Risk Transmission between Green Markets and Commodities

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Abstract

The current study examines the risk transmission between green markets and commodities spanning 3 January 2011 to 20 June 2021. We use two novel methodologies of volatility transmission using dynamic conditional correlation (DCC-GARCH) and the other time-varying parameters vector autoregression (TVP-VAR) technique of connectedness. We found parallel results of risk transmission between green markets and commodities using these measures of connectedness. Results demonstrate that green markets and commodities form a weakly knitted sphere of connectedness where intra-group clustering dominates the inter-group connectedness. Clean energy markets and precious metals form two distinct groups of connectedness for respective markets. However, crude oil, natural gas and wheat remained indifferent to the shocks highlighting their potential to serve as diversifiers due to their low risk bearing features. Further, time-varying dynamics emphasize the occurrence of sizable events that disrupted the operations of green and commodity markets, accentuating the attention of investors, portfolio managers, and financial market participants. Intense spillovers shaped the overall connectedness of the network where green markets (commodities) are fashioned in positive (negative) risk spillovers. Finally, we propose recommendations for policymakers, regulators, investors, portfolio managers, and market participants to devise policies and investment goals to shield their investments from unexpected circumstances.

Keywords: Green markets; Commodities; DCC-GARCH; TVP-VAR; Volatility transmission

JEL Classifications: G10, G11, G19, Q01

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1. Introduction

Green markets have experienced a remarkable growth in their investments since last decade with a total volume of USD 496 billion in the first half of 2021[1] due to their environmental and clean energy initiatives. Investing in the green markets is essentially attributed to the projects that reduce carbon emissions, encourage renewable resources, minimize the use of fossil fuels, and adopt the best possible ways to build a clean eco-system with net-zero emissions. The future of these investments draws the attention of policymakers, regulation bodies, green investors, and governments to evaluate the magnified benefits of green markets as their correlation with other financial markets and commodities is minimal (Pham and Huynh, 2020). Green investments are a focal consideration for financial and institutional investors and regulators, which provide effective channelling of financial resources to tackle the environmental challenges at the global level. Thus, the eventual increase in the overall market growth of green markets forecasts the USD 1 trillion milestones to be achievable by the year 2023[2] substantiating the increasing concentration of policymakers, governments, and investors to carefully consider these investment streams meeting the clean environmental objectives as well as moderating the risk of financial markets in an effective manner.

On the other hand, commodity markets offer diversification potential for various investments and financial markets. Understanding the connectedness between commodities and versatile investments is critical as they are vital to portfolio management and embrace financial regulatory integration for investors (Yoon et al., 2019). While pursuing the important diversification avenues, commodity markets experience different business cycles compared to

[1] Please see: https://www.climatebonds.net/2021/08/climate-bonds-updates-2021-green-forecast-half-trillion-latest-h1-figures-signal-new-surge

[2] Please see: https://www.climatebonds.net/2021/08/climate-bonds-updates-2021-green-forecast-half-trillion-latest-h1-figures-signal-new-surge

other financial markets. Meanwhile, commodities markets are becoming like other financial markets with greater interests of investors as their number is eventually increasing due to their augmented benefits of diversification, low-risk investments, and less susceptibility to external shocks. However, extant literature provides a blend of evidence emphasizing the diversification features of commodity markets for various investment streams. In this way, achieving portfolio diversification has become a difficult task for investors and portfolio managers; hence, more specific information for managing portfolios is essential to plan their diversification strategies. However, there is a lack of literature and empirical evidence that closely examine the volatility transmission between green markets and commodities as both markets are versatile. The former serves the socially responsible motives of investors and the latter, with its physical existence, the latter offers diversification potential for high-risk investments.

