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Risk Connectedness Between Green and Conventional Assets with Portfolio Implications

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Abstract

The increasing concerns of investors toward green bonds and their appealing nature of diversification has motivated the current research to study the risk connectedness between green and conventional assets spanning from August 2014 to December 2020. We first estimate the dynamic equi-correlations through DECO-GARCH. Next, we assess the dynamic and static risk connectedness in the median, extreme low, and extreme high quantiles arguing that spillovers vary across different time periods particularly during economically intense time periods. Finally, we analyzed the hedge ratio and hedge effectiveness between green bonds and other assets. We find that equi-correlations are intense during economic shocks such as the Shale oil crisis, Brexit, US interest rate hike, and COVID-19 pandemic. The volatility analysis at average, lower, and upper quantiles also validate time-varying attributes of green and conventional assets. Further, network figures of green and conventional assets identify potential diversification opportunities. Meanwhile, the hedge effectiveness indicates that green bonds are effective hedge for precious metals and cryptocurrencies. Our findings draw multiple implications for policymakers, green investors, financial market

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participants, and regulatory authorities regarding flight-to-safety during crisis times and maintaining a diverse portfolio to escape potential losses.

Keywords Green assets · Conventional assets · DECO-GARCH · Risk connectedness

1 Introduction

Volatility spillovers and identifying uncertainties in the financial markets are crucial components for portfolio allocation, portfolio design and strategies, and taking benefits from the hedging strategies. The upsurge in the regulatory convergence, investors' environmental orientation, and seeking the most suitable diversification benefits have increased the market integration. These changes have magnified the diversification features and facilitated the portfolio managers to relish the available information for their portfolio optimization (Huang & Liu, 2021). The increased worldwide focus towards green and clean energies is motivated by the environmental concerns and aspirations to step ahead in restructuring the current economy into a climate-resilient economy. The prevailing sustainable investment initiatives have fostered the attention of policymakers, regulators, governments, and worldwide investors to shift from the existing dirty energies to renewable and sustainable energy sources (Halkos & Tsilika, 2021). In this stream, green finance offers sufficient opportunity to switch conventional investments into green investments. The proceeds of green investments are exclusively attributed to environment-friendly, clean energy, and renewable projects backed by these investments (Arif et al., 2021a, 2021b; Berninger et al., 2021; Ferrat et al., 2022; Karim et al., 2021a, 2021b; Reboredo et al., 2020).

First introduced by the European Investment Bank in 2007, green investments provide an innovative solution to financial market participants to channel their financial resources toward sustainability programs and overcome the ongoing challenges of environment and dirty energies. Evidence suggests that green investments are an effective means of financing to overcome the cost of climate-oriented projects (Andersen et al., 2020; Karim & Naeem, 2021; Karim, 2021a, 2021b) toward achieving a low-carbon economy (Leitao et al., 2021). Environmental and climate-friendly investments outperform traditional assets as green assets result in more green innovations (Naeem & Karim, 2021; Ielasi et al., 2018; Nguyen et al., 2020). Following this, multiple stock exchanges worldwide have introduced specialized green investments and assets that satisfy the green concerns of both investors and issuers. Statistics revealed that the size of the green assets has jumped from USD 11 billion in 2013 to USD 350 billion by the end of June 2020 (Climate Bonds Initiative, H1-2020).

Given these contextual underpinnings, the objective of current study is to examine the risk connectedness between green assets and other asset classes. Meanwhile, the increasing activities in green finance have fetched the attention of recent scholars to investigate the underlying nature of green assets with uncovering potential benefits of these investments given the uncertain circumstances of the economic world (Iqbal et al., 2021). Correspondingly, the world has undergone serious shifts and unprecedented crises during the last two decades, which strongly affected financial markets' connectedness and volatility spillovers. One of the severe shocks the world is still

suffering from is the recent global pandemic of COVID-19, where financial markets experienced endangered susceptibility to the unexpected shocks propelled out of this world health emergency (Naeem et al., 2021c). These shocks have driven the interconnection and volatility spillovers of financial assets, where intense risk spillovers spiked the correlations among the markets (Gupta & Shaju, 2021; Kaiser & Welters, 2019; Kang et al., 2021; Karim et al., 2020a, 2020b, 2020c).

In the light of the above arguments, the current study employs a DECO-GARCH and quantile-based connectedness approach that extended the mean-based VAR method of Diebold and Yilmaz (2012, 2014) to fit at the upper and lower tails facilitating the investigation in the median as well as extreme negative and positive shocks. Additionally, we extend our research by decomposing the sample into pre- and post-COVID sub-samples to examine the extreme risk spillovers between green and other asset classes. Nevertheless, the existing studies only focused on the COVID-19 pandemic as a crisis associated with extreme risks. Finally, we analyzed the hedge ratios and hedge effectiveness of green and other asset classes by arguing that adding green assets in the mainstream investment portfolios may offer hedging opportunities to various financial assets.

We achieved research objectives by concluding that equi-correlations between green and other asset classes are time-varying and depicted several spikes and troughs during the sample period spanning August 2014 to December 2020. The main shock events found in the study are the shale oil crisis, Brexit referendum, US interest rate hike, and COVID-19 outburst. The intensive spillovers formed during the periods of high volatility and recovery to normal periods highlight a slope in the graph. The median and extreme low volatility quantiles exhibited comparable twists and turns, whereas high volatility periods sustained a stable high position for the whole sample period. A strong connectedness of green assets is reported with the stock market in the average and lower volatility periods, whereas a complex network is formed at high volatility period. Strong risk spillovers of green assets with other financial assets emphasize their risk mitigation feature, whereas a distinct disconnection of cryptocurrencies from a system-wide connectedness presumes its diversification potential for other assets. The sub-sample analysis denotes strong bidirectional volatility spillovers between green and other asset classes in the post-COVID period. Further, the hedge ratios and hedge effectiveness analysis highlight that green bonds offer better hedge effectiveness for precious metals and cryptocurrencies. Our findings corroborate numerous earlier studies signifying a novel contribution in the existing literature.

Given these results, we proposed plentiful implications for policymakers, green investors, regulation authorities, macro-prudential bodies, portfolio fund managers, and financial market participants. Policymakers can encourage the markets to expand the growth of the green assets due to their trifold benefits, such as diversification, risk-absorbance, and satisfying the eco-friendly motives of investors. Hence, policymakers can restructure and reformulate their existing policies to shelter investors from uncertain economic conditions. Accordingly, regulatory bodies can mandate the regulation of cryptocurrencies as their continuous anonymous trading causes perplexed states among other markets. Investors and portfolio fund managers can include green assets while synthesizing their portfolios to relish their risk mitigation attribute. When market circumstances are unfavorable, the perseverance of green assets can shelter

the investments of green and conventional market investors from extreme volatility periods.

The rest of the paper proceeds as follows. Section 2 presents literature review and hypothesis development; Sect. 3 elaborates Methodology and Data. Section 4 gives empirical results along with a discussion. Section 5 manifests portfolio implications, and Sect. 6 concludes the study with policy implications.

2 Literature Review and Hypothesis Development

Prior studies mainly focused on the advantages and benefits of green assets against other asset classes. For example, Kanamura (2020) and Karpf and Mandel (2017), reported a positive yield differential of green assets, whereas Flammer (2021) and Larcker and Watts (2020) documented an essentially zero-premium on green investments. Conversely, the other strand of literature, like Wang et al. (2020) and Tang and Zhang (2020), witnessed that both investors and issuers can benefit from the issuance of the green asset. Scholars' pronounced interest and greater attention in understanding the nature and features of green assets than conventional assets reflect growth and awareness among academicians and practitioners. Similarly, Russo et al., (2021) examined the determinants of green bond performance for extracting sustainable strategies and policies. Iqbal et al. (2021) used time frequency approach and examined the asymmetry in the sustainable investments. Naeem et al. (2022) investigated the quantile connectedness between green bonds and other assets and found significant volatility transmission between green assets and traditional financial markets. Other studies, for instance, Arif et al. (2021b) and Naeem et al. (2021a) measured the hedge and safe-haven features of green assets and inferred that there is a considerable cushion in green assets to offset the risk of conventional assets. However, the literature offers limited research regarding risk transmission and volatility spillovers between green and other asset classes.

