of retail and institutional investors towards green energy investments (Su, Naqvi, Shao, Li, & Jiao, 2020).

Despite the pronounced expansion of investments in green funds during the last decade, such markets have also experienced adverse impacts from COVID-19 (Ashraf & Goodell, 2021; Corbet, Hou, Hu, & Oxley, 2020, 2022a, 2022b; Goodell, 2020). Accordingly, it is essential to gauge the diversification opportunities of green funds with other asset classes[1] (Kuang, 2021; Mensi et al., 2021; Naqvi et al., 2021). The study investigates the diversification opportunities of investing in green funds with conventional and non-conventional assets. Building on Huynh, Hille, and Nasir (2020) and Le, Abakah, and Tiwari (2021) we examine the diversification opportunities of green funds. We apply time and frequency connectedness in a wavelet framework and network analysis, in order to investigate whether conventional or non-conventional investment assets provide better diversification opportunities when combined with green investment. Our study will be of particular interest to public policy makers as green finance is integral to achieving green public policy objectives (Sachs, Woo, Yoshino, & Taghizadeh-Hesary, 2019; Tamazian, Chousa, & Vadlamannati, 2009).

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[1] Several studies examine diversification opportunities with green funds (Kuang, 2021; Mensi, Shafiullah, Vo, & Kang, 2021; Naqvi, Mirza, Rizvi, Porada-Rochoń, & Itani, 2021; Reboredo, Ugolini, & Aiube, 0000). We contribute to this valuable line of inquiry by specifically focusing on interactions with both broad FinTech funds, and cryptocurrency, directly in the form of Bitcoin.

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Such initiatives are concomitant with financial institutions seeking to attract private capital to finance sustainability related businesses and projects (Aizawa & Yang, 2010).

With this motivation, we investigate diversification opportunities for investors investing in green funds. We investigate whether conventional or non-conventional assets provide better diversification opportunities with green funds. We also examine which indices are safe havens while investing in green funds. We answer these research questions by considering NASDAQ OMX Green Economy Index (QGREEN) as a proxy for green assets. We also consider stock markets, both developed and emerging, with the MSCI World Index and MSCI Emerging Market Index, along with the commodities market through the Standard and Poor's Goldman Sachs Commodity Index (S&P GSCI). For non-conventional asset classes, we consider Global X Fintech ETF (FINX) and Bitcoin (BTC). Initially, we examine the transmission of volatility spillovers from QGREEN to conventional asset classes. We then similarly examine spillovers regarding non-conventional asset classes. Towards these ends, we apply time–frequency connectedness-wavelet analysis and network analysis.

The rationale behind the selection of proxies for asset classes depends on their proximity to what is being represented and to their global representation. Use of QGREEN as a proxy for a green equity index captures a wide range of companies involved with green sustainable projects having low carbon emissions, renewable energy generation, and mitigation of pollution. Similarly, we use the thematic exchange traded fund Global X FinTech (FINX) as a proxy for FinTech. The fund is a fair representation of the financial technology sector stocks that are involved with digital solutions, machine learning, artificial intelligence, mobile-based technologies, and algorithmic trading.

Among conventional asset classes, the MSCI World Index and the MSCI Emerging Markets Index are close proxies of developed, and emerging markets, respectively. They encompass 23 developed and 25 emerging countries. Lastly, the S&P GSCI is one of the most widely recognised benchmarks to represent the global commodity market. This index is especially appropriate as it includes highly liquid commodity futures.

Regarding our results, network analysis evidences that QGREEN, FINX, MSCID, MSCIE, and SPGSCI are strongly correlated with each other while Bitcoin is not. This suggests Bitcoin as a diversification vehicle. Based on wavelet analysis, we notice that there is positive co-movement from QGREEN to FINX, MSCID, MSCIE, and SPGSCI in all scales (small to large) from March 2020 onward. However, co-movement of QGREEN with Bitcoin is not identified. In addition, it is observed that FINX, MSCID, and MSCIE lead QGREEN.

Overall, our results strongly confirm the role of bitcoin as a diversifier for green funds. This highlights an opportunity for investors in bitcoin, concerned about the negative environmental impacts of proof-of-work cryptocurrency mining, to voluntarily offset their investments in green funds. This would achieve both an offsetting contribution to financing of pro-environmental projects, as well as enhance their portfolio diversifications.

Regarding the rest of the paper, Section 2 provides an overview of existing literature towards building hypotheses. Section 3 provides an explanation of the data and methodology, while Section 4 presents the empirical results. Section 5 concludes.

2. Literature

There is potential resonation between green investing, which helps finance projects that mitigate greenhouse gas emissions (Zhang, Zhang, & Managi, 2019), Further, FinTech-based start-ups are often more scalable compared to traditional banks. FinTech, if used with appropriate control and structures, can help to reduce greenhouse emissions (Ignatyuk, Liubkina, Murovana, & Magomedova, 2020; Puschmann, Hoffmann, & Khmarskyi, 2020; Ranchber, 2018; Tao, Su, Naqvi, & Rizvi, 2022), as it has the ability to provide a sustainable model incorporating integration of circular economy practices (Deng, Huang, & Cheng, 2019; Pizzi, Corbo, & Caputo, 2021; Vergara, Agudo, et al., 2021). In contrast, environmentalists are concerned over usage of electricity for mining of cryptocurrencies (Corbet, Lucey, & Yarovaya, 2021).

The global financial crisis of 2008 elevated the importance of portfolio diversification, as it highlighted that connectedness can lead to substantial investment losses. Due to increased climate awareness, issues like water management and climate change have increased the importance of green bond investment, as such instruments can help in the financing of environmental projects . As green bonds develop, they are increasingly considered as an effective hedging tool against both climate and financial risks (Guo & Zhou, 2021; Hammoudeh, Ajmi, & Mokni, 2020). Clean energy stocks and green bonds have been found to provide diversification benefits for investors with energy stocks (Kuang, 2021; Liu, Liu, Da, Zhang, & Guan, 2021), while low or negative correlations of both stocks and commodities with green bonds have also been identified (Nguyen, Naeem, Balli, Balli, & Vo, 2021; Park, Park, & Ryu, 2020).

Studies analyse the relationships between green fund and conventional assets to determine whether they provide the same risk return levels as conventional assets. Pricing differentials have been used to match daily spreads of green labelled and non-green labelled bonds. Interdependence between green bonds and green stocks and major conventional assets like treasury bonds, crude oil and gold have been conducted. Green bonds have been found to be tightly linked with treasury and corporate bonds, while green stocks have been linked quite closely with general stocks (Ferrer, Benítez, & Bolós, 2021). Ferrer et al. (2021) use connectedness methodology to explore the relationship between green bond markets and conventional financial energy markets, while Jin and Han (2018) employing a Carhart four factor model to measure the performance of the green funds. Green fund industry performance has been found to have a positive correlation with R&D and innovations activities, which in turn are found to influence economic performance. It is also found that heightened uncertainty affects volatility and return connectedness between the conventional markets and the green markets (Naeem, Conlon, & Cotter, 2022).