Methodologically, the literature lacks the volatility transmission between green markets and commodities by employing the dynamic conditional correlation (DCC) GARCH analysis which stipulates useful information for investors to choose among investment streams. First, we apply a multivariate generalized autoregressive heteroskedasticity (GARCH) to obtain time-varying volatilities, then processed to obtain DCC estimates. Prior studies have employed the traditional Diebold and Yilmaz (2012) connectedness approach, but it suffers from the disadvantage of window size and rolling window analysis in which loss of observations occurs. In addition, the volatility impulse response functions (VIRFs) are significant determinants of volatility connectedness without involving the rolling windows and loss of observations (Gabauer, 2020). This study employs the time-varying parameters vector autoregression (TVP-VAR) approach of Antonakakis and Gabauer (2017) as it also avoids the problem of rolling window size selection and loss of observations during the estimations are escaped.

Against this backdrop, the current study provides a novel contribution to the existing literature in the following ways. First, we examined the risk transmission between green markets, namely, S&P Green Bond (SPGB), Wilder Hill Clean Energy (WHCL), S&P Global Clean Energy (SPCL), World Renewable Energy (RENX), MSCI Global Green Building (MSGB), and MSCI ACWI Water Utility (MSWT) and commodity markets such as Crude Oil WTI (CWTI), Natural Gas (NTGS), Gold (GOLD), Silver (SLVR), Copper (COPR), and Wheat (WHET) for the period encompassing 3 January 2011 to 30 June 2021. This is a pioneer study to include the blend of green markets and commodities to the best of our knowledge. Secondly, we employed the unique methodologies of DCC-GARCH and TVP-VAR connectedness to overcome window size problems and loss of observations during rolling window analysis. Third, the employed methodologies provide evidence of time-varying attributes where significant economic events incurred during the sample period exhibit high volatility spillovers. Fourth, we proposed significant implications for policymakers, regulation authorities, and investors to devise effective portfolio and risk management strategies.

The findings of our study highlight three different results given the methodologies and techniques employed for the analysis in terms of network connectedness, total connectedness, and NET connectedness. The network connectedness between green markets and commodities illustrates the formation of weakly knitted spheres where DCC-GARCH estimates reveal pronounced intra-group connectedness than inter-group connectedness and crude oil, natural gas, and wheat showed disconnection from the network. In the case of TVP-VAR, the network connectedness exhibits the formation of two hemispheres where green markets and commodities have intricately interconnected the connectedness is yet weaker. Meanwhile, there is a remarkable disconnection of crude oil, natural gas, and wheat among commodities and MSCI water index from green markets, implying their indifference to the external shocks when markets are undergoing severe economic downturns. The substantial disconnection of these markets from the network manifests their potential to offset the risk of uncertainty during turbulent times and provide diversification avenues for various volatile investments. The total connectedness reflected time-varying attributes where intense spillovers indicate crises while recovery to normal circumstances represents gradual troughs in the graph. The major events with intense risk spillovers involve European Sovereign Debt Crisis, shale oil crisis, Chinese stock market crash, Brexit referendum, US interest rate hike, and the COVID-19 pandemic. Similarly, NET connectedness validated the time-varying features of green markets and commodities, with green markets shaping positive risk spillovers and commodities fashioned in negative spillovers. However, significant overlaps between spillovers of green markets and commodities are observed during unfavorable market conditions.

With these significant findings relating to the interconnectedness of green markets and commodities, we proposed significant implications for policymakers, regulatory bodies, investors, and practitioners. Policymakers and regulatory institutions can suggest effective strategies to their respective governments and institutions to facilitate investments in green markets and commodities with less integration. Meanwhile, for academicians, the current study provides several future research directions in terms of connectedness between green markets and commodities where they can employ various methodologies and include other markets to devise a portfolio with low-risk and greater benefits.

The rest of the study is arranged as follows: Section 2 presents the literature review; Section 3 explains the methodology of DCC-GARCH and TVP-VAR; Section 4 elaborates the empirical results; and finally, Section 5 concludes the study along with policy implications.

2. Literature Review

Literature examining the connectedness of green markets with other financial markets is abundant. Similarly, literature also traces those studies that empirically examined the relationship between commodities and their interconnectedness with various asset classes to identify their potential features for these financial markets. In terms of green markets, the study of Pham (2016) is considered the pioneer study to highlight the volatility behaviour of green bonds using the multivariate GARCH model. The volatile nature of green bonds assists the investors and portfolio analysts to affect or to be affected by other markets leading towards net transmitting and net receiving attributes of green bonds. Reboredo et al. (2020) investigated the network connectedness between green markets and other assets of US and European economies and found that strong connectedness persists between green bonds and treasury and corporate bonds, whether they are in short- or long-run with significant useful implications of diversification. Naeem et al. (2021a) examined the asymmetric relationship between green bonds and commodities and validated the presence of asymmetric spillovers between these two asset classes.