While following the methodological contributions of earlier studies, it is argued that studies employed various methodologies to examine the interconnectedness and risk spillovers between green and other asset classes, such as Naeem et al. (2021a) and Arif et al. (2021a) investigated the asymmetric spillovers between green bonds, commodities, and financial markets, respectively. Nguyen et al. (2020) and Reboredo et al. (2020) employed wavelet-based analysis, Naeem and Karim (2021) applied time-varying optimal copulas, Reboredo and Ugolini (2019) utilized VAR models, Pham (2021), and Arif et al. (2021b) used the cross-quantilogram technique, and Broadstock and Cheng (2019) applied GARCH model. While all these studies captured various aspects of connectedness between green and conventional assets, the sophistication of volatility spillovers under extreme economic and financial circumstances has not been explored by the earlier studies. In this vein, policymakers and investors are keen toward comprehending the linkages between green and other assets at extreme tail conditions.

The above literature exhibits a clear void in the existing stream of knowledge where risk transmission between green and other asset classes is glaringly lacking.

Saeed et al. (2021) applied the quantile VAR approach and measured return connectedness of clean energy, green bonds, crude oil, and energy stocks and identified that spillovers are pronounced in the left and right tails. Shahzad et al. (2021) using the quantile generalized forecast error variance decomposition examined the system-wide connectedness of different asset classes and quantified varying behaviour of markets at different economic circumstances. Naeem et al. (2021c) modelled the hedge and safe haven properties of green and Islamic stocks and found sufficient risk bearing potential in the green bonds. Based on these studies, the current study is unique in providing evidence of risk transmission across green assets and conventional financial markets. Thus, the study hypothesizes that:
H1: There is significant risk transmission between green and other asset classes.
Given this hypothesis, the study further examines the mechanism of risk transmission between green and other asset classes using a unique set of methodologies that are explained in the following sections.

3 Methodology and Data

To investigate the risk transmission between green and conventional assets, we employed the multivariate DECO-GARCH model for estimating the dynamic equi-correlation. In the next step, we examine the median, extreme lower, and extreme higher risk spillovers by deploying a quantile VAR and connectedness technique proposed by Ando et al. (2018). Finally, we assessed the hedge ratios and hedge effectiveness of green bonds against other asset classes to highlight portfolio implications. The following sub-sections explain their advantages and methodological approach to compute the results.

3.1 Estimating DECO-GARCH

Since multivariate GARCH (MGARCH) models suffer methodological constraints, DECO-GARCH provides a solution to these limitations with the high-dimensional calculation of systems and their visualization (Engle & Kelly, 2012). The DECO technique is the sub-set of DCC model where all variables are uniformly associated, but their adjacent equi-correlations are time-variant. The substantial advantage of this technique is to provide robust forecasting when economic circumstances are unfavorable and exposed to extreme risks (Clements et al., 2015). Therefore, to unveil the associations between green and other asset classes, the DECO-GARCH model appears to be a perfect fit.

Following Kang et al. (2017), we assume the mean equation for a vector of r_t return series as:

$$r_t = \mu_t + \delta r_{t-1} + \varepsilon_t \tag{1}$$

where μ is vector constant and ε_t is error terms vector.

Afterward, by using the univariate GARCH (1,1), we estimate the conditional volatilities as follows:

$$h_{i,t}^2 = \omega + \alpha\varepsilon_{i,t-1}^2 \beta h_{i,t-1}^2 \tag{2}$$

where $\omega > 0$, $\alpha \geq 0$, and $\beta \geq 0$, and $\alpha + \beta < 1$. To examine the dynamic correlations between green and other asset classes, the DCC model of Engle (2002) is used. Assume that $F_{t-1}[\varepsilon_t] = 0$ and $F_{t-1}[\varepsilon_t \varepsilon_t{}'] = H_t$, where $F_t[\cdot]$ denotes conditional expectation utilizing the set of information at time t. The conditional variance–covariance matrix, H_t, can be illustrated as:

$$H_t = G_t^{1/2} R_t G_t^{1/2} \tag{3}$$

where conditional correlation matrix is given as $R_t = [\rho_{ij,t}]$ and $G_t = diag(h_{i,t}, \cdots, h_{n,t})$ is the diagonal matrix of conditional variances. The quantification of H_t following the dynamic correlations is presented as:

$$R_t = \{\mathcal{Q}_t^*\}^{-1/2} \mathcal{Q}_t (\mathcal{Q}_t^*)^{-1/2} \tag{4}$$

$$\mathcal{Q}_t^* = diag[\mathcal{Q}_t] \tag{5}$$

$$\mathcal{Q}_t = \left[q_{i,j,t}\right] = (1 - a - b)S + \alpha\mu_{t-1}\mu_{t-1}^{'} + b\mathcal{Q}_{t-1} \tag{6}$$

where u_t reflects standardized residuals, a and b are non-negative scalars fitting $a + b < 1$ and the resultant method is the DCC approach. Since $G[R_t] \neq G[Q_t]$, Aielli (2013) argues that estimating covariance matrix Q_t following this procedure generates inconsistent results. Therefore, a consistent DCC model for the correlation-driving process is recommended, described as:

$$\mathcal{Q}_t = (1 - 1 - b)S^* a\left(\mathcal{Q}_{t-1}^{*\frac{1}{2}} \mu_{t-1}\mu_{t-1}^{'} \mathcal{Q}_{t-1}^{*\frac{1}{2}}\right) + b\mathcal{Q}_{t-1} \tag{7}$$

where S^* represents the unconditional covariance matrix of $Q_t{}^{*1/2}u_t$. The DECO approach is obtained through correlation matrix (Q_t) and taking an average of off-diagonal elements where ρ_t is attained from the DCC process (Engle & Kelly, 2012). In this way, the scalar equi-correlation is given as:

$$\rho_n^{DECO} = \frac{1}{n(n-1)}\left(f_n^{'} R_t^{cDCC} f_n - n\right) = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{j=1+1}^{n} \frac{q_{i,j,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{8}$$

To estimate the conditional correlation matrix, the scalar equi-correlation is employed as follows:

$$R_t = (1 - \rho_t) I_n + \rho_t f_n \tag{9}$$

Given these steps, the magnitude of extreme risk transmission between green and other asset classes can be expressed using a single time-varying correlation coefficient.

3.2 Measuring Quantile VAR

Based on Ando et al. (2018), we estimate the dependence of y_t on x_t in each quantile $\tau(\tau \in (0, 1))$ given the conditional distribution of y_t/x_t. The n-variable quantile for the VAR process of pth order is given as:

$$y_t = c(\tau) + \sum_{i=1}^{p} Bi(\tau)y_{t-i} + et(\tau), t = 1, \ldots, T \tag{10}$$

where y_t is the n-vector of dependent variables at time t; $c(\tau)$ and $et(\tau)$ are the n-vector of intercepts and residuals, respectively, at quantile τ; and $B_i(\tau)$ represents the matrix of lagged coefficients at quantile τ, with $i = 1, \ldots, p$, and can be measured following the assumption that residuals meet the population quantile restrictions $Q\tau(et(\tau)|yt - 1, \ldots, yt - p) = 0$. Hence, the population τth for conditional quantile of response y is represented as:

$$Q\tau(et(\tau)|yt - 1, \ldots, yt - p) = c(\tau) + \sum_{i=1}^{p} \widehat{B}i(\tau)y_{t-i} \tag{11}$$

Using the equation-by-equation quantile regression basis, the above model is estimated for each quantile and variables are seemingly unrelated.

3.3 Diebold-Yilmaz Spillover Indices

By employing a quantile variance decomposition, the framework developed by Diebold and Yilmaz (2012, 2014) determines the spillover indices for every quantile τ. Thus, Eq. (10), in the form of infinite order vector moving average process, can be re-written as:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau)e_{t-s}(\tau), t = 1, \ldots, T \tag{12}$$

With,

$$\mu(\tau) = (I_n - B_1(\tau) - \cdots - Bp(\tau))^{-1}c(\tau), A_s(\tau)$$

$$= \begin{cases} 0, s < 0 \\ I_{n,} s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \cdots + B_p(\tau)A_{s-p}(\tau), s > 0 \end{cases}$$

where y_t denotes the sum of residuals e_t at every quantile τ.