Many commodity and green markets are directly affected by stock returns, with connections regarding volatility more than that of returns. This reflects the dependence of green and commodity markets on the performance of stock markets. Further, as there has been strong volatility in the blockchain markets, investors have started exploring ways to diversify as well as the diversification benefits of cryptocurrencies, non-fungible tokens (NFTs), and Defi tokens (Karim & Naeem, 2022). NFTs have displayed particularly effective diversification along with risk-bearing potential (Karim, Lucey, Naeem, & Uddin, 2022). Islamic stocks, S&P 500 stocks, and sustainability index have been found to be transmitters of volatility while green bonds, clean energy bonds, and commodity index reduce the volatility effects and function as recipients of spillovers (Karim & Naeem, 2022; Naeem et al., 2022). Studies have analysed the relationship between carbon prices, green and non-green cryptocurrencies (Pham, Karim, Naeem, & Long, 2022). Green cryptocurrencies have been found to be weakly connected to Ethereum and Bitcoin Ahonen, Corbet, Goodell, Günay, and Larkin (2022).

Stock prices of green companies have been found to be highly volatile and prone to risk from other assets including gold, silver, and crude oil (Dutta, Bouri, & Noor, 2021). Bitcoin has been identified to be directly affected by external shocks (Le et al., 2021). Using three dynamic hedging methodologies (DCC-T-GARCH, DCC-APGARCH, DCC-GJR-GARCH), the connection between carbon market futures and green bond index is also highest during the most significant periods of volatility (Jin, Han, Wu, & Zeng, 2020). Green mutual funds have also been identified to have under-performed compared to conventional mutual funds (Ibikunle & Steffen, 2017; Pham, 2016).

Table 1
Descriptive statistics of analysed variables.

	QGREEN	FINX	MSCID	MSCIE	GPGSCI	Bitcoin
Observations	1098	1098	1098	1098	1098	1098
Minimum	−0.1224	−0.1374	−0.1044	−0.1343	−0.1252	−0.4809
Maximum	0.0925	0.1056	0.0841	0.0691	0.0768	0.2372
Mean	0.0007	0.001	0.0005	0.0004	0.0002	0.0026
Stdev	0.012	0.0166	0.0106	0.0129	0.0142	0.048
Skewness	−1.5085	−1.1125	−1.7243	−1.6789	−1.359	−0.9628
Kurtosis	20.4159	12.1082	25.0212	17.8756	14.1281	11.9894
Jarque–Bera Test	19566***	6965***	29305***	15198***	9511.2***	6776.5***
ADF Test	−9.2291***	−9.3453***	−9.3345***	−9.8139***	−9.5854***	−9.7308***

Note: ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

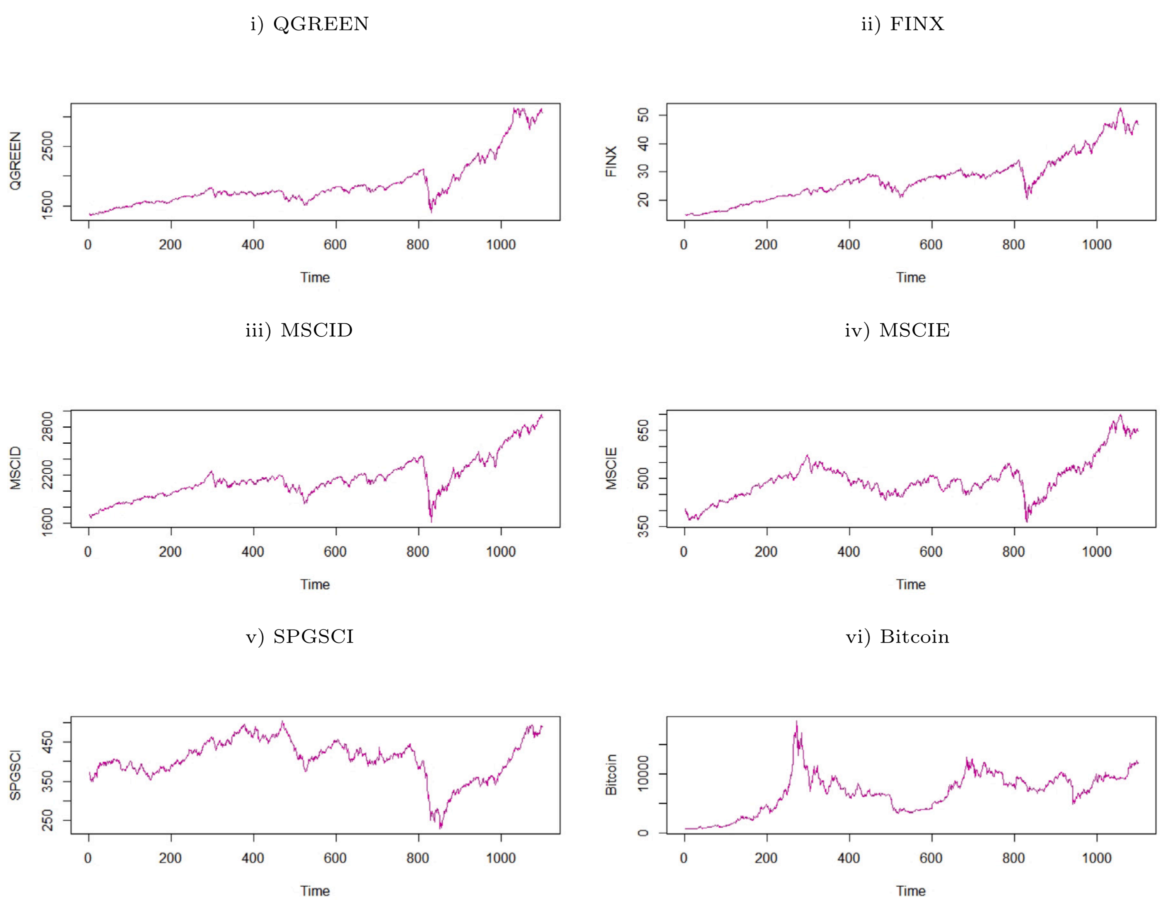

Fig. 1. Time series plot of raw series.
Note: When considering conventional assets, emerging markets, developed markets, and commodities markets are found to best represent a broad broad asset base. The proxies of these markets are MSCI-Emerging Markets (MSCIE), MSCI World Index (MCID), and SPGCI, respectively. For non-conventional assets, we consider green index funds, FinTech investment funds, and cryptocurrencies; where the proxies for the same are QGREEN, FINX, and Bitcoin respectively.

