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Quantile Connectedness Amongst Green Assets Amid COVID-19 and Russia–Ukraine Tussle

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Abstract: With the advent of greening the global economy and the introduction of green financial assets, this study examines the connectedness and spillover effect of green assets using a QVAR approach focusing on the average connectedness and connectedness under extreme market conditions. The time of the study captures the crucial global incidents of COVID-19 and Russia–Ukraine war to investigate the effect of major incidents on the connectedness of green assets. The results of the QVAR analysis reveal that green assets are moderately connected under normal market conditions; however, their connection is strengthened under extreme market conditions. IOTA and SP Green Bonds are the net receivers of shocks from other assets, and SP Green Bonds are connected to green energy indices and green cryptocurrencies during turbulent markets. Since green cryptocurrencies are closely connected, a lower portion of them should be added to portfolios, whereas SP Green Bonds qualify as a good diversifying agent in a portfolio. The study has significant implications for market participants, investors, and policymakers.

Keywords: green assets; green cryptocurrency; green energy; green bonds; dynamic connectedness; QVAR

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1. Introduction

All global financial markets are interconnected either directly or indirectly, which makes intermarket linkages a substantially significant topic in international finance. The COVID-19 pandemic and Russia–Ukraine war have had a significant impact on the volatility of financial assets across the world. While the pandemic caused a global economic downturn and increased uncertainty, with a sharp decline in the prices of equity securities and an increase in market volatility (Baker et al. 2020; Khan et al. 2023), the Russia–Ukraine conflict raised geopolitical tension and further increased the risk of global instability, exacerbating the uncertainty from the pandemic period into a geopolitical upset, which further undermined the market confidence of the investors (Guenette et al. 2022). Studies on return and volatility spillover have implications for portfolio management and hedging decisions by investors.

Drastic climate changes in the past few decades have raised concerns about sustainability. The Paris Agreement (United Nations Framework Convention on Climate Change 2015) and the Sustainable Development Goals (SDGs) of the United Nations (2015) proposed sustainable development measures that emphasized the shift towards eco-conscious investments to mitigate environmental degradation (Pham 2021). In this crucial time, green assets appear on the horizon to serve as a rescue and provide sustainable solutions to the financial markets, allowing investors to reap the benefits of investments while ensuring environmental restoration. The evolution of green financial markets over the years has made green assets qualify as a diversification component of portfolio investments (Chatziantoniou et al.

2021). Researchers such as Arif et al. (2021) and Pham (2021) have confirmed that green assets provide better diversification benefits than traditional portfolio assets.

Green assets include a range of green cryptocurrencies, green energy indices, and green bonds. Green cryptos are special types of digital currencies that are pivoted in energy-efficient algorithms and employ renewable energy in the mining process. Energy-efficient cryptocurrency is referred to as green cryptocurrency (Ren and Lucey 2022) since the Proof of Stake (PoS) hardware energy requirement is reduced by 99.95% (Sharif et al. 2023). Shifting to green cryptocurrency will curb carbon emissions and help restore the environment.

Green assets further include green energy/renewable energy or cleaner energy sources. In compliance with SDGs, there has been a considerable shift in the global energy sector from traditional fossil fuel or coal to renewable energy sources. Green and clean energy sources are considered the key strategic alternatives to ensure environmental protection through the decarbonization of the environment (Van Hoang et al. 2019). A significant fall in the prices and returns of green energy indices was observed during market turbulence caused by Brexit in 2016, COVID-19, and the Russia–Ukraine war in 2022, despite the volatility of indices increased during those moments (Tiwari et al. 2024). The increasing awareness of the environment and the global shift toward sustainability gained policy support for green energy, which has boosted the clean energy market. The increasing trend of investment in green energy has escalated the investment elasticity of the green energy sector, making it a considerable investment option for hedging.

After the Paris Agreement of 2015, the United Nations incorporated a clean climate in the SDGs to fight environmental degradation in 2018. Following this, the European Green Deal (European Commission 2019)further concentrated on greening the economy (Naeem et al. 2021a). The greening process requires a substantial amount of investment, which is unraveled by taking on green bonds to develop low-carbon technological innovations to help restore the environment (Laskowska 2018; Monk and Perkins 2020). Green bonds emerged as a financing tool that provided funds for renewable energy projects or environmental restoration activities such as water projects to promote climate conservation. (Tolliver et al. 2020). Green bonds are a special type of traditional fixed-income bonds, the proceeds of which are used exclusively for environmentally friendly and sustainable projects (Reboredo and Ugolini 2020). According to Moody's, green bonds experienced a 32% decrease in their total amount due to the COVID-19 pandemic. Yi et al. (2021) reported a significant impact of COVID-19 outbreak on the volatility of the green bonds market with an increased cumulative abnormal return of those assets. Arif et al. (2021) proposed green bonds as a diversifier asset for equity investors and a hedging tool for currency investments. However, green bonds provide negligible and negative contributions to volatility reduction during Russia–Ukraine war (Gök and Gemici 2024). The tremendous growth in green bonds attracted the attention of environmentally alert investors who wanted to include them in their portfolios for diversification.

The shift of environmentally friendly investors toward green assets has made them a prominent investment option; hence, their price movements, connectedness with other assets, and spillover effects have become increasingly predominant. The existing literature on green cryptocurrency, sustainable green energy stocks, and green bonds has upheld the use of these assets for diversification. However, the dynamic linkages of green assets among themselves are insignificantly explored. Any evidence of the connectedness and spillover effect among the green assets themselves may influence asset selection and portfolio management along with hedging strategies of the investors and the measures to ensure global financial stability by the policymakers. Thus, the study offers a threefold contribution.

First, this study attempts to investigate the connectedness and spillover effect of green cryptocurrencies, green energy, green bonds, and the ESG index, which represent sustainability. Second, this paper extends the body of knowledge by investigating the connectedness and spillover effect of green investment options through a novel approach of Quantile Vector Autoregressive Q-VAR (Chatziantoniou et al. 2021). This approach is an improved version of the original VAR connectedness approach by Diebold and Yilmaz (2009, 2012) in various manners.

Second, QVAR results are more robust because they are less sensitive to outliers. Standard VAR allows us to investigate the mean connectedness dynamics, whereas QVAR allows us to examine the time-varying connectedness. Moreover, QVAR is more flexible in handling financial market data that contain non-linearity and heteroskedasticity, thus making it a superior choice for analysis. This study analyzed the spillover effect among green assets, particularly during economic downturns and expansion periods. Because of the rise in the interconnected financial world, such studies offer robust strategies and suggestions to investors and policymakers. The Quantile Vector Autoregressive (QVAR) approach is used to analyze these gaps by examining data from Jan 2018 to March 2024. This period is marked by pecuniary and geopolitical events such as the global pandemic of COVID-19 and tension between Russia and Ukraine. This study aims to offer a deep insight into how green assets interact under moderate and turbulent market conditions caused by COVID-19 and the Russia–Ukraine war. QVAR allows insight into these spillovers' directions as well as their intensity, which has not been discussed in previous studies.

Third, green assets act as a safe haven or transmitter of elevated risk through normal and extreme market conditions. The research findings allow us to analyze the dynamic behavioral differentials across quantiles over certain times, showing the dynamic shift of interlinkage among financial assets. This research contemplates the spillover connectedness at lower, middle, and extreme quantiles and then checks the dynamic net pairwise directional contentedness and the overall total connectedness among green assets. This study includes five proxies of green cryptos, which include Cardano, Ripple, Iota, Steller, and Nano, whereas green energy is proxied by SP Global Clean Energy, WilderHill Clean Energy (WNC), and NASDAQ Clean Edge Green Energy Index. The SP Green Bond Index is used to represent green bonds, and for sustainability, the SP global ESG index is included. The data are taken from 3 January 2018 to 27 March 2024, considering a time of high volatility in cryptocurrency pricing, the outbreak of the global pandemic, and the war between Russia and Ukraine.

The findings of the study reveal that all the green cryptocurrencies are connected to each other under normal conditions, and all the green assets are tightly connected under extreme market conditions. SP Green bonds showed the most resilience to market shocks and can be used for diversification. The findings of the study suggest policymakers encouraged private investment toward green projects, and policies should be designed to stimulate sustainable technological advancements.

The rest of the paper is organized in the following manner. The literature review' gives a brief overview of the development of the body of knowledge on cryptocurrency, energy, green cryptocurrency, and green energy, along with green bonds required to finance green energy projects. The section on data and methodology describes the data used in the study, followed by an explanation of the research methodology employed in this study. The empirical results are provided, and a discussion covers the description of the findings. Finally, the conclusion addresses the research and the implications for investors and policymakers.