Given the Cholesky-factor ordering issue, the approach of Koop et al. (1996) and Pesaran and Shin (1998) is employed that retains the variable ordering. It is also indicative of extreme shocks and their orthogonality as the sum of contributions to the forecast error's variance is not equal to 1. Given the forecast horizon H, the generalized forecast error variance decomposition (GFEVD) of a variable attributable to shocks is computed as:

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i^{'}A_h\Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i^{'}A_h\sum A_h^{'}e_i)} \tag{13}$$

where $\theta_{ij}^{g}(\mathrm{H})$ denotes the contribution of the jth variable to the variance of forecast error of the variable i at horizon H, $\sum$ is the variance matrix of the vector of errors, σ_{jj} is the jth diagonal element of the Σ matrix, and e_{i} reflects a vector value of 1 for the ith element and 0 otherwise. Finally, decomposition matrix of each variance entry is given as follows:

$$\widetilde{\theta}_{ij}^{g}(\mathrm{H}) = \frac{\theta_{ij}^{g}(\mathrm{H})}{\sum_{j=1}^{N}\theta_{ij}^{g}(\mathrm{H})} \tag{14}$$

For estimating connectedness of variables at τth conditional quantile, Diebold and Yilmaz (2012, 2014) can be followed. The generalized quantile forecast error variance decomposition is employed for developing the connectedness measure formula. Hence, the total connectedness (TC) index at quantile τ is expressed as:

$$TC(\tau) = \frac{\sum_{i=1}^{N}\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(\tau)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{g}(\tau)} \times 100 \tag{15}$$

The 'TO' directional connectedness is the movement of index i from all other indexes at quantile τ given as:

$$C_{i\leftarrow}(\tau) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N}\widetilde{\theta}_{ij}^{g}(\tau)} \times 100 \tag{16}$$

The 'FROM' directional connectedness is the movement from index i to all other indexes at quantile τ represented as:

$$C_{i\rightarrow}(\tau) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\theta}_{ji}^{g}(\tau)}{\sum_{j=1}^{N}\widetilde{\theta}_{ji}^{g}(\tau)} \times 100 \tag{17}$$

Thus NET connectedness is the sum of Eqs. (16) and (17) given as:

$$NC(\tau) = C_{\rightarrow i}(\tau) - C_{i\leftarrow}(\tau) \tag{18}$$

And, the pairwise connectedness at quantile τ is stated as:

$$PC(\tau) = \widetilde{\theta}^{g}_{ji}(\tau) - \widetilde{\theta}^{g}_{ij}(\tau) \tag{19}$$

The rolling window analysis is employed for spillover measurements as the estimation of connectedness caters VAR lag order 1 and a 10-step ahead forecast error variance decomposition (Diebold & Yılmaz, 2014).

3.4 Measuring Hedge Effectiveness

To compare the hedging capability of green bonds with other asset classes, the out-of-sample hedging effectiveness is measured. While performing the analysis, the hedge effectiveness of the hedged positions between green and other asset classes is assessed to suggest risk transmission and reduction by adding the green bonds in a pool of assets. In this way, we draw several implications for investors and policymakers to inculcate the diversification benefits.

The return of the hedged portfolio is denoted as $r_{hp,t}$ which includes green and other asset classes:

$$r_{hp,t} = r_{sp,t} - \varphi_t r_{GR/AS,t} \tag{20}$$

where $r_{sp,t}$ indicates the return of asset class, $r_{GR/AS,t}$ represents the return on either green bond, and the hedge ratio is denoted by φ_t. Hence, the variance of hedged portfolio is dependent on the available information at time I_{t-1}, and is stated as:

$$var\left(r_{sp,t} I_{t-1}\right) = var\left(r_{GR/AS,t} I_{t-1}\right) + \varphi_t^2 var\left(r_{sp,t}\right) - 2\varphi_t cov(r_{sp,t}, r_{GR/AS,t} I_{t-1}) \tag{21}$$

Using the AGDCC-GARCH (asymmetric generalized dynamic conditional correlation form of the generalized autoregressive conditional heteroscedasticity) model, the hedge ratios are estimated from covariance and conditional volatility. This technique offers robust analysis by examining the second moments of correlations and covariance, which facilitates interpreting the degree of hedge effectiveness of green bonds for other asset classes. Hence, a long position against a short position in green bonds can be hedged as:

$$\varphi_t^* | I_t = h_{sp.GR/AS,t} / h_{GR/AS,t} \tag{22}$$

where $h_{sp.GR/AS,t}$ denotes the conditional covariance between the asset class and green bond return and $h_{GR/AS,t}$ indicates the conditional variance of green bond return. The hedge ratios for green and other asset classes using the GARCH model can be stated as:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \tag{23}$$

A higher *HE* denotes higher hedge effectiveness, whereas lower values indicate lower hedge effectiveness; therefore, a perfect hedge has a value of 1 and 0 otherwise. In addition, the hedge ratio estimates lead toward a hedged portfolio with greater diversification and minimum risk.

3.5 Data and Descriptive Statistics

This study examines the extreme risk transmission between green and other asset classes where data of S&P Green bond index (GRNB), S&P Clean Energy index (CLEN), S&P GSCI Energy index (ENRG), Precious Metals index (PMET), cryptocurrency index (CRIX), and MSCI World index (MSCW) is used for the period spanning August 2014 to December 2020. The data of all asset classes have been sourced from Datastream[1] except for CRIX.[2] Table 1 exhibits details of each index used in the study along with summary statistics and unit root of variables where CRIX yields the highest average return, whereas CLEN, MSCW, and PMET show moderate positive returns. Conversely, ENRG and GRNB reflect the lowest negative returns. The highest variability in the return series is documented by CRIX followed by ENRG and CLEN, while moderate to lower variability is depicted by PMET, MSCW, and GRNB. The marginal negative values of skewness indicate that green and other asset classes have undergone several uncertainties given the uneven economic conditions. The Augmented Dicky-Fuller (ADF) test of stationarity shows high negative significant values confirming the stationarity of the data.

Figure 1 presents the evolution of price and returns series for green and conventional assets. The solid black line shows the evolution of prices for the asset classes, whereas the grey line illustrates the evolution of returns. Figure 1a shows SPGB has undergone tremendous variations in price series while frequency band for return series also highlights thickness manifesting several ups and downs during the sample period. For instance, the initial graph showed higher price series during 2014, and it gradually dropped until 2016. Subsequent evolution of price is indicated during 2016, 2017–2018, and 2020 which corroborates the Shale oil revolution (Naeem et al., 2020), US interest rate price hike (Elsayed et al., 2020), and COVID-19 pandemic (Naeem et al., 2021a, 2021b). Alternatively, the return series displays significant spikes in the graph aligned with the shock events presented earlier. In Fig. 1b, CLEN revealed relatively negative price evolution and moderate return series, which gradually jumped after the COVID-19 pandemic indicating higher demand for these stocks, particularly after the coronavirus outbreak. ENRG (Fig. 1c) dropped from positive to negative prices and retained negative prices until the end of the sample period. Besides, the return series showed a thinner band of evolution with significant spikes during 2016 and 2020, shadowing the Shale oil revolution and the recent pandemic of COVID-19.

Conversely, PMET (Fig. 1d) demonstrates consistent positive price series, whereas the return series exhibits substantial peaks during 2016 and 2020, reflecting back the impacts of the Shale oil revolution and COVID-19 pandemic (Naeem et al., 2020). The remarkable trends in price series are observed by CRIX (Fig. 1e) when the price

[1] Datastream is a renowned database for obtaining the daily time-series data of asset classes.

[2] The data has been sourced from https://coinmarketcap.com/

Table 1 Descriptive statistics and unit root

Detail of Index	Proxy	Mean (%)	Median	Max	Min	SD	Skew	Kurt	ADF
S&P Green Bond index	GRNB	− 0.001	− 0.001	2.007	− 2.420	0.316	− 0.556	9.173	− 25.498***
S&P Clean Energy index	CLEN	0.045	0.070	11.035	− 12.498	1.357	− 1.013	18.280	− 14.034***
S&P GSCI Energy index	ENRG	− 0.088	0.000	15.983	− 30.169	2.450	− 1.517	26.223	− 41.988***
S&P GSCI Precious Metals index	PMET	0.016	0.000	5.715	− 5.442	0.962	− 0.043	7.970	− 41.845***
Cryptocurrency index	CRIX	0.239	0.252	22.027	− 44.664	4.463	− 0.948	13.069	− 40.215***
MSCI World index	MSCW	0.024	0.042	8.061	− 9.997	0.932	− 1.547	26.383	− 12.197***

Max, Min, SD, Skew, Kurt, and ADF represent maximum, minimum, standard deviation, skewness, kurtosis, and Augmented Dickey-Fuller test
*** indicates significance at 1%