3. Data and methodology

3.1. Data

To focus on our specific research questions, we consider the NASDAQ OMX Green Economy Index (QGREEN) as a proxy of the green equity index. Proxies for the stock market are MSCI World Index and MSCI Emerging Market Index while Standard and Poor's Goldman Sachs Commodity Index (SPGSCI) is used as a proxy for the commodity market. Further, Global X Fintech ETF (FINX) and Bitcoin (BTC) measure the FinTech and cryptocurrency markets, respectively. QGREEN, as a proxy for green equities, captures a range of wider companies that are into green sustainable projects having low carbon emissions, renewable energy generation, mitigation of pollution, amongst others. Likewise, Bitcoin is considered as a proxy of the cryptocurrency markets.[2] Some studies considered bitcoin as hedging investments during

[2] Identification of diversification opportunities with non-conventional or emerging asset classes has developed, particularly with regard to during and post sharp market shocks. Celeste, Corbet, and Gurdgiev (2020), Cheah and Fry (2015), Conlon, Corbet, and McGee (2020), Corbet, Hou, Hu, and Oxley (2021a, 2021b), Dyhrberg (2016), Huynh et al. (2020), Katsiampa (2017), Le et al. (2021) and Naeem and Karim (2021). In recent years, diversification with technology and FinTech assets and cryptocurrencies has developed at pace (Corbet, Lucey, & Yarovaya, 2018; Katsiampa, Corbet, & Lucey, 2019a, 2019b; Kliber, Marszałek, Musiałkowska, & Świerczyńska, 2019; Stensås, Nygaard, Kyaw, & Treepongkaruna, 2019; Wang, Zhang, Li, & Shen, 2019), with further directions indicated by studies related to diversification with other non-conventional, or non-traditional investment assets (Akhtaruzzaman,

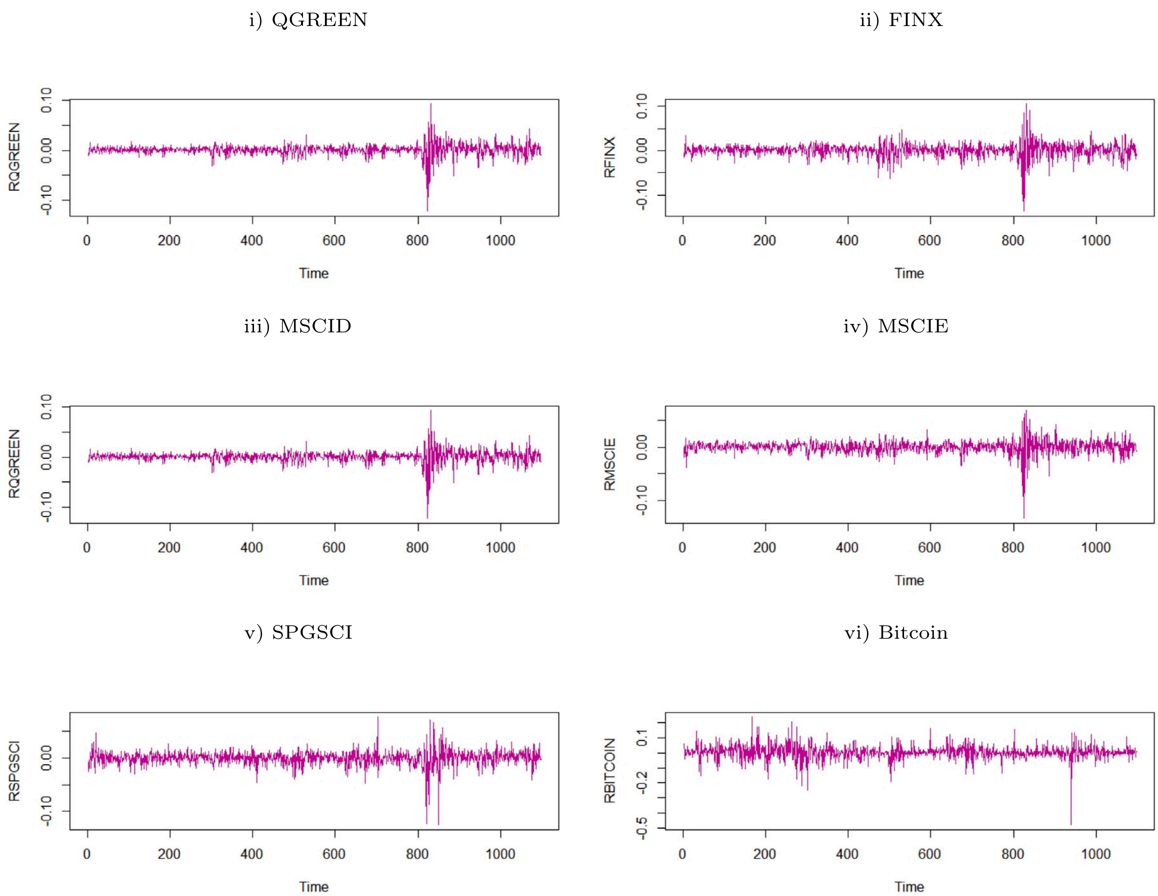

Fig. 2. Time series plot of return series.
Note: When considering conventional assets, emerging markets, developed markets, and commodities markets are found to best represent a broad broad asset base. The proxies of these markets are MSCI-Emerging Markets (MSCIE), MSCI World Index (MCID), and SPGCI, respectively. For non-conventional assets, we consider green index funds, FinTech investment funds, and cryptocurrencies; where the proxies for the same are QGREEN, FINX, and Bitcoin respectively.

the period COVID-19 (Goodell, 2020; Guo & Zhou, 2021; Su et al., 2020). FINX, as a proxy for FinTech, is a thematic exchange-traded fund. Launched in 2009, it is a fair representation of the financial technology sector stocks that are involved with digital solutions, machine learning, artificial intelligence, mobile-based technologies, and algorithmic trading. Among conventional asset classes, MSCI World Index and MSCI Emerging Markets Index are close proxies of developed and emerging markets. They are constituted with 23 developed and 25 emerging countries, respectively. Lastly, the S&P GSCI is one of the most widely recognised benchmarks to represent the global commodity market. The uniqueness of the index is that it includes highly liquid commodity futures and provides diversification opportunities. We collect daily observations extending from 25 October 2016 through 20 April 2021 using Bloomberg. The reason behind considering this period is that the Paris Climate Agreement focused more on green finance at the end of 2015.