2. Literature Review

The unprecedented growth of Bitcoin, particularly its 1300% price hype in 2017, made it a prominent element of an investment portfolio. Gil-Alana et al. (2020) found that in the post-industrialization phase, investors view cryptocurrency as a lucrative investment option as it qualifies to diversify their portfolio well. This quality of cryptocurrency caught the attention of researchers all over the world, and they started examining and assessing the relationship between prices, returns, and volatility trading volumes of cryptocurrencies, particularly Bitcoin, with various asset classes. The presence of a significant spillover effect between Bitcoin and other asset classes might influence the selection of portfolio assets, risk management decisions, and regulatory measures to ensure the sustainability of the financial system. On the other hand, the enormous volume of cryptocurrency consuming significant amounts of energy has raised concerns regarding environmental destruction (Krause and Tolaymat 2018). The evolution of financial technology has proved to be a double-edged sword; on one side, it has added a marvelous financial asset to the trading markets; on the other side, it shows detrimental effects on the environment (Truby 2018; Corbet et al. 2021).

After immense criticism of Bitcoin in terms of energy consumption and conformity with SDGs, the recommended shift toward green cryptocurrency and green energy was already in the air. Green cryptocurrencies consume less energy and are environmentally sound. They use green/renewable energy, such as solar and wind, in the mining process. Their sustainability feature attracted the attention of environmentally concerned investors and researchers. Ali et al. (2024) studied green cryptocurrencies and concluded that green cryptocurrencies provide better diversification benefits than non-green cryptocurrencies. Among several green cryptocurrencies available, Cardano and Tezos offer superior diversification benefits, followed by EOS, Steller, and IOTA. Umar et al. (2023) state that green cryptocurrencies are the main shock transmitters in the whole system, whereas Cardano is the major transmitter among green cryptocurrencies. Zhou and Wang (2024) studied the connectedness and volatility spillover among clean energy, green and non-green cryptocurrency, and oil using the quantile time frequency connectedness approach at the median level, low level of volatility 0.5 and high level of volatility 0.95 percentile. They observed that non-green cryptocurrencies are volatility transmitters, whereas green cryptocurrencies are volatility receivers, especially at high volatility levels. These results were consistent with the findings of Shao et al. (2023), who reported that cryptocurrencies are net transmitters, whereas green assets are net receivers. They further highlighted the strength of connectedness during the COVID-19 pandemic and the Russia–Ukraine war to be stronger, supporting the earlier findings in extreme market conditions.

Parallel to green cryptocurrency, the global energy architecture also started shifting toward green energy; therefore, researchers around the globe have studied the dynamics of renewable energy, not only for profitability but also to ensure sustainability (Dawar et al. 2021). Tiwari et al. (2022) confirmed that the clean energy market dominates the system and is a major transmitter of shocks. Contemporaneously with the funding of green energy projects, the concept of green bonds gained a lot of attention. Tiwari et al. (2022) explored the connectedness between energy markets and green bond markets and observed the dominating transmission effect of clean energy markets over the rest of the markets; however, green bonds and active global wind are the primary receivers of shocks. Braga et al. (2021) provided empirical evidence and suggested that risk in green investment can be reduced by issuing government green bonds, as private green bonds are riskier and show higher price volatility. Pham (2021) reported a weak connection between green bonds and green equity markets under balanced market conditions and a strong link when markets are turbulent and that the spillover is transient as the connectedness fades over moderate and longer time periods. In a recent study by Nguyen et al. (2021), the authors conclude a high co-movement among clean energy, commodities, and stocks with green bonds. Syed et al. (2022) employed NARDL and found an asymmetric association between green bonds, bitcoins, and cryptos. The linkages between green and black bonds are delicately influenced by financial market volatility, economic policy uncertainty, oil prices, and investor's sentiments toward green bonds (Broadstock and Cheng 2019). Yadav et al. (2022) concluded that green bonds are highly influenced by the variation in the traditional bond markets but weakly linked to the stock market as well as risky energy commodities.

Dynamic Connectedness and Spillover Effect

Dynamic connectedness checks the strength and direction of the influence of one variable over another. It helps predict how a change in one variable might ripple through and affect the other variable. The spillover effect can be positive as well as negative. Researchers have used many approaches to study the dynamic connectivity of cryptocurrencies and other assets. Diebold and Yılmaz (2014) estimated the spillover effect of a range of variables employing the generalized variance decomposition method. Polat and Günay (2021) picked major cryptocurrencies on the grounds of market capitalization, studied the volatility connectedness between them, and noticed the connectedness to be strong during a crisis. Okorie and Lin (2020) studied the volatility spillover effect between 10 cryptocurrencies and crude oil using a multivariate GARCH model. Attarzadeh and Balcilar (2022) utilized a time-varying parametric vector autoregressive approach to unfold that clean energy transmits shocks in return to Bitcoin and oil, which are subject to volatility shocks. Le (2023) explored the relationship between cryptocurrency and energy volatility through a quantile vector autoregressive method. Every method employed has a specific feature that unravels the hidden facts in the data and thus helps in understanding the strength and direction of the connection. Naeem et al. (2020) examined the time-varying spillover between global energy markets using (Baruník and Křehlík 2018) and the wavelet coherence method and noticed that spillovers are agile and receptive. Reboredo et al. (2020) studied the connectedness between financial markets and green bonds using structural VAR and proclaimed a strong connection between currency, fixed-income markets, and green bonds market. However, the relationship is different from the stock market. Yadav et al. (2022) used daily data. They employed the Dynamic Conditional Correlation (DCC), Diebold and Yilmaz (2012), and Baruník and Křehlík (2018) models found a lack of dynamic linkages of volatility in the short run from the green bonds to the energy and crypto market. Rather, green bonds are net receivers, and cryptocurrency and energy markets are the largest but least transmitters of the volatility. The total spillover is higher in the long run than in the short run. Similar findings about green bonds and clean energy stocks are reported by Chai et al. (2022).

An abundance of literature is available on varied dimensions of green assets and their link with other assets. Another strand of research focuses on the interconnectedness and spillover effect between specific assets using different techniques, particularly emphasizing the cryptocurrency along with numerous other variables of interest such as energy, carbon emission, economic policy, economic policy uncertainty, stocks, currencies, oil, traditional energy, traditional bonds, clean energy, and green bonds. However, there is a dearth of research exploring the interconnectedness and spillover effect of return and volatility together between green cryptocurrency, green energy, and green bonds. The research on cryptocurrencies is still in its early stages but is expanding briskly (Giudici and Polinesi 2021). This study attempts to add to the body of knowledge some evidence of interconnectedness and spillover of return and volatility between green cryptocurrencies, green energy, and green bonds using QVAR.

3. Methodology

This paper unravels the interconnectedness and spillover effect of the major green assets present in the market, including green cryptocurrencies, green energy, and green bonds. Five proxies of green cryptocurrencies are used: Cardano, Ripple, Iota, Stellar, and Nano. Three clean energy proxies include S&P Global Clean Energy, WilderHill Clean Energy, and the NASDAQ Clean Edge Green Energy Index. The proxy of green bonds is the S&P Green Bond Index, and for sustainability, the S&P Global ESG Index is included. Daily closing prices of all cryptocurrencies are taken from the https://www.investing.com/ database (accessed on 27 March 2024). Other variables data are collected from the data stream. The sample period is 3 January 2018 to 27 March 2024. For the calculation of returns, this study considered the log returns as they are more stochastic in nature and follow the zero mean and constant variance more closely than the closing price data. All market data is in US dollars:

$$R_{j,t} = \ln(P_{j,t}/P_{j,t} - 1) \times 100$$

Examination of the size and direction of interconnectedness among green assets is explored through the QVAR (Quantile-Vector Autoregression) approach by (Ando et al. 2022; Chatziantoniou et al. 2021) is used to explore the mechanism of quantile propagation between different market variables. The approach used in this study is based on the seminal work by Diebold and Yilmaz (2012), and Diebold and Yılmaz (2014) introduced the application of quantile regression methods to the connectedness framework employing generalized vector autoregression (VAR) framework for rolling window dynamic analysis. The QVAR approach is well-suited for this study because of its ability to capture the complex and heterogeneous nature of financial markets. Traditional econometric models, such as Vector Autoregression (VAR), often assume homogeneity across different market conditions. However, this assumption becomes very basic when dealing with asymmetric and nonlinear dynamics. In contrast, the QVAR(p) model allows us to estimate the connectedness among variables at different quantiles of the conditional distribution of variables. This suppleness in QVAR makes it a suitable technique for exploring the market dynamics that standard VAR models might fail to address. In financial markets and particularly green assets, situations change quickly from low volatility to extreme volatility states. QVAR is more appropriate in such cases, and it can easily examine the behavior of assets in different market conditions, such as the global COVID-19 pandemic and the Russia–Ukraine war. Financial markets have fat tails and asymmetric return distribution, which other standard models cannot address appropriately. QVAR can handle the non-linearities and heteroskedasticity in the financial data and thus enhance the robustness and reliability of our findings.