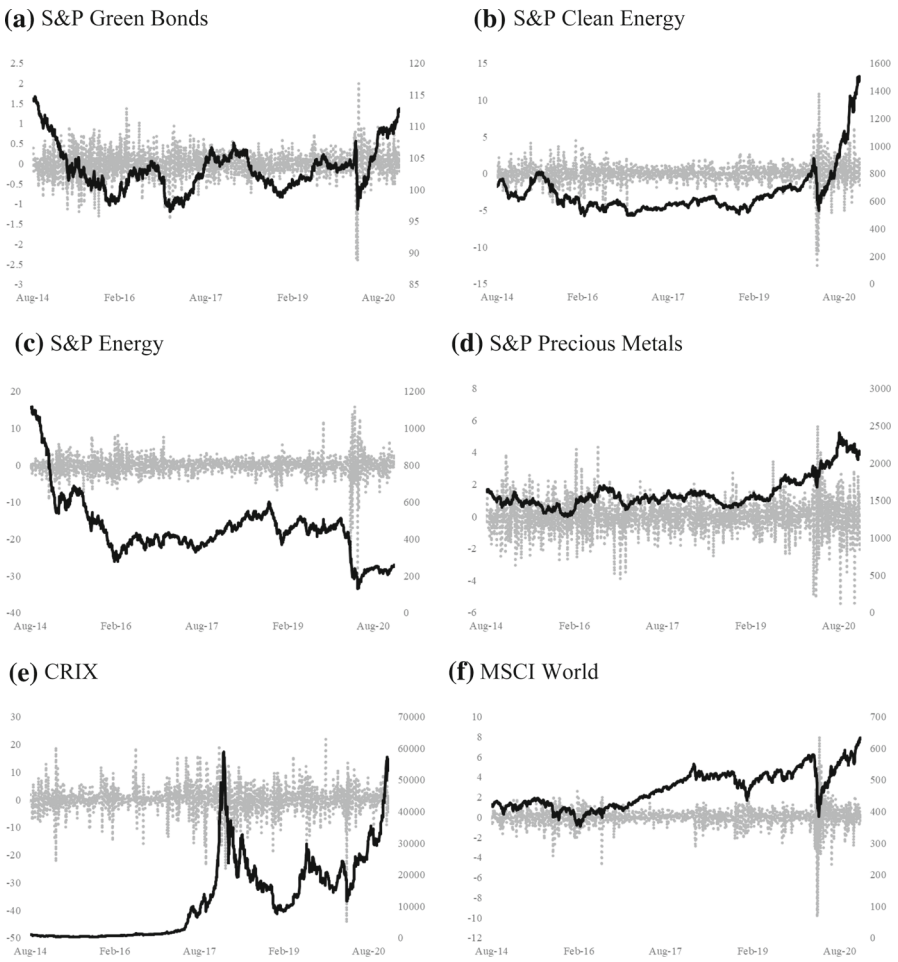


Fig. 1 Evolution of price and return series. *Note*: Evolution of the price (solid black line) and log-transformed return (dotted grey line) series of S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index from August 2014 to December 2020. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

significantly dropped at the end of 2017 due to the cryptocurrency bubble burst (Lucey et al., 2021). Then again, the price inclined significantly after the coronavirus outbreak (Yarovaya et al., 2020). Nonetheless, the return series revealed several jumps in the graph, referring to significant economic situations. Finally, Fig. 1f retained sizeable positive price trends with minute variations in the return series and a sharp spike during COVID-19, indicating the world stocks suffered the adverse effects of the pandemic (Abakah et al., 2021).

4 Empirical Results

4.1 Dynamic Equi-correlations Using DECO-GARCH

Figure 2 demonstrates dynamic equi-correlations using the DECO-GARCH method, presenting time-varying attributes of various asset classes. The graph manifests significant spikes and troughs, indicating that markets have been exposed to distressing situations and investors need to adjust their portfolios given the uncertainty of the global dynamics. The initial spike in the graph during 2014 echoes the oil price crisis where variations in the oil prices generated high correlations among the asset classes due to recoupling (contagion) effect on the financial markets. In line with Mansour-Ibrahim (2022), Naeem et al. (2021c), Mensi et al. (2020), and Balli et al. (2019), the oil price burst in 2014 intensified the correlations of markets leading towards a jump in the graph. Concurrently, the subsequent decline in the correlations denotes that markets return to stable periods (Kang et al., 2017). The successive spike in the graph during 2016 reflects the Brexit referendum where United Kindom's decision to exit the European Union created a bewildering situation for the overall economy and global markets (Xiao et al., 2019). Nevertheless, the gradual slope on the graph after the Brexit denotes that markets have entered the recovery period out of shock situation (Naeem et al., 2021b).

Notably, a sharp increase in the correlations during 2017–2018 indicates a US interest rate hike where a sudden increase in the interest rates created uncertainty in the financial markets that led to an abrupt spike in the graph. In consonance with Kang et al. (2021), our findings confirm that US interest rate hike elevated the significant correlations among financial markets. Finally, the consequent rise in the graph during

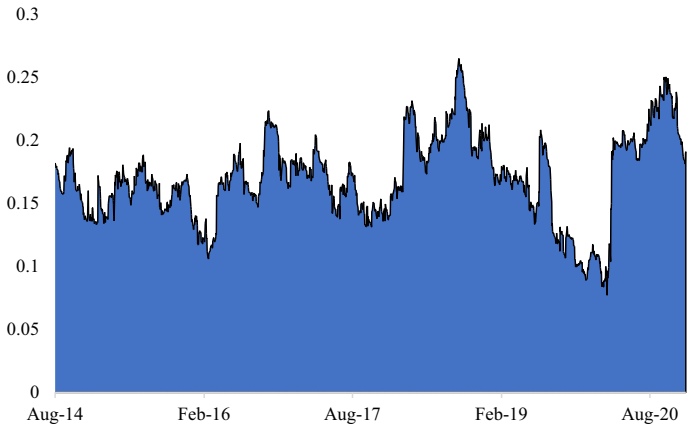


Fig. 2 Dynamic equi-correlation using DECO-GARCH. *Note*: Dynamic equi-correlation among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index estimation using the DECO-GARCH of Engle and Kelly (2012)

2019–2020 redirects the onset of the COVID-19 pandemic where a global health emergency announced by the World Health Organization (2020) hoisted the correlations among markets revealing a sudden uncertain condition the economy. Several studies, for instance, Wang and Xu (2021), Zheng et al., (2021), Le et al. (2021), Tiwari et al. (2021), Naeem et al., (2021a, 2021b), and Shahzad et al. (2021), stated that the global pandemic of COVID-19 has embarked unprecedented challenges for the global economy and financial markets where increased correlations in the form of a sharp spike during 2019–2020.

4.2 Dynamic Volatility Spillovers in the Quantile VAR

Figures 3, 4 and 5 present time-varying dynamic volatility spillovers using the quantile VAR model for the average volatility (50th), extreme low volatility (5th), and extreme high volatility (95th) quantiles, respectively for the rolling-window size $w =$ 260 days. The basic argument persists here is the variation of volatilities across different economic time periods. At extreme low volatility periods, markets are in their lower returns while at extreme high volatility periods, markets exhibit abnormal trend in their returns. However, at median quantiles, markets are at their average returns which mainly reflects normal market conditions. Figure 3 shows the total connectedness index (TCI) for average volatility where significant jumps are prevalent during 2014–2017, echoing the oil price crisis, Brexit referendum, and US interest rate hike. Meanwhile, the TCI remained at 45% until 2017, showing modest average volatility of all asset classes, particularly during the crises mentioned above. The gradual decline in the TCI is observed afterward until Feb-2020, indicating the emergency state around the globe due to the COVID-19 outbreak where TCI leveled up to 80%, manifesting pronounced connectedness among the markets. In line with Bouri et al. (2021), Naeem

Fig. 3 Dynamic volatility spillover in the quantile VAR (median quantile Tau = 0.5). *Note*: This Figure shows the rolling-window version of total volatility connectedness at 50th quantile among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. The rolling-window size 260 days

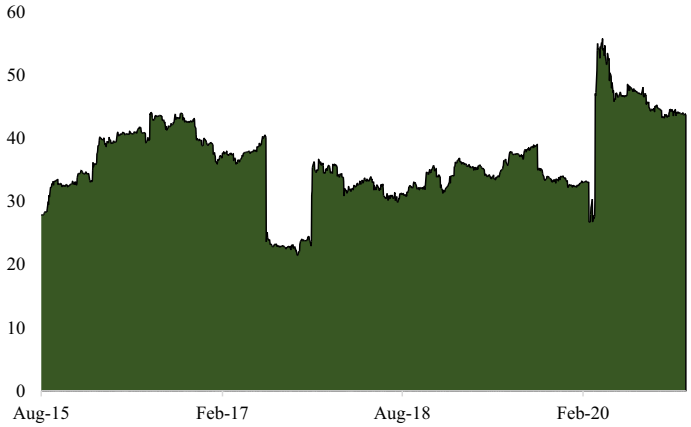


Fig. 4 Dynamic volatility spillover in the quantile VAR (extreme low quantile Tau = 0.05). *Note*: This Figure shows the rolling-window version of total volatility connectedness at 5th quantile among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. The rolling-window size 260 days