3.2. Methodology

We employ network and wavelet analysis to examine the co-movement among constituent variables. Network analyses show the overall relationship between the variables, while wavelet analyses focus on the co-movement or connectedness of variables over time. Wavelet analysis sub-divides time series into elementary functions, determining shocks from initial waves of seniority, expressed with regard to time and scale frequency. Prior studies have worked with GARCH-family models or used rolling window methodologies to measure the time varying relationships in the time domain (Dajcman, Festic, & Kavkler, 2012; Liow, Huang, & Song, 2019). Wavelet analysis examines the co-movement of series over time and frequency in various horizons (short, medium, and long runs) (Conlon & Cotter, 2012; Conlon, Cotter, & Gencay, 2018; Conlon, Crane, & Ruskin, 2008). We use wavelet analysis through continuous wavelet, cross wavelet, and wavelet coherence.

Continuous wavelet transforms extract frequency information in a particular period and are the most preferred technique in wavelet analysis. The number of wavelets is not defined in the continuous wavelet analysis, as this is self generated according to the time span of the data analysed. This also helps to interpret and identify patterns, and other difficult to identify information. It breaks the time series into elementary functions, which are in turn are derived from a senior wavelet. This senior wavelet is identified where the series should have a zero mean. Its square should integrate to unity and fulfil the admissibility condition. Most commonly used senior wavelets are those of the Morlet wavelet, which is made up of a complex exponential multiplied by a Gaussian envelope. Due to its complex structure, it can help in computing the phase of wavelet transform of every series from the complex part, in turn providing information about the position in the cycle of a time series. It is expressed mathematically as follows:

$$W_t^{\varepsilon}(\Omega) = \sqrt{\frac{\Phi_t}{\Omega}} \sum_{t=1}^{n} X_n \varepsilon \Psi \theta \left[(\eta\varepsilon - n) \frac{\phi_t}{\Omega} \right] \quad (1)$$

Sensoy, & Corbet, 2020; Akyildirim, Corbet, Lucey, Sensoy, & Yarovaya, 2020; Chemkha, BenSaïda, Ghorbel, & Tayachi, 2021; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Kyriazis, Papadamou, & Corbet, 2020; Sensoy, Silva, Corbet, & Tabak, 2021).

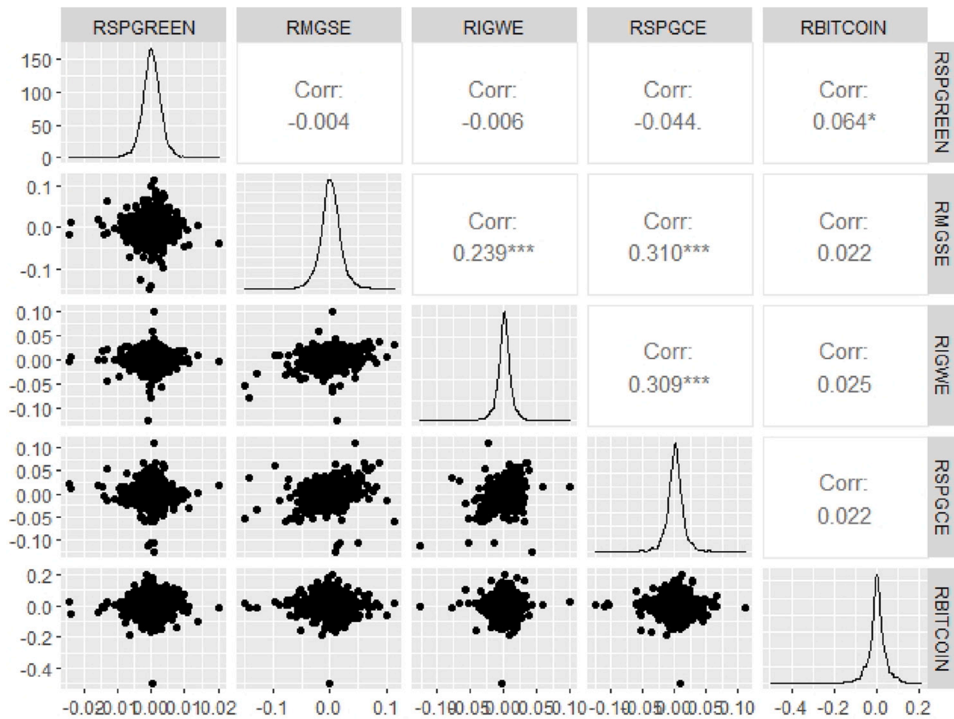

Fig. 3. Unconditional correlation and overall distribution pattern.
Note: ***, **, and * denote significance at 1%, 5%, and 10% significance level respectively. Plots of the distribution and the pairwise correlations of QGREEN, when compared with the other included conventional and non-conventional asset returns.

where, $n = 1, \ldots, N$, while s represents the scales analysed. Φ_t indicates the time period analysed, and the wavelet power $|W_t^{\epsilon}(\Omega)|^2$, presents the local phase.

Cross wavelet transform analysis provides the correlation of two time series in the time–frequency. Hudgins, Friehe, and Mayer (1993) introduced the concept of cross wavelet analysis to provide the bivariate extension of wavelet analysis. As a part of the senior wavelet, the cross-wavelet spectrum can be decomposed into real and imaginary parts. The information about the amplitude and phase of the two-time series can be separated into its real and imaginary parts. This helps in attaining the time dependent phase and amplitude across frequency. The power of the cross-wavelet spectrum can be defined as the absolute value of the local covariance between the two-time series at each time and frequency which helps to compare two different time series. It can be expressed by following equation:

$$D\left(\frac{|W_n^x(s)W_n^{y*}(s)|}{\sigma_x\sigma_y} < p\right) = \frac{Z\upsilon(p) *}{\upsilon}\sqrt{\left(p_k^x p_y^x\right)} \quad (2)$$

where $Z\upsilon(p)$ denotes the probability p for the associated pdf, the wavelet power spectra (WPS) are biased for low-frequency oscillations. Further, wavelet coherency captures the localised correlation coefficient in time–frequency space. The relationship may vary from being completely coherent, that is a value of one compared to that of being completely incoherent when estimated to be zero. The coherence coefficient is computed by squaring the local correlation coefficient between data of two time series (Hu & Si, 2021; Siddiqui, Ahmed, & Naushad, 2020). Monte Carlo simulations are applied where at least one of the processes can be modelled by the Gaussian white noise. The wavelet cross spectrum is not found to be useful for evaluating the significant interrelationship among the variables. Therefore, wavelet coherency has been found to be a better method. It is shown mathematically as follows:

$$R_n^2(s) = \frac{\left|S(s^{-1}W_n^{XY}(s))\right|^2}{S(s^{-1}W_n^X(s))S(s^{-1}W_n^Y(s))} \quad (3)$$

where W_n^{XY} is the CWT, s represents smoothing operator normalising time, and $R_n^2\epsilon[0,1]$ is the wavelet squared coherency.