The QVAR(p) model is formulated as follows:

$$x_t = \mu(\tau) + \sum_{j=1}^{p} \beta_j\ (\tau) x_{t-j} + u_t\ (\tau) \tag{1}$$

where τ shows the quantiles and x_t shows the vector of n endogenous variables, including green assets $\mu(\tau)$; $\beta_j\ (\tau)$ shows the coefficient matrix where $u_t\ (\tau)$ is an error vector. P shows the lag length. By applying Wold's theorem, the QVAR(p) equation can be altered to a quantile vector moving average representation QVMA(∞): $Q\tau(x_t|Ft-1) = \mu(\tau) + \sum_{i=0}^{\infty} B_i\ (\tau) U_{t=1}$ with

$$B_i\ (\tau) = \varphi_1(\tau) B_{i-1}(\tau) + \varphi_2(\tau) B_{i-1}(\tau) + \ldots$$

for i = 1, 2. . ..; $B_0\ (\tau)$ and $B_i\ (\tau) = 0$ for i < 0. I_n . I_n is an $n \times n$ identity matrix. QVMA will be used to calculate the H-step ahead generalized forecast error variance decomposition (GFEVD) as Equation (2):

$$\omega^{g}_{ij,\tau}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^T A_h(\tau) \sum ej \right)^2}{\sum_{h=0}^{H-1} \left(e_i^T A_h(\tau) \sum A_h(\tau)^T e_i \right)} \tag{2}$$

The variance matrix is denoted by Σ for the error term vector, and σ_{jj} is the standard deviation of the error term of j. e_i is the N × 1 vector, which is 1 for element i, and 0 otherwise. Next, the normalized Generalized Forecast Error Variance Decomposition (GFEVD; Koop et al. 1996) is used for the robustness check in Equation (3):

$$\omega'^{g}_{ij,\tau}(H) = \frac{\omega^{g}_{ij,\tau}(H)}{\sum_{j=1}^{k} \vartheta^{g}_{ij,\tau}} \tag{3}$$

$\omega'^{g}_{ij,\tau}(H)$ represents the percentage of the forecasted error variance in I that is explained by j. i is in quantile τ. The spillover indexes are estimated by taking the overall spillover among the variables:

$$FROM_{i,\tau}(H) = \frac{\sum_{j=1, j\neq i}^{n} \omega^{g}_{ij,\tau}(H)}{n} \times 100 \tag{4}$$

$$TO_{i,\tau}(H) = \frac{\sum_{j=1,j\neq i}^{n} \omega_{ij,\tau}^{g}(H)}{n} \times 100 \quad (5)$$

$$NET_{i,\tau}(H) = TO_{i,\tau}(H) - FROM_{i,\tau}(H) \quad (6)$$

$$TCI_{\tau}(H) = \frac{\sum_{i,j=1,j\neq i}^{n} \omega_{ij,\tau}^{g}(H)}{n} \times 100 \quad (7)$$

Equation (4) shows FROM, the effect of shocks from all variables j on i, whereas Equation (5) demonstrates the shocks effect of i on all other variables j. The net connectedness index mentioned in Equation (6) shows the net spillover from i variables to all other variables j in the systems. The values could be both positive and negative and demonstrate whether the variable i is transmitter or shock receiver within the system. TCI in Equation (7) calculates the overall connectedness among the variables in the system, and in Equation (8), the Net Pairwise Directional Spillover (NPDS) is calculated as the difference between spillover transmitted from I variables to j variable and those transmitted from j to i.

$$NPDS_{\tau}(H) = \frac{\sum_{i,j=1,j\neq i}^{n} \omega_{ji,\tau}^{g}(H) - \omega_{ij,\tau}^{g}(H)}{n} \times 100 \quad (8)$$

This study examines the quantile connectedness at 0.5, 0.50, and 0.95 quantiles. These quantiles analyzed the connectedness among green assets during high, middle, and low market conditions. Window size strongly influences the dynamics of connectedness. Therefore, the rolling window approach in QVAR is used to assess the model parameters dynamically over time. A fixed number of the freshest observations are used first and then moved to this "window" as a fresh dataset. This approach is suitable in financial time series, where the relationship among variables may change over time. In different market conditions, a 200-observation window is common because it offers a balanced and stable response, which is very important for exploring dynamic network connectivity. Large windows are less sensitive to individual fluctuations. Small windows increase the volatility, whereas large windows decrease the volatility. Therefore, a window size of 200 is considered in line with recent research by Antonakakis et al. (2020) and Ghosh et al. (2023).

4. Descriptive Statistics

Table 1 presents the descriptive statistics of the returns of green assets in the sample. Most green assets show negative mean returns except for the S&P Global ESG, S&P Global Clean Energy, and Nasdaq Clean Edge Green Energy Indexes. Green cryptocurrencies show higher volatility than other green assets. The standard deviation of all the green cryptocurrencies is above 6.262. Most of the green assets show negative skewness with significant kurtosis value, highlighting the existence of extreme returns. The Jarque Bera test value indicates that the null hypothesis of normally distributed returns is strongly rejected. The ADF unit root test confirms that the asset returns are stationary, explaining the nonexistence of unit roots with constant mean and variance over time.

Table 1. Descriptive Statistics.

	Cordano	Ripple	IOTA	Steller	Nano	SP Green Bonds	SP-G ESG	SP-G Clean Energy	WCN	Nasdaq Clean Energy
Mean	−0.031	−0.098	−0.147	−0.115	−0.166	−0.012	0.030	0.023	−0.007	0.031
Variance	40.745	42.538	44.257	39.213	61.559	0.157	1.087	2.859	7.375	5.597
SD	6.383	6.522	6.652	6.262	7.845	0.396	1.042	1.691	2.715	2.365
Skewness	−0.035	0.543	−0.609	0.619	0.348	−0.069	−1.047	−0.344	−0.121	−0.260
Kurtosis	4.658	16.226	8.181	10.906	12.175	4.898	16.149	7.201	8.021	3.841
JB	1476.741	17,971.8	4651.4	8187.9	8187.9	1633.2	18,019.5	3557.8	4377.6	1022.6
ADF	−10.031	−11.594	−11.803	−11.934	−11.855	−10.767	−11.307	−10.496	−10.787	−10.783

Note: JB test: p value < 2.2×10^{-16} for ADF test PV = 0.01.

Figure 1 shows the pairwise correlation between the green assets. A high and positive correlation exists between S&P ESG and WCN and between S&P Global Clean Energy and Nasdaq Clean Edge Green Energy, depicting the perfect alignment of their price movements. The green cryptocurrency generally presents low and positive or zero correlation, as it is between Nano and Ripple (0.2) and IOTA and Green Bonds (0.1). However, Steller shows a high positive correlation with Ripple and Cordano.

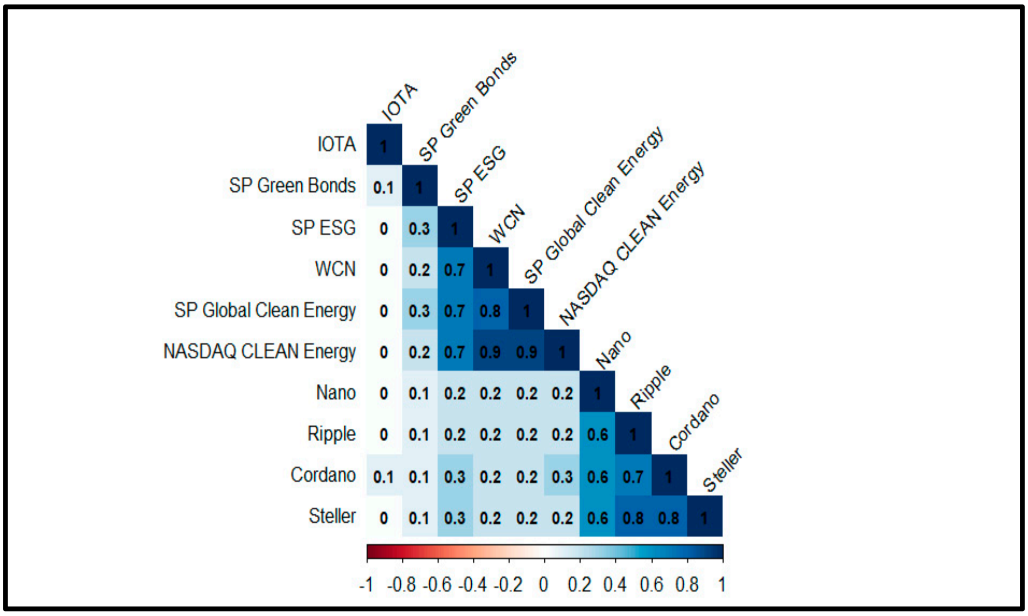


Figure 1. Pairwise Correlation of Green Assets.

Figure 2 represents the dynamic daily closing prices of all the green assets under study from 2018 to 2024. All the green cryptocurrencies and green energy proxies show a dip in their prices during 2018–2020, with a sharp rise after 2020, especially in 2021. This time reflects the COVID-19 pandemic and tension between Russia and Ukraine. The closing prices of all green cryptocurrencies showed a downward trend until early 2020. This negative trend can be associated with the meltdown of Bitcoin prices in 2018 due to regulatory concerns raised by a few governments and negative publicity of cryptocurrency hacking.