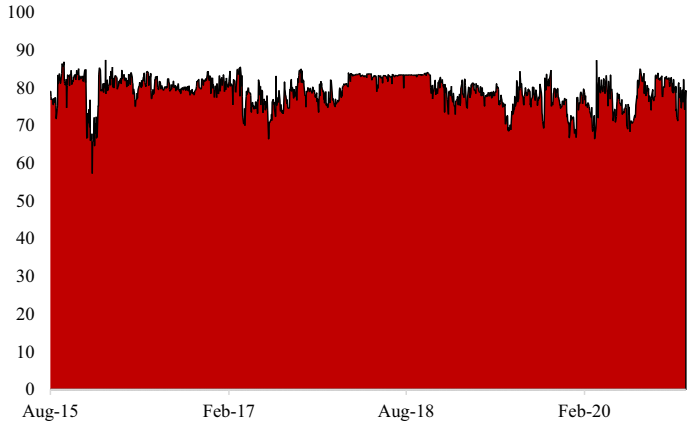


Fig. 5 Dynamic volatility spillover in the quantile VAR (extreme high quantile Tau = 0.95). *Note*: This Figure shows the rolling-window version of total volatility connectedness at 95th quantile among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. The rolling-window size 260 days

et al. (2021c), and Farid et al. (2021), markets exposure to risk spillovers is dominant during the COVID-19 pandemic substantiating the contagion effect on financial assets.

The TCI in extreme low quantile (Fig. 4) illustrates similar patterns compared with the average volatility where connectedness remained modest for the whole sample period except for 2018, where the decline in the graph shows normal market conditions after the US interest rate hike. However, the substantial jump in connectedness during

the COVID-19 outbreak reiterates the higher exposure of markets to the uncertainties generated due to this global pandemic (Adekoya & Oliyide, 2020; Le et al., 2021).

The dynamic volatility spillover in the extreme high volatility (95th quantile) in Fig. 5 reveals that TCI reaches up to 85% with few insignificant fluctuations in the correlations among the asset classes. The higher volatility in the extreme risk spillovers manifests a higher sensitivity between green and conventional assets coinciding with Bouri et al. (2021) and Naeem et al. (2021a), who also reported extreme risk transmission in lower and upper quantiles.

4.3 NET Directional Volatility Spillovers in Quantile VAR

Figures 6, 7, and 8 display the net directional volatility spillovers indicating the contribution of each financial asset to the volatility risk spillovers in the median, extreme low, and extreme high quantiles. The NET volatility connectedness in the median quantile (Fig. 6) signifies positive CLEN, CRIX, and MSCW during the start of the period. PMET maintained near to zero volatility among other asset classes, whereas GRNB and ENRG showed negative volatility spillovers in the median quantile. During 2019–2020, some interesting spillovers were observed where CLEN, ENRG, and CRIX showed positive risk spillovers reaching up to 13%, whereas GRNB, PMET, and MSCW formed negative risk spillovers attaining the TCI of about − 12%. For average volatility, the findings also highlight that almost all asset classes are imperiled with the COVID-19 outburst where CLEN, ENRG, and CRIX transmitted risk spillovers to GRNB, PMET, and MSCW during COVID-19 pandemic. Our findings corroborate Naeem et al. (2021c), Shahzad et al. (2021), and Zhang et al. (2021), who documented extreme volatility in the markets subjected to the pandemic of COVID-19.

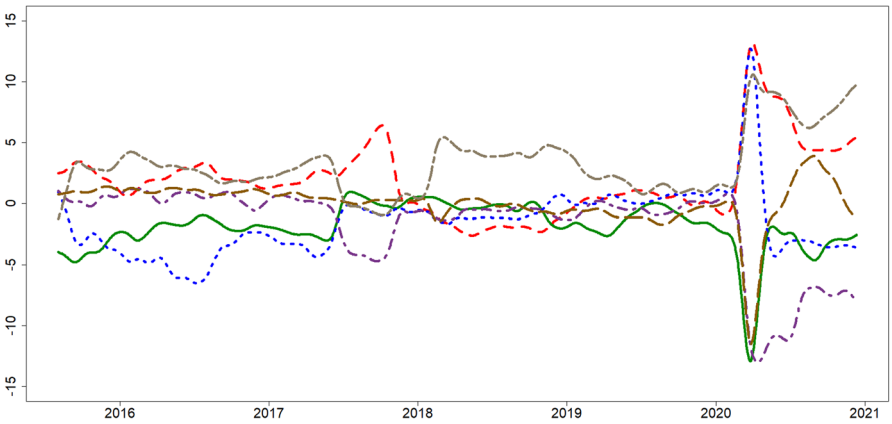


Fig. 6 Net directional volatility spillovers in the quantile VAR (median quantile Tau = 0.5). *Note*: This Figure shows the rolling-window version of NET volatility connectedness at 50th quantile among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. The rolling-window size 260 days. Green, red, blue, purple, grey, brown represent green bonds, clean energy, energy, precious metals, CRIX, MSCW, respectively

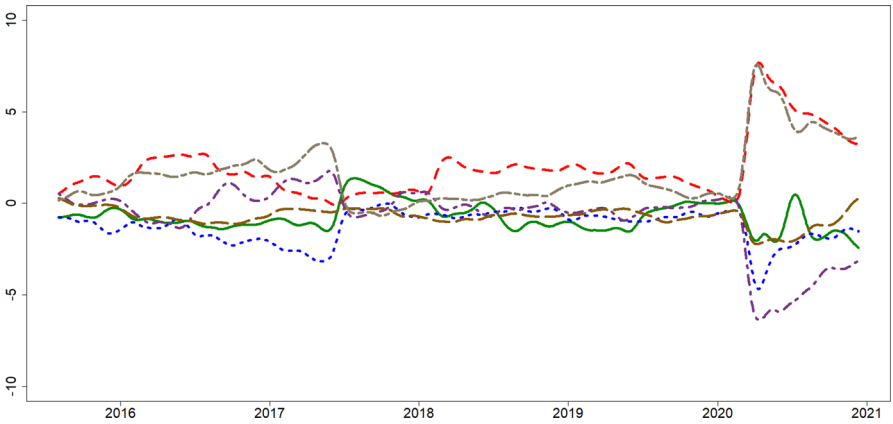


Fig. 7 Net directional volatility spillovers in the quantile VAR (extreme low quantile Tau = 0.05). *Note*: This Figure shows the rolling-window version of NET volatility connectedness at 5th quantile among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. The rolling-window size 260 days. Green, red, blue, purple, grey, brown represent green bonds, clean energy, energy, precious metals, CRIX, MSCW, respectively

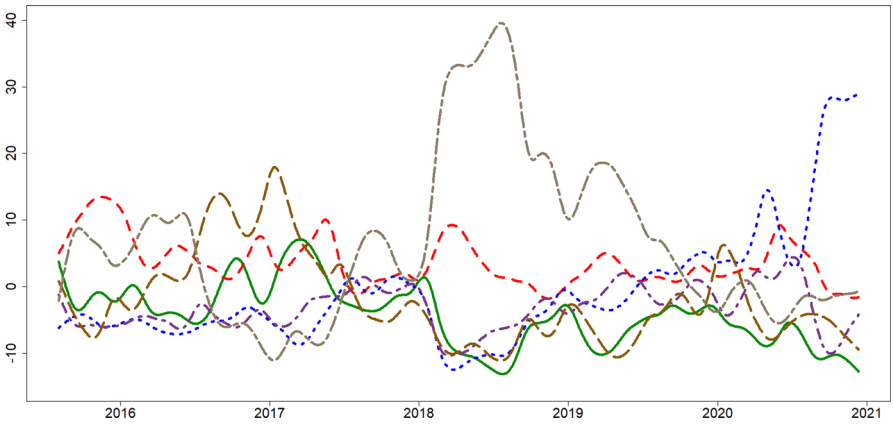


Fig. 8 Net directional volatility spillovers in the quantile VAR (extreme high quantile Tau = 0.95). Note: This Figure shows the rolling-window version of NET volatility connectedness at 95th quantile among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. The rolling-window size 260 days. Green, red, blue, purple, grey, brown represent green bonds, clean energy, energy, precious metals, CRIX, MSCW, respectively