Finally, we implement a network analysis to focus on the key results. A network is a node which is connected by different linkages. Network analysis is a prominent tool to help in estimating the different patterns of many complex systems. A wide variety of network measures which has numerous nodes helps to decode the linkages patterns helping in transmission of valuable information. The node centrality measures add to the information provided by other node characteristics. The existence and identification of key nodes which can reach other nodes helps in framing effective policy implementation. In finance, the network analysis helps in revealing suitable effects resulting from interconnected nodes.[3] After deriving the importance of the nodes, the accuracy of the network can be checked by computing the confidence interval (95% CI). Following steps are considered in network analysis: (i) Estimation of the network structure to check the association among variables; (ii) Analysis of the network structure of the constituent variables; and (iii) Testing the network parameters accuracy.

4. Results

We report summary statistics of QGREEN, and other assets in Table 1. We consider emerging markets, developed markets, and commodities markets to represent a broad conventional asset base. The proxies for these markets are MSCI-Emerging Markets (MSCIE), MSCI World Index (MCID), and SPGCI, respectively. For non-conventional assets, we consider green index funds, FinTech investment funds, and

[3] The network consists of two broad edges; one is directed edge and another one is un-directed edge. A directed edge is the edge that connects through an arrowhead depicting one way effect. Further, an un-directed edge is a connecting line which depicts mutual association without arrowheads. Edges furnish the information related to the direction and strength of the association between the nodes. The edge can be positive and negative which is presented by coloured line.

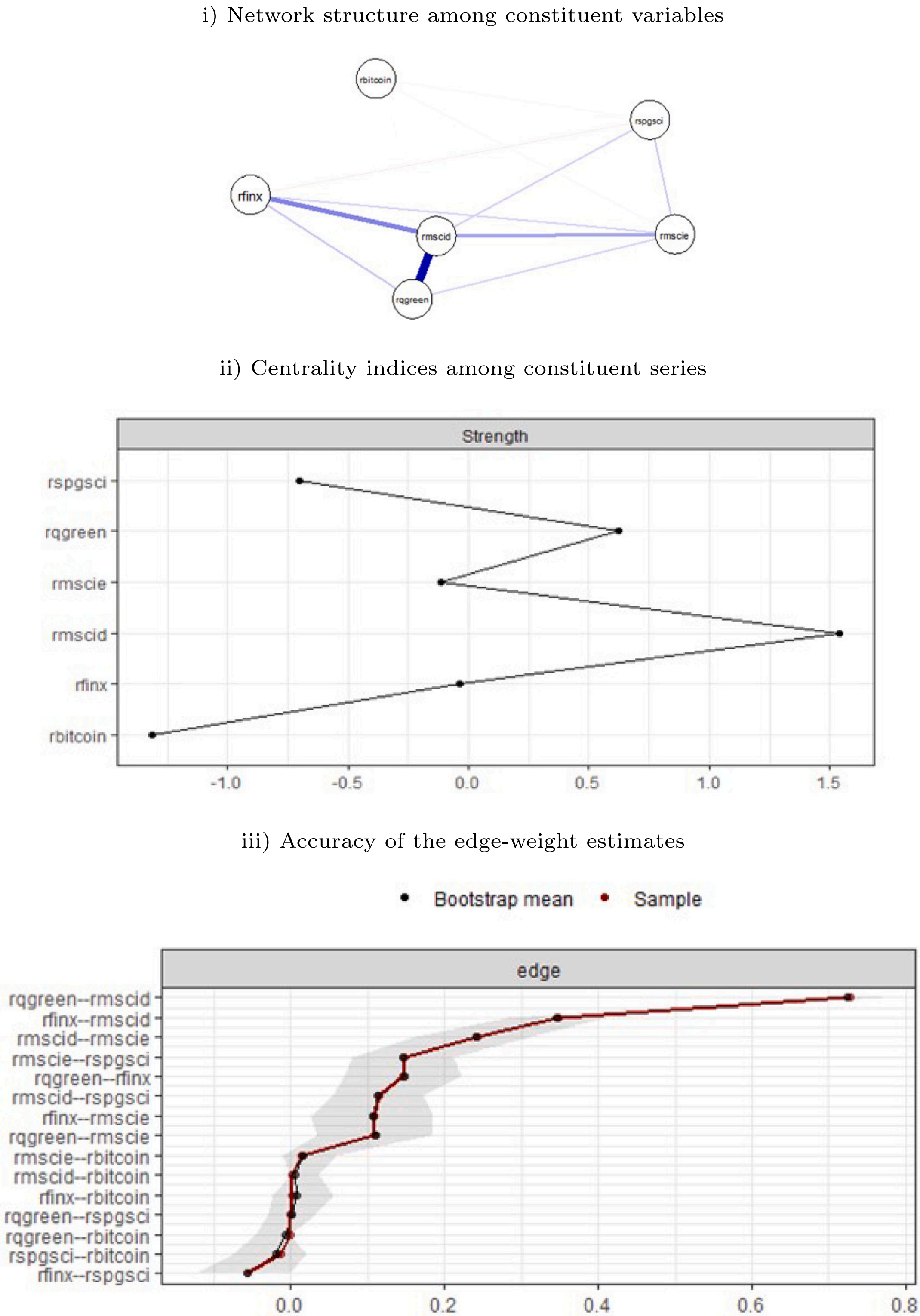

Fig. 4. Identified network structure and centrality indices.
Note: To identify the strength of relationship, and association between the variables, centrality indices are also shown in the above figure. The horizontal and vertical axis contain the strength of association and variables respectively.

cryptocurrencies; where the proxies for these are QGREEN, FINX, and Bitcoin, respectively. The maximum return is witnessed with Bitcoin (23.0%) followed by FINX (10.6%), while MSCIE realised the lowest return (6.9%). Further, the average highest return is provided by Bitcoin (0.0026) and FINX (0.001).

It is observed that technology-based assets (cryptocurrency and FinTech) both outperform the other compared variables. The outperformance of tech-based assets could be attributed to FinTech, blockchain-based smart contracts, and investments in digital currencies changing the landscape of financial systems, thus providing synergies