Furthermore, pronounced spillovers are observed within the same class assets. However, significant connectedness is observed between gold, silver, and green bonds. In another study, Naeem et al. (2021b) explored the asymmetric nexus between green bonds and commodities using the cross-quantilogram approach and documented a heterogeneous relationship across three individual commodities named energy, metals, and agriculture. The authors narrated the strongest hedge benefits of green bonds against variations in natural gas, few industrial metals and agriculture commodities. The authors also recommend employing green bonds in the long time horizons to augment the portfolio performance.

Arif et al. (2021a) investigated the time-frequency connectedness between green bonds and traditional financial markets, particularly during COVID-19 and reported high intergroup connectedness for green markets. Concurrently, in another study, Arif et al. (2021b) hexamined hedge and safe-haven characteristics of green bonds for multiple markets have employing the cross-quantilogram and documented that green bonds act as a diversifier for various sets of markets.

Nguyen et al. (2020) explored the comovements among green bonds, commodities, clean energy, and conventional bonds using the time-frequency connectedness and signified strong correlations after crises such as the global financial crisis. Reboredo (2018) configured tail dependence between green bonds and multiple financial markets and identified strong correlations between green bonds and financial assets, emphasizing the diversification avenues of green bonds for financial markets. Hammoudeh et al. (2020) investigated the nexus among green bonds, clean energy index, US conventional bonds, and CO2 emissions using the time-varying Granger causality test and narrated significant causality switching from US treasury bonds to green bonds. Naeem and Karim (2021) examined the tail-dependence between bitcoin and green financial assets and found a significant hedge facility of green markets for bitcoin, particularly the clean energy index. Ferrer et al. (2021) applied the methodology of time-frequency connectedness to examine the return and volatility connectedness between green and other asset classes. Findings uncover that connectedness is higher when market conditions are uneven and during shorter time periods.

Concerning commodities markets, Hernandez et al. (2018) investigated the hedge and diversification avenues of agriculture and precious metal commodities using the extreme quantile approach. The study found a positive impact of extreme lower quantiles of oil returns on the respective quantiles of gold, silver and rice returns. The authors also reported that these commodities do not offer hedge opportunities for oil market; hence, their diversification potential is substantiated to shield the investments from uncertainty and extreme risks. Yoon et al. (2019) examined the network connectedness and spillovers between financial and commodity markets using the network spillover methodology. The authors concluded from their study that US stock market is the top risk transmitter of spillovers, whereas precious metals and stock exchanges are net recipients of spillovers. In addition, adding different classes of commodities and stocks lessens the magnitude of total spillovers, which offer significant diversification benefits in a portfolio of stocks.

Pradhan et al. (2020) explored the macroeconomic factors and frequency domain causality for precious metals in India using the frequency domain rolling-window analysis and causality dimensions. The authors reported mixed results for causality between gold and silver for different frequency lengths. Mensi et al. (2019) inspected the asymmetric volatility connectedness between bitcoin and precious metals using the high-frequency data and applying the methodology of Diebold and Yilmaz (2014) and Barunik et al. (2017). The findings highlight that significant volatility spillovers are found between bitcoin and precious metals and frequency spillovers are time-varying. Meanwhile, semi-volatility analysis exhibits that bitcoin is the net transmitter of spillovers. In a previous study, Mensi et al. (2017) investigated the time-varying risk spillovers between precious metals and major stock markets using the traditional DY[12] model, where they found evidence of volatility spillovers between precious metals and stock markets.

Further, the spillovers are time-varying with intense volatility spillovers during Global Financial Crisis and European Debt Crisis. Ji et al. (2018) examined the information spillovers and connectedness networks in the oil and gas markets using the ensemble empirical mode decomposition technique. The author found that the information transmits between oil and gas returns as their behavior varies across different time scales. Moreover, the total spillover connectedness is dynamic and carries volatile characteristics.