The NET directional connectedness in extreme low quantile (Fig. 7) indicates comparable results of average volatility where CLEN and CRIX showed positive risk spillovers for 2014–2017. In contrast, GRNB, PMET, and MSCW are closer to zero, and ENRG showed negative risk spillovers during Shale oil crisis, Brexit, and US interest rate hike. Afterward, the graph showed closer to zero risk spillovers, and a

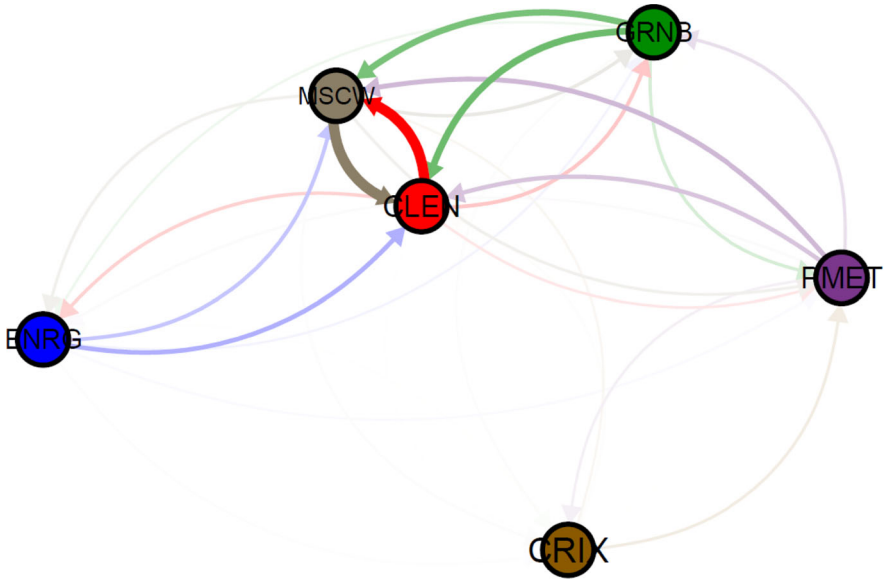
sudden increase in volatilities is narrated during COVID-19 outbreak where CLEN and CRIX transmitted risk spillovers to GRNB, ENRG, MSCW, and PMET. However, the NET directional spillovers in extreme high quantiles showed remarkable shifts in the movements of green and other asset classes where initially CLEN and CRIX dominated the risk spillovers of GRNB, ENRG, PMET, and MSCW during 2014–2016. The graph illustrates a switch in the risk spillovers of CRIX during 2017, where it received high volatility from other asset classes due to the cryptocurrency bubble burst (Karim et al., 2022a, 2022b; Lucey et al., 2021). Nevertheless, an interesting move in the CRIX market during 2019 confirms its ten times higher volatility than conventional markets (Bariviera & Merediz-Sola, 2021). Overall, higher volatility in the median, upper, and lower quantiles suggests that markets have experienced several ups and downs, particularly when the economic circumstances are unfavorable and the global financial system is exposed to high risk.

4.4 Volatility Spillovers Based on Quantile VAR and COVID-19

After explaining the dynamic analyses, the next step presents network diagrams of net pairwise directional spillovers (Figs. 9, 10, and 11) for the median, low, and high volatility conditions. Each Figure is separated into a network diagram and net directional risk spillovers for each asset class over the sample period. Figure 9a displays the network volatility connectedness between green and conventional assets, where CLEN is strongly connected with MSCW and connectedness is lower with other markets. In the case of GRNB, strong connectedness of GRNB is observed with CLEN and MSCW. The remaining asset classes show modest to lower connectedness with CLEN and GRNB, whereas CRIX shows substantial disconnection from the network. The strong connectedness of CLEN and GRNB with MSCW is in line with Ferrer et al. (2021) and Nguyen et al. (2020), who reported strong risk spillovers between green bonds and the clean energy/stocks market. However, our findings negate the results of Elsayed et al. (2020), who narrated lower connectedness of CLEN with other assets. The disconnection of CRIX from the system echoes the diversification potential of cryptocurrencies for various investment opportunities such as energy and stock markets (Bekiros et al., 2021; Gkillas & Katsiampa, 2018). Summary measures of connectedness network (Fig. 9b) illustrate that CLEN and MSCW are the net transmitters of risk spillovers in the median quantile, whereas GRNB, ENRG, and PMET are the net receivers of volatility spillovers. CRIX showed the lowest system-wide connectedness conquering the results of Akyildirim et al. (2020), who reported high volatility of cryptocurrencies disconnects them from the overall system of connectedness. The net transmitting role of green assets stresses that they can be an effective alternative in overcoming the risk volatilities of the system (Naeem et al., 2021a, 2021b).

At the extreme low volatility (Fig. 10), the pattern of connectedness seems quite similar to the median volatility. The strong connectedness between green assets and the stock market is evident, whereas weak spillovers are formed with PMET and ENRG. Notably, CRIX showed disconnection from the system-wide connectedness indicating its diversification potential for other assets. The summary measures of the

(a) The network of volatility connectedness



(b) Summary measures of connectedness network.

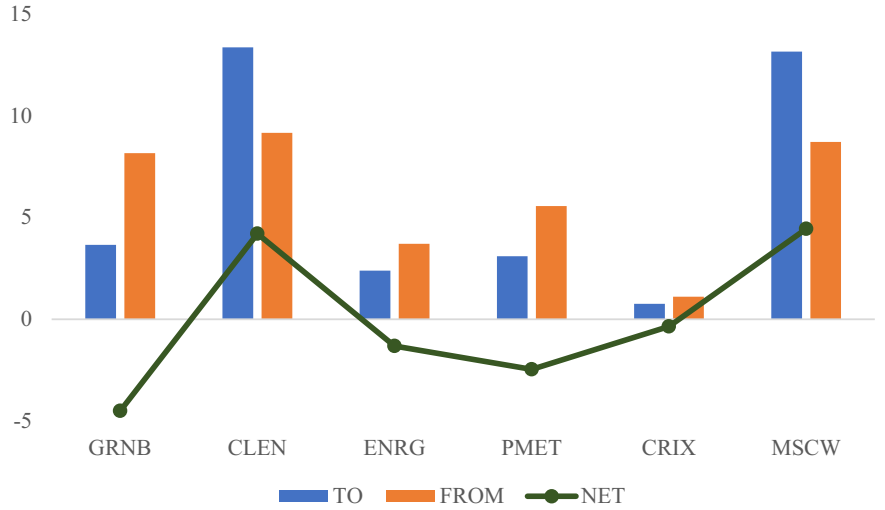
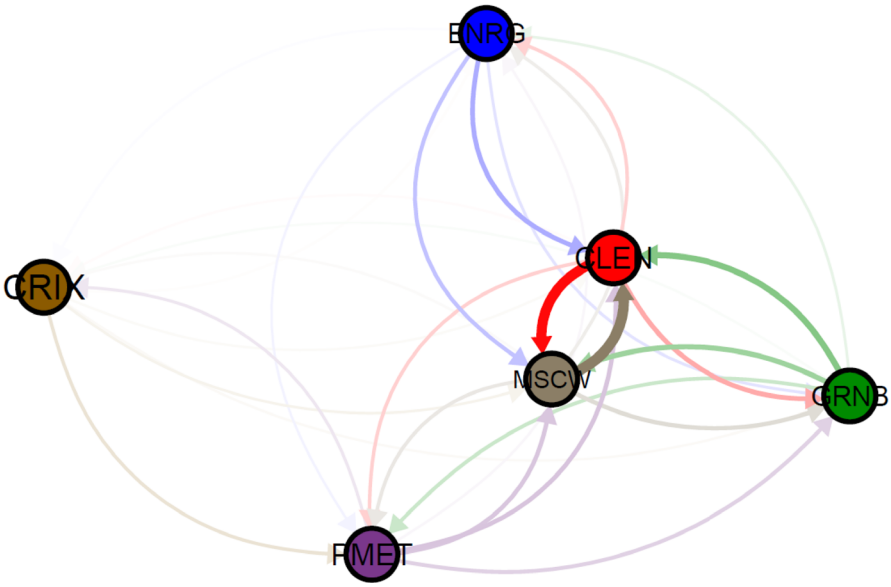


Fig. 9 Volatility spillovers based on quantile VAR (median Tau = 0.5). *Note*: **a** Shows the network connectedness among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. **b** Shows the three summary measures of the connectedness network. TO, FROM, and NET

(a) The network of volatility connectedness



(b) Summary measures of connectedness network.