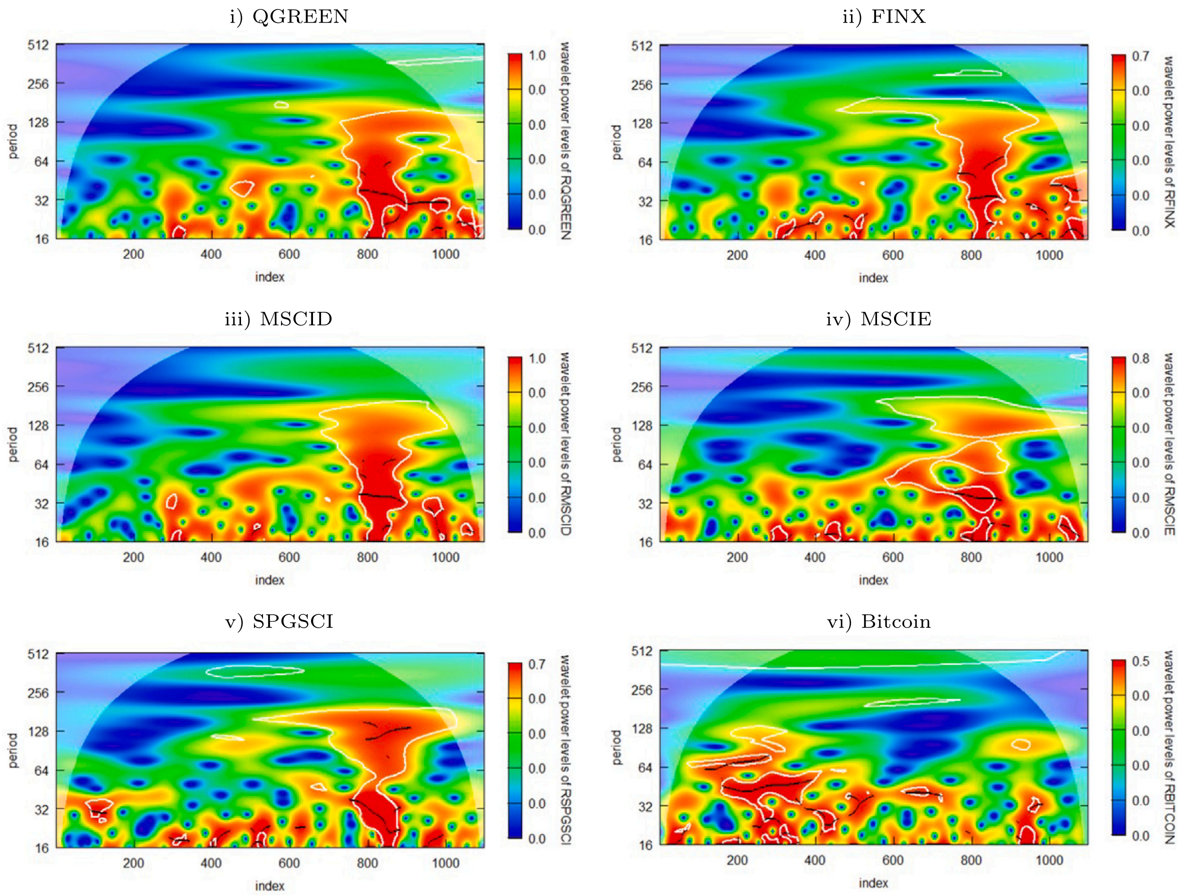

Fig. 5. Continuous wavelet power (CWT) of constituent series.
Note: In the above figure, we apply continuous wavelet, cross wavelet transform and wavelet coherence analyses depicting the continuous wavelet of green index, conventional and non conventional assets. The frequencies or scales and time are shown in Y-axis and X-axis respectively, where we categorise the scale across five different cycles, identified across 16–32, 32–64, 64–128, 128–256 and 256–512 days. Further, these cycles are categorised as short-scale (16–32 and 32–64 days), medium-scale (64–128 days) and long-scale (128–256 days).

and potential (Ahram, Sargolzaei, Sargolzaei, Daniels, & Amaba, 2017; Furman & Seamans, 2019; Macchiavello & Siri, 2022). The COVID-19 pandemic led to the indomitable emergence of financial technology as a new business model for financial institutions (Alon, 2020).

Further, each series has negative skewness; MSCI World Index (−1.72) followed by MSCI Emerging Market Index (−1.68). QGREEN (−1.51), SPGCI (−1.36), FINX (−1.11), and Bitcoin (−0.96). Focusing on the Augmented Dickey–Fuller (ADF) test, we confirm the stationarity in the returns of each asset class. Further, Figs. 1 & 2 plot the graphical inspection of constituent series and return, which are found to be stochastic. There is no autocorrelation of the residuals.

We also check the overall distribution pattern of the selected green index in comparison with both conventional and non-conventional assets, as presented in Fig. 3. We observe that QGREEN, FINX, MSCID, MSCIE, and SPGSCI are strongly and positively correlated, consistent with Mizerka, Stróżyńska-Szajek, and Mizerka (2020) and Qin, Su, and Tao (2021). However, the degrees of association between Bitcoin and the rest of the constituent series are found to be weak and insignificant. We attribute this to the peculiar behaviour of Bitcoin as a speculative asset (Gronwald, 2019). QGREEN and MSCID are found to have highest correlation (+0.948), consistent with Mensi et al. (2021), while Bitcoin and SPGSCI have the least correlation (−0.010). Additionally, each series shows asymmetry in form of their respective distribution pattern and are not found to be normally distributed. Respectively, it can be inferred that all the assets exhibit an insignificant correlation with Bitcoin. Consequently, technology-based assets may provide significant diversification opportunities. With the advent of blockchain, Fintech, and cryptocurrency markets, the technology-based assets have shown tremendous growth and resiliency. The adoption of AI and robotics by business processes have increased significantly (Furman & Seamans, 2019).

Importantly, for the focus of this paper, our results strongly support that bitcoin is a diversifier of investment in green assets. Therefore, we suggest that bitcoin investors concerned about the environmental impacts of proof-of-work mining can offset bitcoin investing with green investing. In this way bitcoin investors can offset their carbon footprint while improving their portfolio diversification.

Next, we employ network analysis to investigate the association of QGREEN with both conventional and non-conventional assets. Our selected network analysis considers network structure, centrality indices, and accuracy of edge weights, as presented in Fig. 4. The network structure is displayed based on the relationship amongst the selected variables. Nodes, reflecting powers of relationships, are found to be connected with all of the variables except for that of Bitcoin. This result signifies that both QGREEN and MSCID are highly connected as their nodes are dark blue. This is also confirmed by pairwise correlations, presented in Fig. 3. The results are consistent with previous results and with the studies of Mensi, Naeem, Vo, and Kang (2022).