As discussed in all these studies, the evidence lacks the empirical studies which collectively examine the risk transmission between green markets and commodities using the DCC-GARCH and TVP-VAR approach. Thus the contributions of this study are substantial, which help to fill the existing gap in the literature.

3. Methodology

The current study examines the risk transmission between green markets and commodities and employs two techniques for estimation purposes. Firstly, we utilized the DCC-GARCH to measure the dynamic conditional correlational (DCC) volatility connectedness, and secondly, we applied the time-varying parameters vector autoregressions (TVP-VAR) technique on the DCC volatility estimates obtained from DCC-GARCH.

3.1 DCC-GARCH

For examining the time-varying conditional volatility, we employed the two-step DCC-GARCH model following Engle (2002). The initial model can be written as:

$$y_t = \mu_t + \epsilon_t \qquad \epsilon_t | F_{t-1} \sim N(0, H_t), \tag{1}$$

$$\epsilon = H_t^{1/2} u_t \qquad u_t \sim N(0, I), \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

Here F_{t-1} denotes the availability of the information up to t -1, whereas dimensional vectors y_t, μ_t, ϵ_t and u_t represent the estimated time series, conditional mean, error term, and standardized error term, respectively. Meanwhile, R_t, H_t, and $D_t = diag\left(h_{11t}^{\frac{1}{2}}, \dots, h_{NNt}^{\frac{1}{2}}\right)$ are $N \times N$ dimensional matrices which illustrate dynamic conditional correlations, time-varying conditional variance-covariance matrices, and the time-varying conditional variances in an orderly manner.

As a first step, D_t estimates GARCH model for each independent series following Bollerslev (1986). In this way, one shock and one persistency parameter, based on Hansen and Lunde (2005) are assumed as follows:

$$h_{ii,t} = \omega + \alpha \epsilon_{i,t-1}^2 + \beta h_{ii,t-1} \tag{4}$$

The second step involves computing the dynamic conditional correlations as below:

$$R_t = diag\left(q_{iit}^{-\frac{1}{2}}, \dots, q_{NNt}^{-\frac{1}{2}}\right) Q_t\, diag\left(q_{iit}^{-\frac{1}{2}}, \dots, q_{NNt}^{-\frac{1}{2}}\right) \tag{5}$$

$$Q_t = (1 - a - b)\bar{Q} + \ a u_{t-1} u'_{t-1} + b Q_{t-1} \tag{6}$$

Here conditional and unconditional standardized residual variance-covariance matrices are represented by Q_t and $\bar{Q}$ through $N \times N$ positive-definite dimensional matrices, respectively. In addition, $a(\alpha) and\ b(\beta)$ represent non-negative shock and persistency parameters which fulfills the condition of $a + b < 1(\alpha + \beta \leq 1)$. Q_t and R_t exhibit time-varying characteristics as long as $a + b < 1$ is fulfilled otherwise, the model will be converted into CCC GARCH where R_t is constant over time.

3.2 Volatility Impulse Response Function (VIRF)

It is interesting to note that traditional connectedness approaches (Diebold and Yilmaz, 2012; 2014) rely on the generalized impulse response function (GIRF) being independent of the orders of variables and measure the *J*-step-ahead of a shock for variable *i* on the variable *j:* $GIRF(J, \delta_{j,t} F_{t-1} = E\left(y_{t+j} \middle| \epsilon_{j,t} = \ \delta_{j,t}, F_{t-1}\right) - E\left(y_{t+j} \middle| \epsilon_{j,t} = 0, F_{t-1}\right)$. In a similar way, the VIRF is the impact of a shock for a variable *i* on variable *j*'s conditional volatilities, stated as:

$$\Psi^g = VIRF(J, \delta_{j,t} F_{t-1} = E\left(H_{t+j} \middle| \epsilon_{j,t} = \ \delta_{j,t}, F_{t-1}\right) - E\left(H_{t+j} \middle| \epsilon_{j,t} = 0, F_{t-1}\right) \tag{7}$$

Where $\delta_{j,t}$ is equal to one with a selection vector at *j*th position and zero otherwise.