This adversity was further caught up by the COVID-19 pandemic, where the cryptocurrency market experienced a sharp decline in the prices of Bitcoin and crashed in March 2020, known as "Black Thursday". This market crash spread negative sentiments, and panic selling was seen in the global market, affecting the green cryptocurrencies as well and making the impact of the pandemic even more prominent. Parallel to this, the awareness of green energy options started picking up pace, and with the fading of COVID-19, it reached an all-time high. This trend was not sustained, and a downward trend followed.

When the cryptocurrency was melting down, the green bonds sustained the pandemic period and peaked in mid-2020. However, they started falling after that. The downward trend in green bonds can be associated with the higher uncertainty in the financial markets in the post-COVID-19 and Russia-Ukraine war era. People were struggling for liquidity, and therefore, there was a selling pressure on fixed investments. Several central banks around the world lowered their interest rates to lift the economy (Schrank 2024), thus making green bonds less attractive. It is noteworthy that green bonds show resilience in times of crisis and thus qualify as a good diversifying element in an investment portfolio.

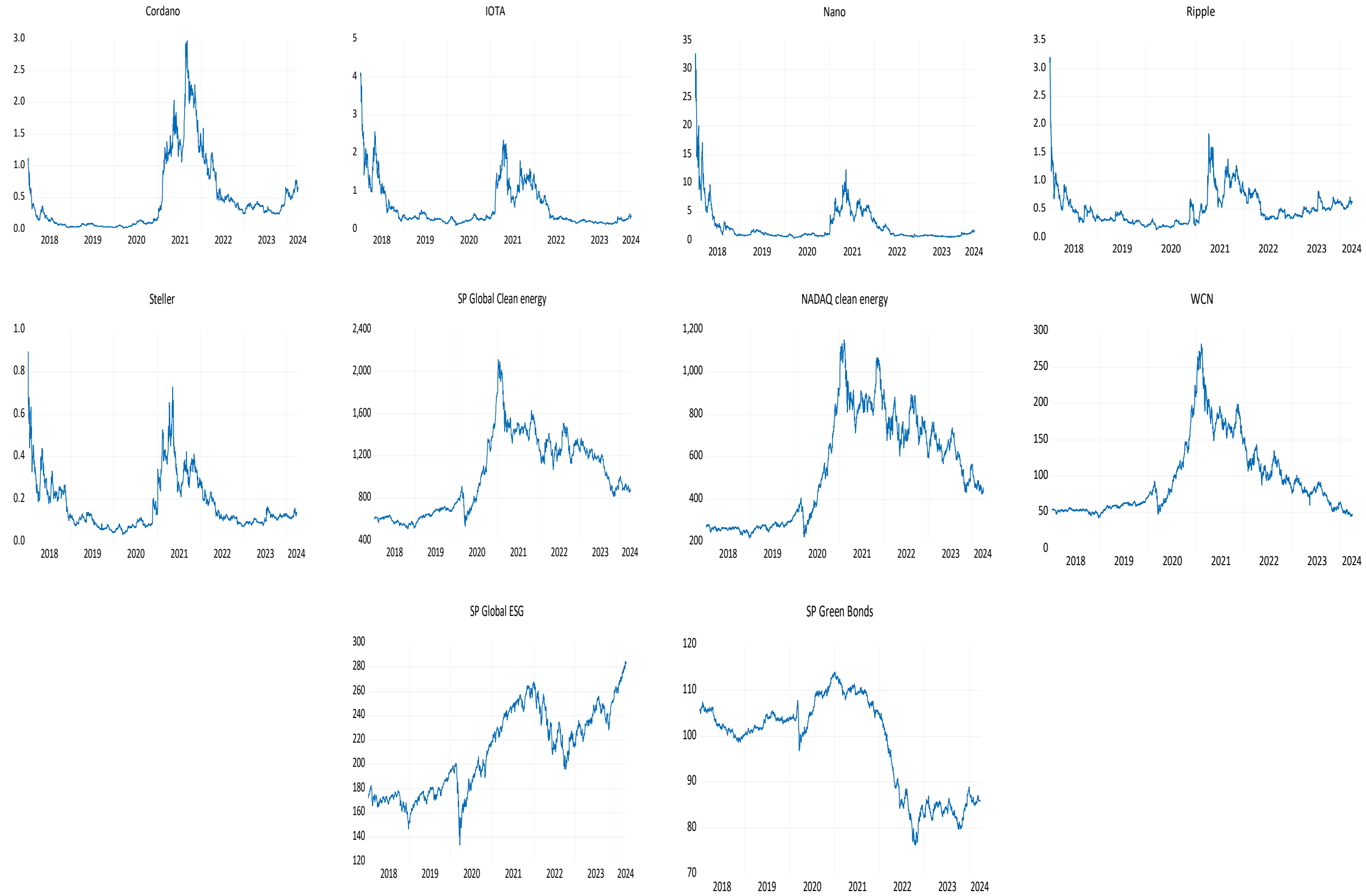


Figure 2. Graphs of the Closing Prices of the Series of Green Assets.

All the proxies of clean energy and ESG showed a surge in 2020 during turbulent market conditions but started falling after reaching the peaks of the global pandemic. This downward trend in the green energy sector can be attributed to rising interest rates in 2021 to combat inflation after the pandemic. High interest rates increased the cost of borrowing, thus causing many green energy projects to report low profits. Green energy projects also suffer on their supply side because of geopolitical tension on certain fronts. These elements affected the sentiment of environmentally conscious investors, and they shifted their focus from green energy, thus causing a downward trend in prices.

Figure 3 represents the returns of the green assets. These graphs further substantiate the findings of Figure 1 that high volatility of return in all the green assets can be seen throughout the period, particularly around 2020. A sharp dip in the returns during this time can be associated with the COVID-19 pandemic. However, the effect on the green assets of the Russia–Ukraine war in 2022 is lesser in magnitude compared to COVID-19. Green bonds have shown a significant decrease in returns in 2022, which can be linked to the effect of Russia–Ukraine tension. The effect continued even after that in the form of high volatility in green bond returns. S&P Global Clean Energy and Nasdaq Clean Edge Green Energy Index showed high volatility during the whole sample period compared to all the green assets in the group. WCN showed a marked drop in its return in 2023, substantiating the reasons mentioned above.

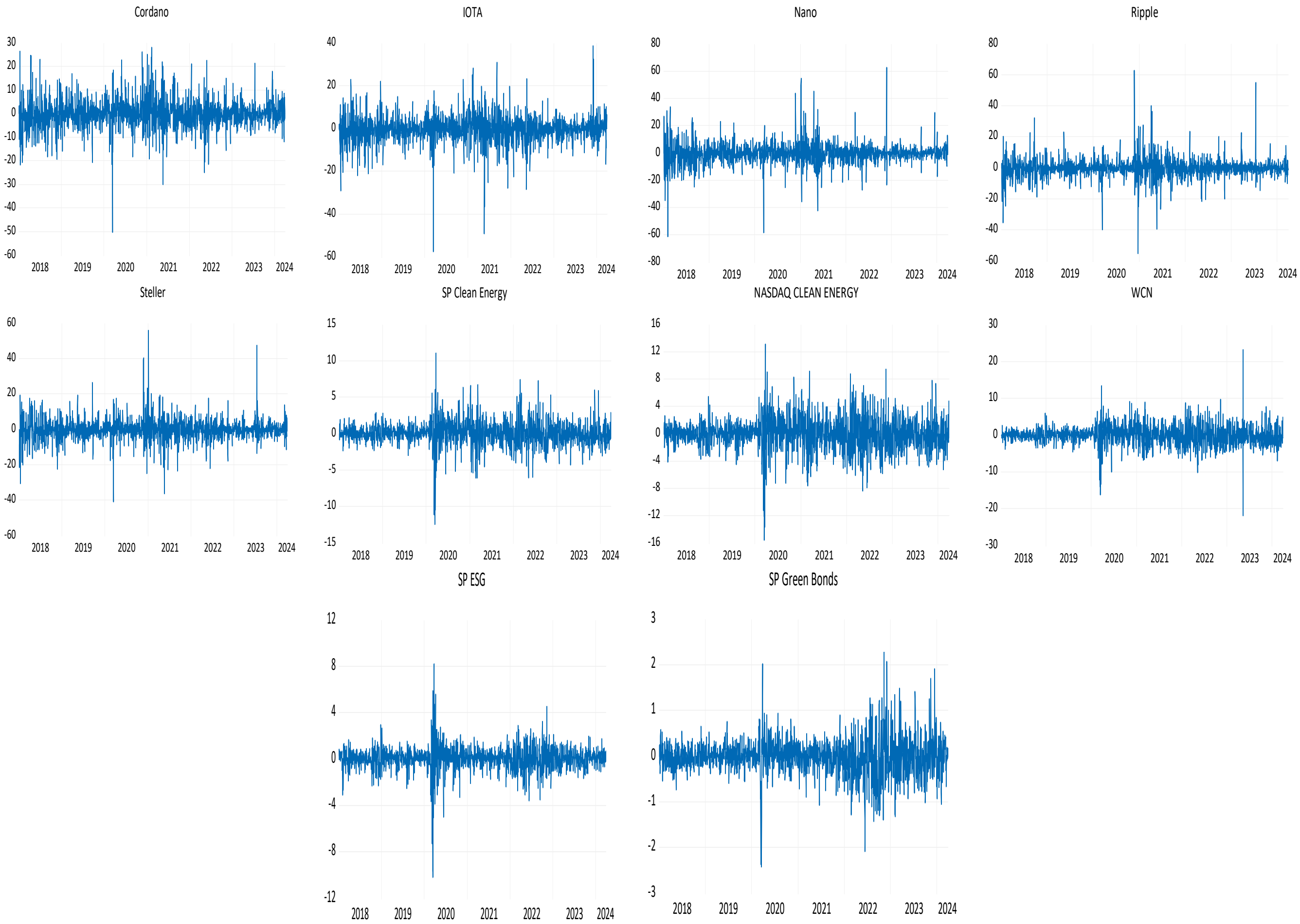


Figure 3. Graphs of Green Assets Returns.