Bitcoin is identified to be a strong diversifying asset. To identify the strength of relationship, and association between the variables, centrality indices are also identified, as shown in Fig. 4. The horizontal and vertical axis contain the strength of association and variables, respectively. MSCID displays the highest strength, while Bitcoin and SPGSCI are identified respectively to possess zero and negative strengths of interaction. This is intuitive as both of these assets are unconventional. In

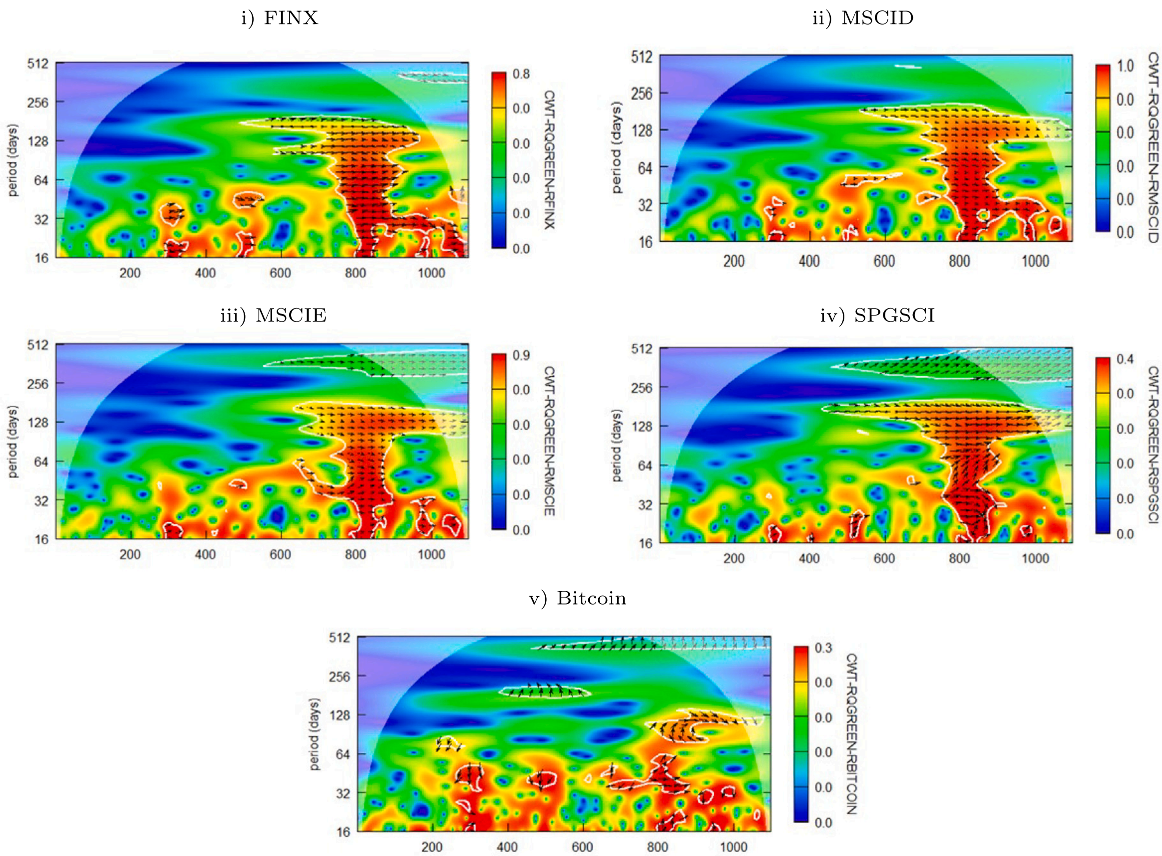

Fig. 6. Cross Wavelet Transform (CWT) among series, QGREEN used as the base of comparison.
Note: In the above figure, we employ cross wavelet transform (XWT) to examine the frequency connectedness of the green indices with conventional and non-conventional asset classes. Right-facing (left-) arrows signify positive (negative) association respectively.

contrast, listed companies as sometimes deploying FinTech to promote funds used in green projects, can, through such linkages, appear in a similar set. Further, bootstrapped confidence intervals are employed to check the edge robustness that presents the visual inspection of estimates inferring that each of QGREEN, FINX, MSCID, MSCIE and SPGSCI are strongly connected with each other while Bitcoin is not related to these assets. This provides further evidence that Bitcoin can be used for portfolio diversification. Results, consistent with (Qin et al., 2021), strengthen our evidence that Bitcoin can be used for portfolio diversification, and that Bitcoin investors can use green assets to diversify while offsetting carbon footprints generated by supporting proof-of-work mining.

Next, we apply continuous wavelet, cross wavelet transforms, and wavelet coherence analyses. Fig. 5 depicts the continuous wavelet of the green indices, and conventional and non-conventional assets.[4] In Fig. 5, we observe that the wavelet power is not uniform across the examined frequencies and period of investigation. There is low power observed when analysing QGREEN, FINX and MCID during the period between October 2016 and September 2017 across all scales (short-scale through large-scale) while there is high power identified for analyses based on MSCIE, GSPCI, and Bitcoin in the short-scale analyses between 2016 and 2021. Otherwise, high power analyses present quite varied results during the period between 2020 and 2021 in both the short- and medium-scale analyses. Bitcoin does not present any wavelet power in medium- and large-scale analyses, therefore it can be inferred that Bitcoin has not been influenced by the selected variables, even considering the COVID-19 outbreak. The reason could be the peculiar behaviour of Bitcoin as elicited its unique structure (Gronwald, 2019). However, other constituent series are all identified to be directly affected with evidence of high power identified between 2020 and 2021. Previous studies find that the negative impact is sharp with short duration, followed by quick recovery (Guo & Zhou, 2021).

Further, we employ cross wavelet transform (XWT) to examine the frequency connectedness of the green indices with conventional and non-conventional asset classes (Fig. 6). Right-facing (left-) arrows signify positive (negative) association. With regards to both XWT and QGREEN with each of the constituent series, there is no evidence of connectedness identified in either the short, medium, and long-term for October 2016 through February 2020. However, from March 2020 onwards, there is evidence of an immediate phase of comovement between QGREEN and each of FINX, MSCID, MSCIE and SPGSCI in all analysed scales. These co-movements are found to be positive, as shown by the majority of the arrows running from right to left. It can be inferred that these arrows are in phase and significant at the 5% significant level. We notice that interdependence is strong from 2020 onwards in all the scales. However, the co-movement of QGREEN with Bitcoin is weaker as there is co-movement only in the medium scale (64–128) at the end of 2020. Here high cross-wavelet coherence is identified in both 2020 and 2021, where the relationship between constituent variables is found to vary substantially. These results of time-varying co-movement are consistent with the findings of previous studies that during COVID-19, all financial assets had higher volatilities, with the exception of BTC. The results show financial markets becoming volatile

[4] The frequencies or scales and time are shown in Y-axis and X-axis respectively, where we categorise the scale across five different cycles, identified across 16–32, 32–64, 64–128, 128–256 and 256–512 days. Further, these cycles are categorised as short-scale (16–32 and 32–64 days), medium-scale (64–128 days) and long-scale (128–256 days).