For conditional variance-covariances by employing DCC-GARCH model of Engle and Sheppard (2001), the VIRF is accomplished in three steps. The first step involves the univariate GARCH (1,1) which forecasts the conditional volatilities $(D_{t+h}|F_t)$ in terms of

$$E\left(h_{ii,t+h} \middle| F_t\right) = \ \omega + \ \alpha \delta_{1t}^2 + \ \beta h_{ii,t} h = 1 \tag{8}$$

$$E\left(h_{ii,t}\middle|F_t\right) = \sum_{i=0}^{h-1} \omega(\alpha+\beta)^i + (\alpha+\beta)^{h-1} E\left(h_{ii,t+h-1}\middle|F_t\right) h > 1 \quad (9)$$

In the second step, $E(Q_{t+h}|F_t)$is predicted as:

$$E(Q_{t+1}|F_t) = (1-a-b)\bar{Q} + a u_t u_t' + b Q_t h = 1 \quad (10)$$

$$E(Q_{t+h}|F_t) = (1-a-b)\bar{Q} + aE(u_{t+h-1}u_{t+h-1}'|F_t) + bE(Q_{t+h-1}|F_t) h > 1 \quad (11)$$

where $E(u_{t+h-1}u_{t+h-1}'|F_t) \approx E(Q_{t+h-1}|F_t)$ which facilitates forecasting the dynamic conditional correlations.

In the final step, the conditional variance-covariances are measured as:

$$E(R_{t+h}|F_t \approx diag\left[E\left(q_{iit+h}^{-\frac{1}{2}}\middle|F_t\right), \ldots, E\left(q_{NNt+h}^{-\frac{1}{2}}\middle|F_t\right)\right] E(Q_{t+h}) diag\left[E\left(q_{iit+h}^{-\frac{1}{2}}\middle|F_t\right), \ldots, E\left(q_{NNt+h}^{-\frac{1}{2}}\middle|F_t\right)\right] \quad (12)$$

$$E(H_{t+h}|F_t) \approx E(D_{t+h}|F_t)E(R_{t+h}|F_t)E(D_{t+h}|F_t) \quad (13)$$

3.3 Dynamic Connectedness

The generalized forecast error variance decomposition (GFEVD) is estimated based on VIRF which can be explained as the variance one variable casts on others. These are normalized variance shares which equals to one after summing up. In other words, all variables collectively explain 100% of variable *i*'s forecast error variance which is computed as follows:

$$\widetilde{\emptyset}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{j-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{j-1} \Psi_{ij,t}^{2,g}} \quad (14)$$

Here $\sum_{j=1}^{N} \widetilde{\emptyset}_{ij,t}^{g}(J) = 1$ and $\sum_{j=1}^{N} \widetilde{\emptyset}_{ij,t}^{g}(J) = N$. The aggregate effect is presented in the numerator of the *i*th shock whereas denominator is the cumulative sum of all the shocks. The total connectedness index (TCI) using the GFEVD is created as:

$$C_t^g(J) = \sum_{i,j=1,i\neq j}^{N} \widetilde{\emptyset}_{ij,t}^g(J) \tag{15}$$

Similarly, the spillovers which variable *i* transmit to the variable *j* are known as total directional connectedness 'TO' others and are known as:

$$C_{i\rightarrow j,t}^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \widetilde{\emptyset}_{ij,t}^g(J)}{\sum_{j=1}^{N} \widetilde{\emptyset}_{ij,t}^g(J)} \tag{16}$$

On the other hand, the spillovers variable *i* receives from *j* variable are termed as total directional connectedness 'FROM' other and are calculated as:

$$C_{i\leftarrow j,t}^g(J) = \frac{\sum_{j=1,i\neq j}^{N} \widetilde{\emptyset}_{ij,t}^g(J)}{\sum_{i=1}^{N} \widetilde{\emptyset}_{ij,t}^g(J)} \tag{17}$$

Subtracting the two equations from each other leads to the NET total directional connectedness which explains the influence of variables *i* on the network,

$$C_{i,t}^g = C_{i\rightarrow j,t}^g(J) - C_{i\leftarrow j,t}^g(J) \tag{18}$$

Assuming that the variable *i* has positive (negative) NET total directional connectedness then variable *i* is the net transmitter (receiver) of shocks explaining that variable *i* drives (driven by) the network connectedness.