5. Empirical Results and Discussion

This study employs a quantile VAR approach to explore the dynamic connectedness through spillovers among green assets, including green cryptocurrencies (Cordano, Ripple, IOTA, Stellar, and Nano), clean energy indices (S&P Global Clean Energy, Nasdaq Clean Edge Green Energy, WCN), sustainability index (S&P Global ESG) and green bonds (S&P Green bonds) in different quantiles. Quantile models are smart enough to capture market dynamics and are resilient to outliers (Lee and Lee 2023). The quantile approach is utilized to gauge the spillover effect of the market on the distribution middle range and its upper and lower tails associated with normal, bearish, or bullish market conditions. Thus, results are analyzed at three quantiles: the 50th quantile, in which the median reflects normal market conditions; the 5th (lowest) quantile; and the 95th quartile (extreme upper quantile) are used to assess the effect of the bearish and bullish market conditions on the returns of green assets. Furthermore, dynamic net pairwise connectedness and dynamic total connectedness are also examined to reveal the size and direction of the spillover effect they have on each other.

The median results in the 50th quantile are presented in Table 2. The last column, titled “From Others”, exhibits the total effect received of the assets from others. The third to the last row in the table represents “To Others”, which shows the total effect of shocks transmitted to the other assets. The row “Inc. Own” shows that the values of the variables and the influence received from other variables provide a bigger picture of the total interactions. However, “NET” values, positive or negative, represent the “net effect” estimated as the “difference between from others/received values and to others/transmitted values”, indicating whether the assets are net transmitters or receivers of the influence from other assets. Positive values show the net transmitter of shocks, whereas negative values show the receiver of shocks. The value of the Total Connectivity Index (TCI) figure is estimated by adding all the net values.

Table 2. Average/Median Dynamic Connectedness Using QVAR at 50th Quantile.

	Cordano	Ripple	IOTA	Steller	Nano	SP Green Bonds	SP ESG	SP-G Clean Energy	WCN	Nasdaq Clean Energy	From Others
Cordano	**34.74**	17.88	0.92	20.58	13.55	1.06	3.4	2.32	2.6	2.95	65.26
Ripple	18.41	**36.88**	0.59	22.72	11.96	0.72	2.67	1.83	2.25	2.48	63.63
IOTA	18.94	15.13	**23.3**	16.36	13.74	0.86	3.48	2.50	2.54	3.15	76.7
Steller	20.14	21.59	0.75	**34.05**	12.93	0.87	2.87	2.06	2.23	2.52	65.95
Nano	16.16	13.68	0.62	15.48	**42.94**	1.00	3.11	2.10	2.28	2.63	57.06
SP G Bonds	2.60	1.91	0.51	1.95	2.34	**65.3**	7.61	7.48	4.59	5.70	34.7
SP ESG	3.66	2.79	0.52	3.15	2.85	3.20	**35.73**	14.63	14.95	18.52	64.27
SP CLEN	2.43	1.96	0.48	2.21	1.92	2.88	13.71	**32.62**	20.31	21.48	67.38
WCN	2.67	2.2	0.48	2.22	1.93	1.20	13.43	19.14	**31.67**	25.04	68.33
Nasdaq CLEN	2.74	2.22	0.52	2.33	2.07	1.49	15.91	19.54	23.77	**29.4**	70.6
To Others	87.74	79.36	5.38	87.0	63.3	13.28	66.18	71.61	75.53	84.48	**TCI**
Inc. Own	122.48	115.73	28.68	121.06	106.25	78.59	101.91	104.23	107.2	113.88	**63.39**
NET	22.48	15.73	**−71.32**	21.06	6.25	**−21.41**	1.91	4.23	7.2	13.88	

The median quantile results reveal that IOTA (5.38%) and S&P Green Bonds (13.28%) transmit the fewest shocks to others, whereas all other green assets spillover more than 63% of the shocks. The most significant spillover generator includes Cordano (87.74%), with negligible difference in Steller (87%), followed by other green assets such as NASDAQ Clean Energy(84.48%), Ripple (79.36%), and WCN (75.53%).

S&P Green Bonds (34.7%) receive the least shocks from others, and the rest of all the assets receive more than 57% shocks from others. IOTA (−71.32%) and S&P Green bonds (−21.41) are the net receivers, and all other green cryptocurrencies and green assets are net transmitters. The Total Connectedness Index (TCI) value is 63.39%, which indicates a strong average connectedness in the system.

Moreover, the elements on the diagonals represent their own variable shock, while the remaining portion depicts the shocks from other markets. Evidence reveals that green cryptocurrencies, green energy, and S&P ESG returns (23.3%) to (42.94%) are driven by within-index shocks, and (76.7%) to (57.06%) are driven by network interactions. Only S&P Green Bonds return (65.3%) evolution is pivoted in within-index shocks, and (34.7%) is derived by the other markets. This suggests that S&P Green bonds receive lesser shocks from the markets and can be considered a potential diversifier in the green assets' portfolio under normal conditions. Pham (2021) studied green bonds and equity and found weak connections among the assets under steady market conditions but strong connections during extreme market conditions. Yadav et al. (2022) concluded that green bonds are marginally connected with the energy and cryptocurrency market, and these weak dynamic linkages can be associated with a lower degree of competition. The same findings are presented by Naeem et al. (2021b) and Reboredo and Ugolini (2020).

Table 3 shows the results of extreme market conditions estimated at the 5th quantile, results presented in Panel A, and at the 95th quantile results in Panel B. The Total Connectedness Index (TCI) for returns is 86.11% and 85.58%, respectively, depicting high connectedness in the system under extreme conditions, suggesting that a large portion of the shocks in one asset is attributable to the transmission to and from other markets in the system. The evidence revealed in Table 3, Panel A and B, shows that green assets behave in a similar manner under extremely low and high market conditions. All the green assets receive shocks from others of more than 83.73% and transmit spillover effect to others of more than 84.36%, except for IOTA and S&P Green bonds in both the panels, which transmit slightly lower shocks to others in the system. Under both extreme conditions, IOTA, Nano, and S&P Green Bonds are net receivers. The examination of the diagonal figures in the table reveals that under bearish market conditions, the returns of all the green assets in the sample ranging from (11.04%) to (14.64%) in panel A and (12.42%) to (16.27%) in bullish market conditions drive their returns from the within index evolution and the more than (85.36%) in low market conditions and (83.73%) in high market conditions derive their returns based on shocks received from the system. Our findings are similar to Zhou and Wang (2024), who also reported high connectedness among green and non-green cryptocurrencies in extreme conditions at 5th and 95th quantiles.

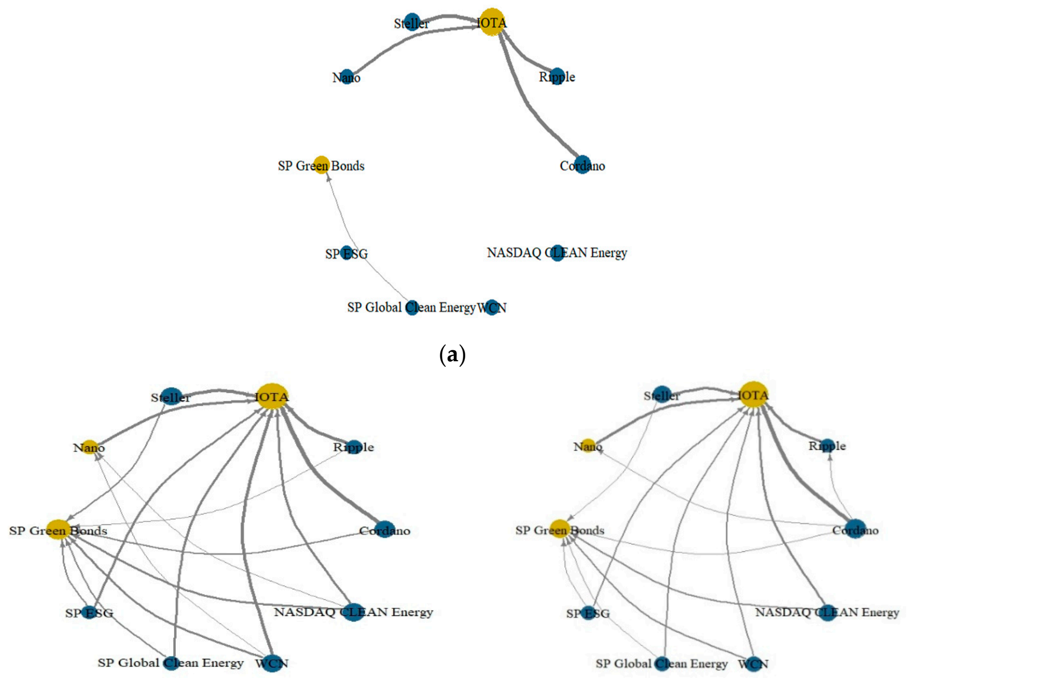
Table 3. Quantile Connectedness Using QVAR at 5th and 95th Quantiles.