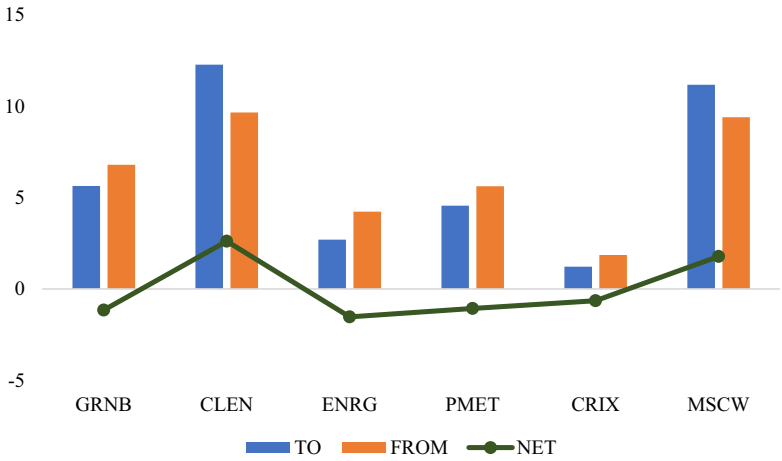
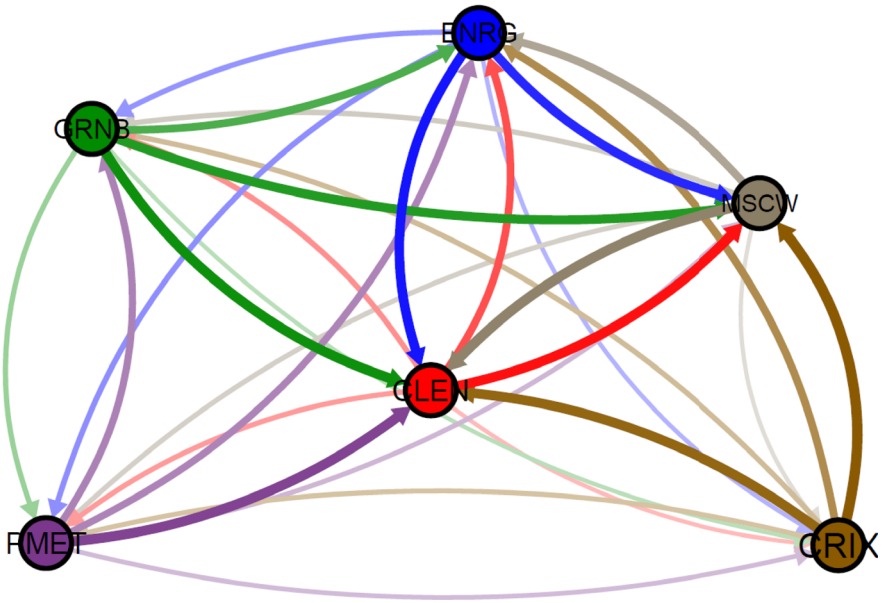


Fig. 10 Volatility spillovers based on quantile VAR (extreme low quantile Tau = 0.05). *Note*: **a** Shows the network connectedness among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. **b** Shows the three summary measures of the connectedness network. TO, FROM, and NET

(a) The network of volatility connectedness



(b) Summary measures of connectedness network.

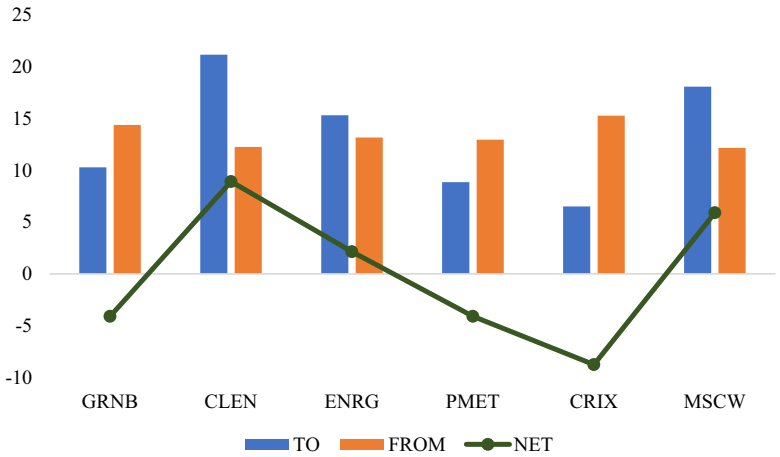


Fig. 11 Volatility spillovers based on quantile VAR (extreme high quantile Tau = 0.95). Note: **a** Shows the network connectedness among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. **b** Shows the three summary measures of the connectedness network. TO, FROM, and NET

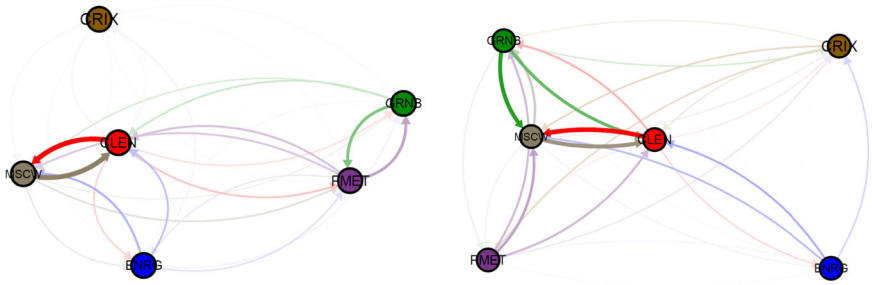
connectedness network (Fig. 9b) recall the net transmitting role of CLEN and MSCW, whereas the remaining asset classes are the net recipients of risk spillovers. The significant connectedness of green and other asset classes magnifies that during the crisis periods, asset prices keep on fluctuating while forming significant spikes and troughs due to underlying extreme events. The panic-driven sentiment by the investors in these crisis times describes their behavior in searching for the best diversification investment opportunities for the sake of higher returns with relatively stable price movements. Given these circumstances, the extreme risk spillover network in the upper quantile should be instinctively different from those of average and low volatility networks. Therefore, Fig. 11 illustrates the risk spillovers in extreme high quantile where a strong network connectedness between green and other asset classes is observed. With its central role in the network, CLEN emphasizes that green assets are strongly connected in a system of various financial markets. CLEN receives substantial risk spillovers in the extreme high volatility periods validating its greater diversification potential for other asset classes, specifically when markets are undergoing sharp fluctuations. The summary measures of the connectedness network in Fig. 11b show that CLEN, MSCW, and ENRG are the net transmitters of volatility spillovers whereas GRNB and PMET receive moderate risk spillovers. However, CRIX, being the most disconnected financial asset, accentuates that investing in cryptocurrencies during volatile periods can benefit investors in terms of substantial returns (Aalborg et al., 2019; Nascimento et al., 2022).

For extending our research in examining the effect of exogenous shocks on volatility connectedness, we performed a pre- and post-COVID sub-sample analysis. Figure 12 demonstrates the impact of COVID-19 on volatility connectedness between green and other asset classes for average (the median quantile), extreme low (the extreme left tail), and extreme high (the extreme right tail). At the median quantile, during pre-COVID, two distinct clusters are formed where CLEN-MSCW-ENRG form one cluster and GRNB-PMET form another cluster. CRIX showed extraordinary disconnection from other asset classes. After COVID-19, strong bidirectional spillovers are formed between green and other asset classes where GRNB and CLEN transmitted risk spillovers to MSCW, whereas PMET and ENRG transmitted weak risk spillovers MSCW. Reiterating, CRIX exhibited disconnection from other financial assets. The varying patterns of green and other financial assets before and after COVID-19 feature markets' vulnerability due to heterogeneous factors of different markets. As soon as the pandemic hit the economy, the asset volatility elevated, which ultimately increased the risk spillovers of the financial markets. The strong bidirectional connectedness of GRNB and CLEN among other assets indicates that green markets outperform other asset classes when exposed to uncertainties. However, a consistent disconnection of CRIX from the system demonstrates the diversification potential of cryptocurrencies during volatile periods as they are insensitive to market shocks (Corbet et al., 2018).