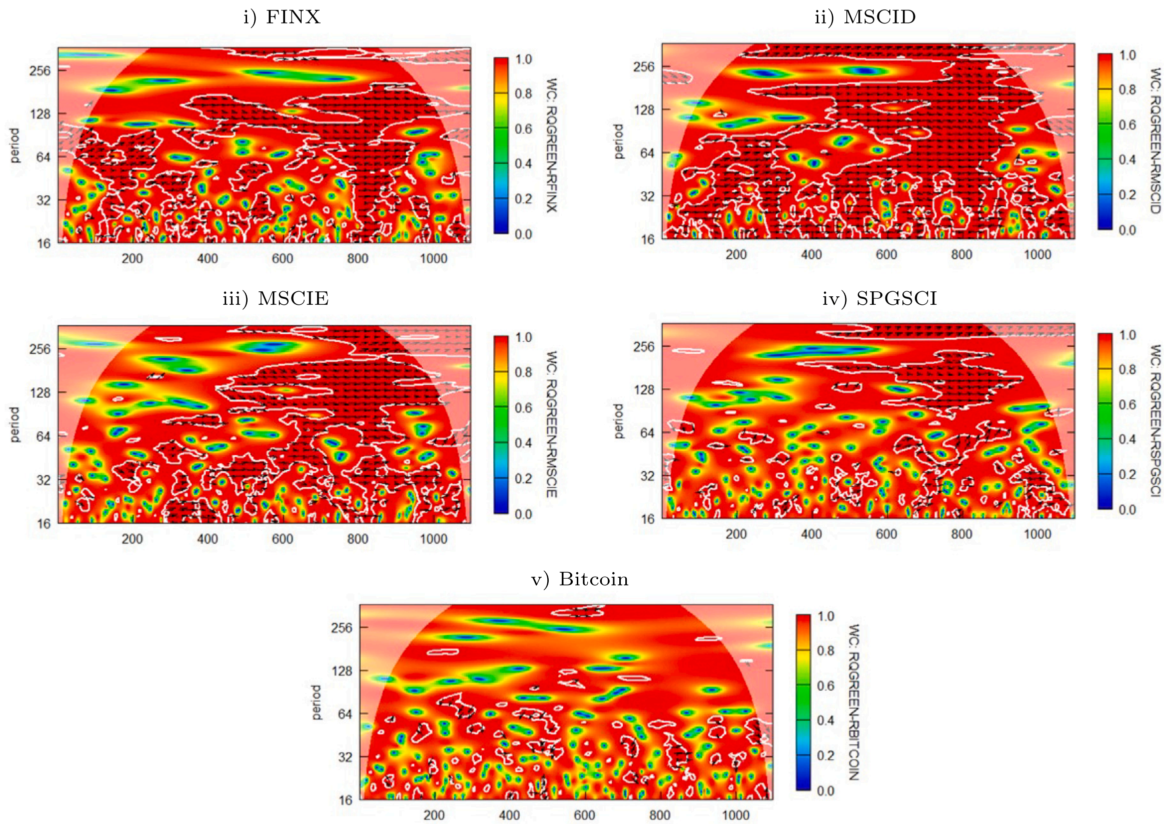

Fig. 7. Wavelet Coherence of QGREEN with conventional and non conventional assets.
Note: The above figure displays the wavelet coherence from which islands and arrows are depicted to indicate the estimated coherence; the red islands (near to coefficient 1) and blue islands show the strong and weaker coherence respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

at the times of strengthening of the pandemic. However, the covariance of QGREEN strengthens as the frequency increases which infers that the association of QGREEN with the constituent series is more directly affected by long-term shocks, rather than by short-term shocks.

Finally, we employ a wavelet coherence (WC) analysis to investigate the lead and lag relationship of QGREEN with selected variables. Fig. 7 displays the wavelet coherence. Islands with arrows depict estimated coherence, with red (near to coefficient 1) and blue islands showing respectively stronger and weaker coherence. Results indicate the existence of strong coherence in the medium scale throughout the entire sample, as shown by a preponderance of red islands.

However, in the short-term sample, there is a mixture of red and blue islands. Strong coherence is detected during 2020 in both samples, where most of the arrows in all the scales (small to large) are depicted to run from left to right. This indicates that FINX leads QGREEN. The reason for this could be that the FinTech industry triggers sustainable growth and promotes green projects. Consequently, FinTech complements green and sustainable finance (Macchiavello & Siri, 2022). We also see strong coherence during the COVID-19 outbreak, contra diversification opportunities. QGREEN with MSCID have strong coherence in short-scale analyses in each of the years 2016, 2017, 2019 and 2021. However, coherence is weaker in both 2018 and 2021. During 2016 and 2017, there is no coherence identified. But where interaction is identified, MSCID is found to lead QGREEN. Coherence between QGREEN with MSCIE is found to increase over time, denoted by the arrows moving from left to right. MSCIE is leading QGREEN. Results are consistent with Mensi et al. (2022) and Mizerka et al. (2020). We attribute lead and lag interactions to companies being listed and having green investment practices. Further, mixed estimates are identified between QGREEN with SPGSCI. This could be because of many interactions of sectors within renewable energy and commodities. For instance, carbon or renewable energy credits. While when considering interactions with Bitcoin, weak coherence is identified, as denoted by many blue islands between 2016 and 2021. This lack of interaction evidences substantive and significant diversification opportunities, and especially opportunity to use green investments both to diversify against bitcoin and to offset the carbon impacts of bitcoin mining.

5. Conclusions

Understanding the interconnections of green-related financial instruments with traditional and non-traditional financial assets is important for policymakers, investors, and portfolio managers. Considering the importance of green finance to achieving green policy objectives, it is important to highlight benefits of ‘green portfolio management’, or how green financial products potentially integrate into diversified portfolios to facilitate investor diversification. Understanding how green finance facilitates diversification and provides safe havens will motivate individual investors to invest in green products, which will in turn will help societies finance transitions to sustainability. However, interactions of green financial instruments with FinTech products and cryptocurrencies remain unexplored.

We examine the connectedness of green assets with FinTech assets and cryptocurrencies using network and wavelet analyses. Results indicate that global stock market performance, along with the returns of emerging markets, commodity markets, and FinTech are strongly correlated with green indices. However, Bitcoin is an exception to this, with Bitcoin and green assets being effective diversifiers for each other. Wavelet analyses confirm these results.

Results suggest that as the Bitcoin investor network evolves, and Bitcoin becomes increasingly popular with individual investors, individual investors can concomitantly invest in green finance to diversify

Bitcoin holdings. Our results offer compelling motivation for individual investors, particularly cryptocurrency investors, to invest in green finance. Enhanced individual investor interest in green finance will assist fulfilment of green policy objectives. Further, cryptocurrency advocates, in response to objections to the environmental impact of proof-of-work mining, can signal to their investor base by concomitantly investing in green finance as a tandem environmental off-set and as a useful portfolio diversifier. Further, Fintech and crypto assets are found, at least some times, to outperform other financial assets. Therefore the identified magnitude of connectedness in the portfolios can help in garnering more returns. This helps policymakers frame more supportive policies towards FinTech assets. FinTech assets have been attracting worldwide attention due to their high returns during the pandemic periods. Policy decisions to support a decarbonised economy in turn should promote green bonds. This will in turn help countries transition to climate resilient economies.

Data availability

Data will be made available on request.

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