	Cordano	Ripple	IOTA	Steller	Nano	SP Green Bonds	SP ESG	SP-G Clean Energy	WCN	Nasdaq Clean Energy	From Others
Panel A—Directional Connectedness and Spillover at 5th Quantile											
Cordano	**13.83**	11.30	7.83	11.96	10.64	8.16	9.10	8.67	9.16	9.35	86.17
Ripple	11.75	**14.05**	7.72	12.48	10.42	7.94	8.87	8.54	9.14	9.17	85.95
IOTA	11.39	10.60	**11.04**	11.07	10.41	8.28	9.23	9.05	9.46	9.47	88.96
Steller	11.84	11.99	7.73	**14.25**	10.44	7.90	8.82	8.64	9.14	9.25	85.75
Nano	11.41	10.75	7.74	11.27	**14.62**	7.99	8.86	8.82	9.18	9.36	85.38
SP G Bonds	10.79	8.88	8.05	9.51	8.71	**15.21**	10.02	10.10	9.91	10.12	84.79
SP ESG	9.39	8.69	7.43	9.38	8.63	8.87	**13.56**	10.75	11.56	11.74	86.44
SP CLEN	8.85	8.26	7.29	9.06	8.46	8.89	10.66	**13.67**	12.32	12.54	86.33
WCN	8.84	8.36	7.12	9.09	8.19	7.92	10.72	11.79	**14.64**	13.33	85.36
Nasdaq CLEN	8.97	8.44	7.20	9.12	8.46	8.13	10.93	11.73	13.03	**14.00**	86.70
To Others	91.93	87.27	68.11	92.93	84.36	74.09	87.12	88.08	92.90	94.32	
Inc. Own	105.76	101.32	79.15	107.18	98.98	89.30	100.68	101.75	107.53	108.33	**TCI**
NET	5.76	1.32	**−20.85**	7.18	**−1.02**	**−10.70**	0.68	1.75	7.53	8.33	**86.11**
Panel B—Directional Connectedness and Spillover at 95th Quantile											
Cordano	**14.60**	10.96	8.11	11.67	10.64	8.82	8.86	8.75	8.73	8.86	85.40
Ripple	11.88	**14.40**	7.86	12.45	10.50	8.28	8.76	8.60	8.60	8.67	85.60
IOTA	11.61	10.14	**12.42**	11.10	10.54	8.55	8.88	8.83	8.98	8.95	87.58
Steller	12.35	11.71	8.47	**15.57**	10.69	8.07	8.57	8.41	8.55	8.61	85.43
Nano	11.63	10.54	8.06	11.43	**15.50**	8.46	8.59	8.55	8.50	8.73	84.50
SP G Bonds	9.74	8.81	8.14	9.07	9.02	**16.27**	9.93	10.01	9.37	9.65	83.73
SP ESG	9.37	8.68	7.23	8.92	8.32	8.87	**14.33**	11.17	11.31	11.78	85.67
SP CLEN	9.21	8.41	7.50	8.80	8.40	9.14	10.78	**13.79**	11.86	12.11	86.21
WCN	9.05	8.30	7.31	8.49	8.14	8.18	11.11	12.02	**14.21**	13.21	85.79
Nasdaq CLEN	8.94	8.31	7.12	8.50	8.16	8.19	11.49	12.14	13.07	**14.08**	85.92
To Others	93.79	85.85	69.80	90.43	84.41	76.56	86.98	88.46	88.97	90.58	
Inc. Own	108.39	100.25	82.22	105.01	99.91	92.83	101.31	102.25	103.18	104.65	**TCI**
NET	8.39	0.25	**−17.78**	5.01	**−0.09**	**−7.17**	1.31	2.25	3.18	4.65	**85.58**

Polat and Günay (2021) also confirmed strong connectedness among cryptocurrencies during a crisis. Since green assets have become part of the mainstream investment options, they are more frequently included in diverse portfolios, and this integration has enhanced the connectedness of these assets, especially during times of crisis. Particularly during COVID-19, the awareness of climate change and focus on sustainability shifted the investment trend toward green assets, and hence, they show more connectedness among themselves.

5.1. Network Plot of Green Assets Connectedness

To further explore the pairwise connectedness among the green assets in the sample during 2018–2024, a network plot of all green assets is presented in Figure 4a, representing 50th quantile—moderate market conditions—and Figure 4b,c represents 5th and 95th quantile to capture extreme market conditions. Each node shows a green asset, and the size of the node indicates the extent to which the asset contributes to the system-wide spillover. The lines denote the direction of connectivity between assets, whereas the thickness of the lines shows the strength of the relationship between them. The diagram represents that all the green assets are not well connected; only green cryptocurrencies are linked under normal market conditions, as depicted in the 50th quantile, whereas all green assets are closely connected in the extreme market conditions shown in the 5th and 95th quantiles.



(**a**)

(**b**) (**c**)

Figure 4. Pairwise Connectedness of the Green Assets Employed. (**a**) 50th Quantile. (**b**) 5th Quantile. (**c**) 95th Quantile.

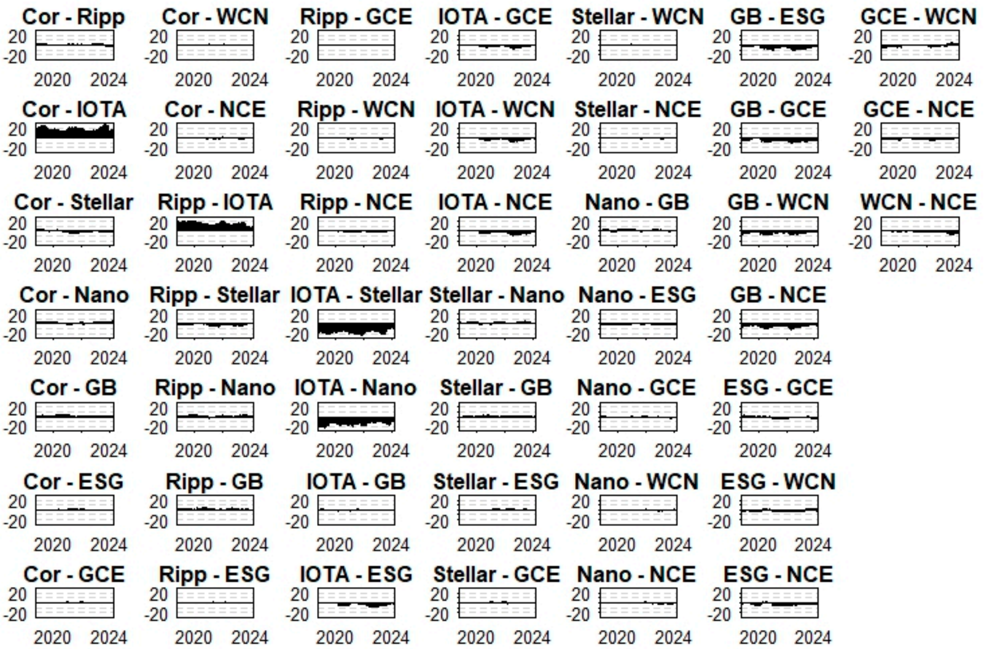
In Figure 4a, representing the 50th quantile, the diagram shows that all green assets in the system are not closely connected to each other under normal market conditions. The big yellow nodes, present that IOTA and S&P Green Bonds are the net receivers of shocks from the system, whereas all other green assets are spillover generators with different magnitudes. The broader the line, the stronger the connection between the assets, such as in the case of return spillover of IOTA, with Stellar, Ripple, and Cordano suggesting stronger interactions and showing that IOTA is receiving more shocks from these green cryptocurrencies. Overall results show that green cryptocurrencies in the sample have a strong connection among themselves but an insignificant relationship with clean energy and green bonds. Similar results have also been reported by Kamal and Hassan (2022).

Figure 4b,c represent the extreme market conditions at the 5th and 95th quantiles. The presence of a strong connection in the green asset market can be seen in the network plot under extreme market conditions. The direction of the spillover is almost the same under both market conditions; however, the spillover effect, represented by the thickness of the lines, appears to be stronger in the low market conditions (5th quantile) in comparison to the high market state (95th quantile). S&P Green bonds and IOTA are the major receivers of shocks in the system, and these results align with the findings of Khalfaoui et al. (2022). Tiwari et al. (2022) also reported that green bonds are the primary receivers of shocks in the system. S&P Clean Energy, WCN, Nasdaq Clean Edge Green Energy, and S&P ESG are spillover transmitters in extreme conditions. This study supports the findings of Umar et al. (2022) and Zhou and Wang (2024) that cryptocurrency exhibit time-varying connectedness and are highly sensitive to market deviations.