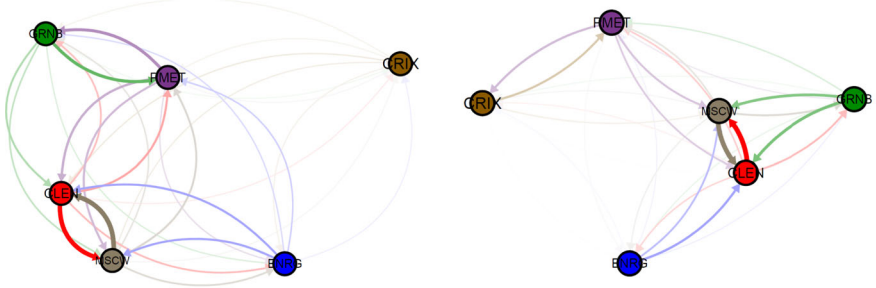
Overall, using the quantile connectedness approach, we provide evidence of time-varying and asymmetric extreme risk spillovers between green and other asset classes. We contend that our findings contribute to the existing strand of literature by empirically assessing the connectedness in the median, extreme low, and extreme high

(a) Pre-COVID **(b) Post-COVID**

I) Median Quantile Tau = 0.50



II) Extreme Low Quantile Tau = 0.05



III) Extreme High Quantile Tau = 0.95

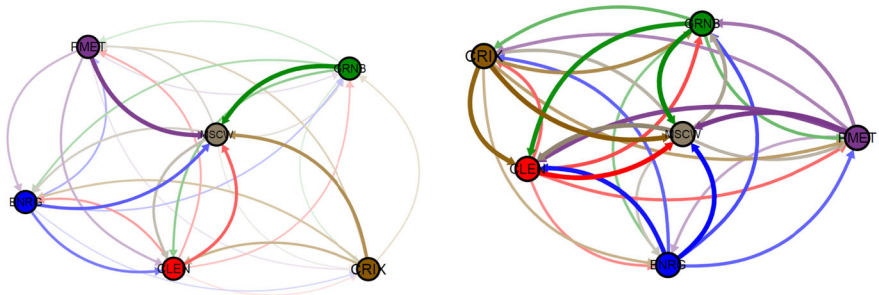


Fig. 12 Volatility spillovers based on quantile VAR – Sub-sample analysis. Note: This Figure shows the network connectedness among S&P Green Bond Index, S&P Clean Energy Index, S&P GSCI Energy Index, S&P GSCI Precious Metals Index, Cryptocurrency market (CRIX) Index and MSCI World Index. **a** and **b** Represent pre-COVID and post-COVID, respectively

volatility periods. In the next step, we are examining the hedge ratios and hedge effectiveness of green and other asset classes to assess whether green assets can act as a hedge for various asset classes to draw portfolio implications.

5 Portfolio Implications

Hedge ratio and hedge effectiveness are measured to investigate the potential of hedge features for a particular financial asset. Batten et al. (2021) assert that a perfect hedge is said to have a value of 1 and zero indicates no hedge characteristics. Table 2 illustrates hedge ratios and hedge effectiveness of green and other asset classes. The HR of PMET-GRNB is highest, followed by CRIX, CLEN, ENRG, and MSCW, which manifest that a $100 long position in GRNB can be a hedge against a short position of $193 in PMET, $112 in CRIX, $63 in CLEN, $28 in ENRG, and $22 in MSCW. In addition, the hedge effectiveness shows the highest value for PMET-GRNB portfolio, whereas a value closer to zero of CRIX-GRNB indicates no hedge effectiveness of green assets for cryptocurrencies. The rest of the portfolios showed negative hedge effectiveness values inculcating the declining effect of adding green assets in their portfolios. The moderate hedge effectiveness of GRNB for PMET is in line with Naeem et al. (2021b) and Reboredo and Ugolini (2019), reporting significant linkage of green assets with international markets as they provide hedging properties for various financial markets. Moreover, the hedge effectiveness of GRNB for CRIX coincides with Naeem and Karim (2021), who demonstrated the hedging ability of green assets for bitcoin. Given the present evidence, investors need to carefully monitor and choose different asset classes to diversify their portfolios with greater hedge effectiveness potential.

In light of the above empirical results, our findings stipulate several portfolio implications for green investors, institutional investors, financial market participants, portfolio fund managers, and asset allocators. Green investors having greater interests in sustainable and environment-friendly initiatives can benefit from this study to analytically assess the diversification potential of green assets and examine their long-term advantages in terms of hedge effectiveness. With a blend of financial assets, institutional investors are required to monitor the uncertainties in the existing portfolio

Table 2 Summary statistics of the hedge ratios and hedge effectiveness

	Mean	Min	Max	HE
CLEN	0.636	− 3.706	3.198	− 0.075
ENRG	0.288	− 4.767	5.967	− 0.015
PMET	1.939	0.831	2.984	0.213
CRIX	1.129	0.232	3.720	0.020
MSCW	0.227	− 4.732	2.273	− 0.258

Fixed window rolling analysis was used to calculate the hedge ratios in order to estimate the one step ahead forecast. Multivariate normal distribution was used for estimating the ADCC-GARCH estimates. For all specifications, a constant and an AR(1) term was included in the mean equation

mix and devise appropriate strategies accordingly. Fear-based sentiments assert that investors seek those risk-aversive opportunities with greater diversification features. In this way, green assets provide sufficient risk-absorbance capacity for investors, whether individual or institutional, to rescue their investments from abrupt circumstances.

Correspondingly, financial market participants can redesign their portfolios when an underlying asset, cryptocurrency, is extremely volatile. Portfolio fund managers and asset allocators can also consider these findings useful for restructuring their portfolios. As earlier empirical studies document (Naeem & Karim, 2021; Naeem et al., 2021a; Nguyen et al., 2020; Reboredo et al., 2020), green assets are valuable investment streams that offer multiple benefits of diversification, risk mitigation, and meeting the green interests of investors. Hence, the study unfolds several beneficial outcomes for financial partners.

6 Conclusion

The basic objective of the study is to contribute to the existing body of knowledge in measuring risk connectedness between green assets and other financial markets to identify the mechanism of risk transmission. We achieved this objective by utilizing the data of green and conventional assets during August 2014 to December 2020. We step-by-step achieved our research objective by using the unique methodology of DECO-GARCH, we estimated the equi-correlations of green and conventional assets in the first step. The next step involves measuring the quantile connectedness using the quantile VAR approach in the median, extreme lower, and extreme higher quantiles for the given sample period. The final step includes calculating the hedge ratios and hedge effectiveness for devising useful strategies of portfolio implications.

Our findings highlight time-varying characteristics using the equi-correlations where intense periods denote higher correlations among the markets and vice versa. The most significant distressed periods unveiled in the study are Shale oil revolution, Brexit referendum, US interest rate hike, and the recent pandemic of COVID-19. The volatilities in the median and lower quantiles showed comparable results where CLEN, CRIX, and MSCW exhibit higher volatility. GRNB, PMET, and ENRG showed moderate volatilities. The connectedness framework revealed substantial spillovers between green and other asset classes, and the system-wide connectedness displayed that CLEN and MSCW are the net volatility transmitters, whereas GRNB, ENRG, and PMET are net receivers of risk spillovers. Interestingly, the CRIX market showed sophisticated disconnection from all markets, narrating its diversification potential during a crisis. The portfolio implications highlight that GRNB offers moderate hedge effectiveness for PMET and CRIX.

With these findings and portfolio strategies, our study contains significant useful implications for policymakers, regulatory bodies, financial markets, asset managers, and portfolio fund managers where policymakers can encourage the markets to invest more in the green assets due to their trifold benefits, such as, diversification, risk-absorbance, and satisfying the eco-friendly motives of investors. Thus, policymakers

can restructure and reformulate their existing policies to shelter investors from uncertain economic conditions. Accordingly, regulatory bodies can mandate the regulation of cryptocurrencies as their continuous anonymous trading causes a bewildering state among other markets. Investors, asset managers, and portfolio managers can include green assets in their portfolio synthesis to relish their diversification potential and risk-mitigation feature in the face of unintended economic conditions. In this way, our findings offer sufficient fresh insights on the risk transmission between green and other asset classes to investigate whether green assets can provide risk mitigation features against conventional markets. The findings are of considerable importance for both practitioners and academicians. As highlighted above, practitioners, for instance policymakers, regulation bodies, and financial market participants can consider these findings for portfolio diversification. For academicians, the study stipulates useful future avenues to model the risk transmission mechanism by using tail dependence or copula approaches to add to the current body of knowledge.

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Declaration

Competing Interests The authors have not disclosed any competing interests.

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