5.2. Dynamic Net Pairwise Directional Connectedness

To further substantiate the investigation on the connectedness between pairs of green assets, dynamic net pairwise directional connectedness estimations are calculated at the 5th, 50th, and 95th quantiles. Figure 5a shows the 50th quantile pairwise connections under moderate market conditions. In the pairwise graph, the connectedness between two assets from 2020–2024 is shown. If the connectedness appears on the positive side of the graph, then it represents that the first asset in the pair written on the left side is a net transmitter of shock from the second asset, presented on the right side. Similarly, if the connectedness is shown on the negative side of the graph, it means that the first asset written on the left side is a net receiver of shock from the second asset presented on the right side during that period.

(**a**)



Note: Findings are based on a 200-day rolling-window QVAR model with a lag length of order 1 (AIC) and a 10-step-ahead forecast.

(**b**)

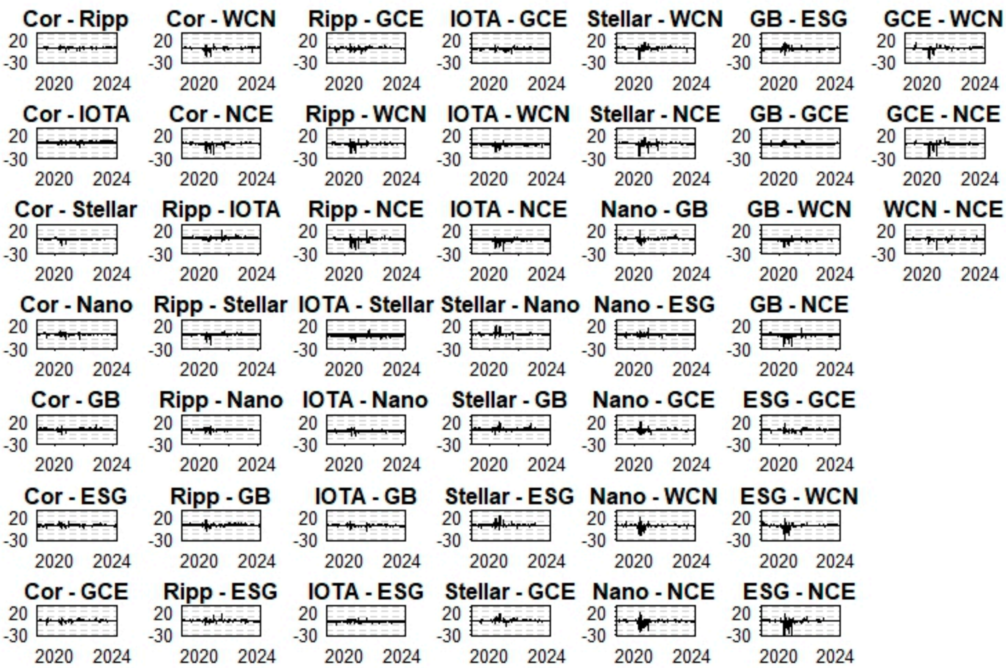
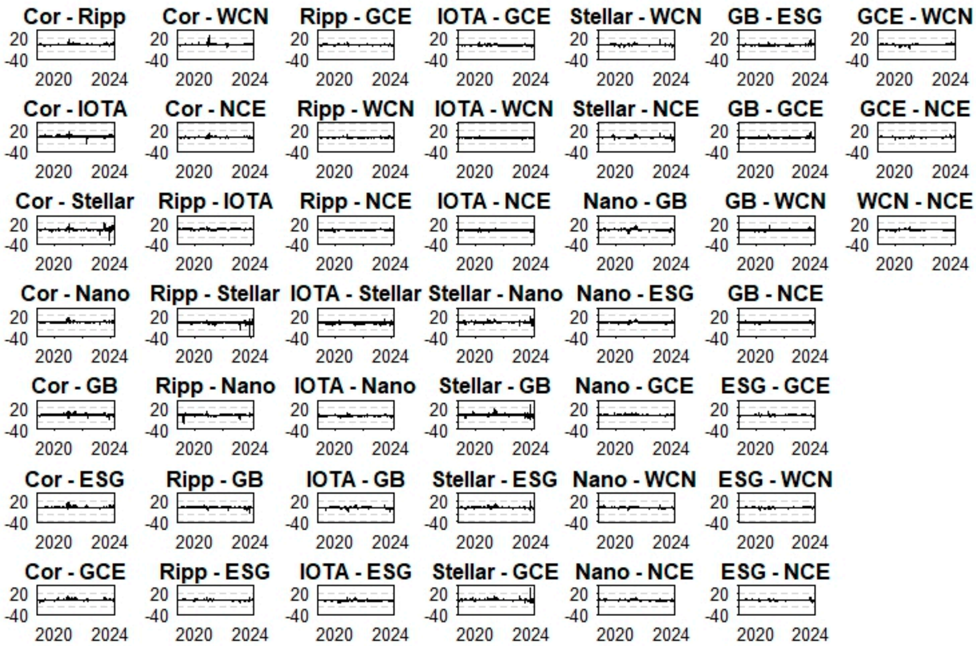


Figure 5. *Cont.*

(**c**)



Note: Findings are based on a 200-day rolling-window QVAR model with a lag length of order 1 (AIC) and a 10-step-ahead forecast.

Figure 5. (**a**) Dynamic Net Pairwise Directional Connectedness at 50th Quantile. (**b**) Dynamic Net Pairwise Directional Connectedness at 5th Quantile. (**c**) Dynamic Net Pairwise Directional Connectedness at 95th Quantile.

Pairwise spillover is generally insignificant in the median quantile except for the transmission effect from Cordano and Ripple to IOTA, and IOTA has also received shocks from Stellar and Nano. The dynamic net pairwise directional connectedness at the 5th quantile- low market condition is presented in Figure 5b. Under these conditions, green cryptocurrency is generally the receiver of shock, particularly during the COVID-19 period. Cordano, Ripple, and IOTA have received spillovers from WCN, Stellar, and Nano. The other extreme condition captured at the 95th quantile presented in Panel B substantiates the previous findings.

Activity was evident around 2020, the period of COVID-19, when Cordano transmitted shocks to WCN and Steller and received shocks from IOTA, especially during the Russian–Ukraine war. Ripple also received spillover from Steller, especially after the Russia–Ukraine war, whereas Steller transmitted shocks to S&P Green Bonds, S&P ESG, and WCN. Green bonds also showed significant transmission of shocks towards WCN and received shocks from the S&P clean energy index.

5.3. Dynamic Total Connectedness

The study also reports the time-varying dynamic analysis of the spillover over the sample period. The results of total connectedness analyses are presented in Figure 6a–c at three quantile levels. Under normal conditions depicted in Figure 6a the total connectedness varies over the sample period, with values ranging from 45% to 70%, showing a stable network with consistent baseline connectivity and periodic fluctuations in the overall connectivity. The most prominent peaks are in 2020–2021 and later in 2022–2023, confirming the periods where connectivity is stronger, which can be associated with the COVID-19 pandemic and Russia–Ukraine war conflict in February 2022.

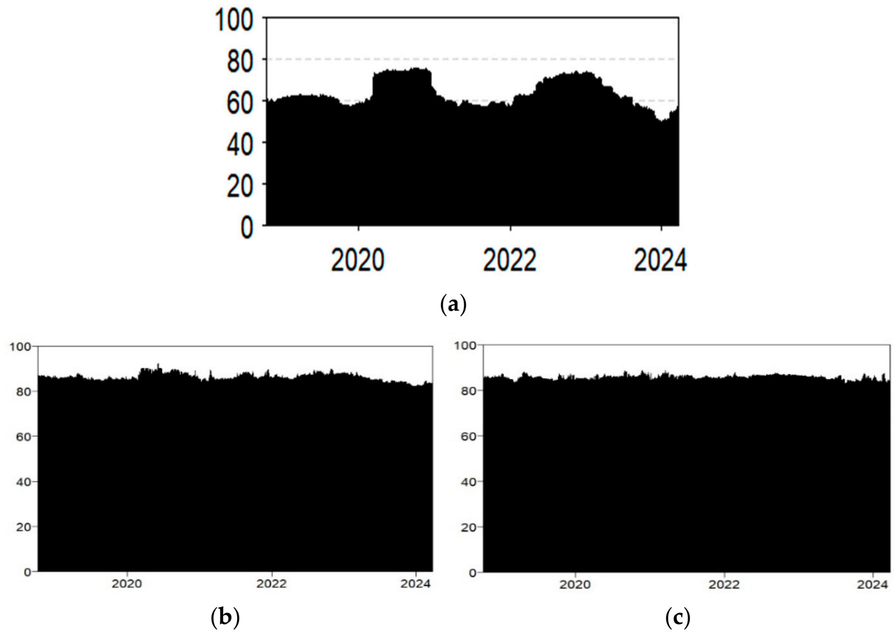


Figure 6. Dynamic Total Connectedness. (**a**) 50th Quantile. (**b**) 5th Quantile. (**c**) 95th Quantile. Note: Findings are based on a 200-day rolling-window QVAR model with a lag length of order 1 (AIC) and a 10-step-ahead forecast.

In Figure 6b,c results of the 5th and 95th quantiles show a high total connectedness of above 80%. The connectedness spikes can be seen more at the 5th quantile, which indicates the turbulent market conditions. At the 95th percentile, total connectedness values are even higher and fluctuate around 85%, depicting the strong interdependence among the green assets.

These peaks possibly correspond to the global events in early 2020, such as COVID-19 and, in early 2022, the Russia–Ukraine war, where markets seem to become more synchronized and lead to higher connectedness. Total connectedness remains high in lower and extreme market situations, showing a strong and persistent relationship among the green assets. These findings are consistent with Tiwari et al. (2024), who also found that total connectedness among green energy stocks and Bitcoin was higher under extreme market conditions, and connectedness was lower under moderate market conditions. A time-varying connectedness is observed in the results, and these findings are in line with the conclusions of Tiwari et al. (2022) and Mensi et al. (2021). Based on the findings of this study, portfolio investors are suggested to vigilantly observe their portfolios consisting of green assets, especially under extreme market conditions.

6. Conclusions and Recommendations

The Paris Agreement (United Nations Framework Convention on Climate Change 2015) and the Sustainable Development Goals (SDGs) of the United Nations created awareness about environmental restoration and sustainability that eventually shifted investors toward green assets in the financial markets. Against the backdrop of this emerging financial landscape, this study explores the connectedness and spillover effect between green assets in the system using the QVAR approach that can capture extreme events. The connectedness and spillover are checked at normal and extreme market conditions using QVAR at the 5th, 50th, and 95th quantiles. The dynamic net pairwise directional contentedness and overall total connectedness among green assets in the system are also addressed to explore the connectedness among green assets further. Five proxies of green cryptocurrencies are studied such as Cordano, Ripple, Iota, Steller, and Nano, whereas green energy is proxied by S&P Global Clean Energy, WilderHill Clean Energy (WCN), and NASDAQ Clean Edge Green Energy Index. The S&P Green Bond Index is used to represent green bonds, and for sustainability, the S&P Global ESG index is included. To deeply study the impact of extreme market conditions, the time of the study is set to include the outbreak of the global COVID-19 pandemic and the unfortunate tension between Russia and Ukraine. It is worth mentioning that green assets, particularly green cryptocurrencies, started declining after touching the peaks in 2021 for multiple reasons, such as economic headwinds, regulatory factors, and shifts in investor sentiments. Geopolitical upset and supply chain disruptions due to the Russia–Ukraine war contributed to increased uncertainty in the market. In fact, the period under study covers two major global events, COVID-19 and the Russia–Ukraine war, which significantly impacted the financial markets across the world. This study aims to check the effect of extreme market conditions caused by those events on the spillover effect and connectedness among green assets.

The results of the study are presented in two sets—under moderate market conditions at the 50th quantile and extreme market conditions at the 5th and 95th quantile. Under normal market conditions, the connectedness among the green assets is less, and they mostly derive their returns from index shocks. Only IOTA and SP Green Bonds are net receivers, whereas all other green assets are net transmitters. S&P Green Bonds absorb the least shocks from others. The green assets showed high connectedness among themselves under extreme market conditions. IOTA, Nano, and S&P Green Bonds are net receivers of shock. The within-index evolution drops under extreme conditions, and all the green assets accept and send heavy shocks to and from the market.

There is abundant financial literature on diversification, but little is known about the diversification traits of green assets, specifically regarding sustainability. The findings of this study provide credence to the overall market participants, investors who want to maintain their investment portfolios, and policymakers who want to ensure global sustainability.

Considering these results, investors can manage their portfolios by balancing the highly volatile cryptocurrencies with the relatively stable performance of green indices. All green cryptocurrencies are observed to have strong connections among themselves under all market conditions; however, they get connected to other green assets in the market under extreme conditions. Green cryptocurrencies such as Cordano, Ripple, and Stellar are the major volatility transmitters. IOTA is a major receiver of spillover effects from other green cryptocurrencies and green energy indices. Investors can allocate a smaller portion of their portfolio to these green cryptocurrencies to reduce the risk in a highly volatile period. Moreno et al. (2022) mentioned that past studies have confirmed the inclusion of cryptocurrency in a portfolio with traditional assets to increase diversification.

Major global events such as the COVID-19 pandemic and the Russia–Ukraine conflict increased uncertainty in the financial markets. It severely impacted the connectedness among the assets and within the financial system. All green assets showed high connectedness and spillover effects during COVID-19 and the Russia–Ukraine war. Moreover, the S&P Green bond index and the clean energy indices maintained their trading volumes during the outbreak of COVID-19 in 2020 and during the war in 2022. However, the green finance market experienced a significant and unprecedented effect of the COVID-19 pandemic, with a connectivity and spillover effect. The Russia–Ukraine war had a mild influence on the spillover of the green finance market (Zhang et al. 2023b). The marginal connection of S&P Green Bonds with other green assets, particularly green cryptocurrencies, and sustained returns during the global pandemic against general downfall during that period makes it a good diversifying asset in a portfolio (Yadav et al. 2022). Green bonds are found to receive 84.79% spillover from other assets in extreme low market conditions and 83.73% in extreme high market conditions. However, this greater connection of green bonds under extreme market conditions is greater with green energy indices than with green cryptocurrencies. In fact, S&P Green Bonds receive only 34.7% spillover from other elements in the market under normal market conditions; therefore, it is considered a stable green asset and can be considered as a potential diversifier in the green assets portfolio.

Nevertheless, the downward trend in green bonds after 2020 can be attributed to several factors, such as adjustments in the interest rates by many central banks to boost the economy. Moreover, people were generally struggling with their liquidity, so there was selling pressure towards fixed investments. Under normal conditions, the connectedness of green energy and green bonds with the rest of the green market is marginal; thus, green energy and green bonds assist investors in hedging the risk generated by the market.

The findings of the study provide several implications for investors and policymakers, especially regarding green assets. First, to encourage the shift toward green assets and ensure environmental restoration and sustainability the regulatory framework should be reset. Traditional carbon emission projects should be discouraged, and fluent regulations should be introduced for green projects. Moreover, to expedite the transformation of the global economy to a low-carbon economy, policies should be designed to facilitate the access and flow of funds required to shift toward a green economy. Government bodies and policymakers should raise awareness about environmental issues and encourage green technologies to ensure sustainability, enhancing general participation in green investment projects (Naeem et al. 2021a). These measures will ensure the achievement of SDG 7 (Affordable and Clean Energy) and 13 (Climate Action) aimed at environmental restoration.

Furthermore, incentivized government policies will attract private investment into green projects as well. Secondly, the weak regulatory framework and high carbon footprint of cryptocurrencies, particularly Bitcoin, encouraged environmentally conscious investors to focus on green cryptocurrencies. Policymakers should focus on stimulating technological advancement targeted to improve energy-efficient algorithms to transform the hostile effects of cryptocurrency into environment-friendly digital currency (Zhang et al. 2023a).

Thirdly, businesses and investors have diverted their focus on environmental restoration and sustainability, which has stretched the spectrum of green assets from green cryptocurrencies to green energy. Green bonds have now been introduced to finance green projects. Policymakers should protect green bonds against interest rate adjustments and extreme market shocks to ensure a consistent supply of funds to green projects. They should focus on strengthening the international financial market mechanisms to absorb the extreme events such as COVID-19 and Russia–Ukraine war and to prevent the investors from significant losses. Governments should subsidize the cost of issuing green bonds and should provide guarantees to reduce the risk associated with bonds and attract risk-averse investors. Measures should be taken to ensure an active secondary market for green bonds, and policies should be designed to build investor confidence and maintain the returns on bonds.

The study provides useful implications for all market participants, particularly portfolio investors. First, all the green cryptocurrencies are highly connected under all market conditions therefore, smaller portions should be allocated in a portfolio. Second, SP Green Bonds are the net receivers of shock and, even under normal market conditions, are marginally connected with the system; therefore, they qualify to be a good diversifying agent in the portfolio. Third, investors must be vigilant about their portfolios under extreme market conditions, as green assets, in particular, increase their connectedness under extreme market conditions.

Future studies should consider other green assets to explore the connectedness among the entire green asset community further. The macroeconomic factors and their impact on the green assets' connectedness under different market conditions can give deeper insight into the phenomenon. For further understanding, robust econometric methods should be used, such as time-varying Markov switching copulas (Abakah et al. 2021) to capture nonlinear dependences among the green assets and fractional integration methods (Abakah et al. 2020) to check the degree of persistence or long memory properties of the green assets.

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