3.4 TVP-VAR Technique

After estimating volatility connectedness through DCC-GARCH, in the next step we examined the connectedness of green markets and commodities using the time-varying parameter vector autoregressions (TVP-VAR) technique on the DCC volatility estimates obtained from DCC-GARCH. The TVP-VAR approach is primarily proposed by Primiceri (2005) and Antonakakis and Gabauer (2017) extended this methodology later. This model significantly describes whether changes in the connectedness of green markets and commodities are derived from the shocks or from the extension of the change mechanism. The model also provides specific characteristics to measure potential structural breaks and offers important reasons to understand the relationship among variables. The model is presented as:

$$y_t = \beta_{0,t} + \beta_{1,t}y_{t-1} + \ldots\ldots + \beta_{p,t}y_{t-p} + u_t = X_t^{'}\Theta_t + u_t, \tag{19}$$

$$X_t^{'} = [1, y_{t-1}^{'}, \ldots\ldots, y_{t-p}^{'}] \tag{20}$$

Where vector for the dependent variable is presented as y_t ($n \times 1$) and $\beta_{0,t\ldots p,t}$ denote ($n \times n$) time-varying coefficients which are rewritten as Θ_t matrix. X_t represents ($n \times k$) matrix comprising intercepts and lags of the time-dependent variables. u_t denotes structural shocks with ($n \times 1$) heteroskedastic distribution term with zero mean and time-varying variance-covariance matrix Ω_t. Given the log-differenced returns of green markets and commodities, the variance-covariance matrix is segregated as:

$$\Omega_t = M_t^{-1}H_t(M_t^{-1}) \tag{21}$$

Where M_t^{-1} shows simultaneous relationships of variables and H_t presents stochastic connectedness. Moreover, the time-varying transitioning parameters are observed as follows,

$$\Theta_t = \Theta_{t-1} + \nu_t \qquad \nu_t \approx N(0, S) \tag{22}$$

$$\alpha_t = \alpha_{t-1} + \xi_t \qquad \xi_t \approx N(0, Q) \tag{23}$$

$$ln\, h_{i,t} = ln\, h_{it-1} + \sigma_i\eta_{i,t} \qquad \eta_{i,t} \approx N(0,1) \tag{24}$$

Eqs. (22) and (23) estimate the time-varying parameters following a random walk process, and Eq. (24) examines the stochastic connectedness following the independent random walk. Primiceri (2005) suggested that there is an independent change among variables for simplifying the inference and increasing the efficiency of the estimates. It highlights that both key equation error term and transition equation are independent.

We further estimated the generalized impulse response function (GIRF) and generalized forecast error variance decompositions for measuring the dynamic connectedness. For this reason, TVP-VAR is transformed into vector moving average (VMA) based on Wold theorem:

$$y_t = K'(N_t(v_{t-2} + \emptyset_{t-1}) + \emptyset_t) \tag{25}$$

$$= K'(N_t(N_t(v_{t-3} + \emptyset_{t-2}) + \emptyset_{t-1})\emptyset_t \tag{26}$$

$$\vdots \tag{27}$$

$$= K'\left(N_t^{k-1} v_{t-k-1} + \sum_{j=0}^{k} N_t^j \emptyset_{t-j}\right) \tag{28}$$

By employing a limit on Eq. (28) where *k* tends to ∞, we obtain

$$y_t = lim_{k\to\infty} K'\left(N_t^{k-1} v_{t-k-1} + \sum_{j=0}^{k} N_t^j \emptyset_{t-j}\right) = \sum_{j=0}^{\infty} K' N_t^j \emptyset_{t-j} \tag{29}$$

Where it directly follows:

$$y_t = \sum_{j=0}^{\infty} K' N_t^j K \mu_{t-j} \quad A_{jt} = K' N_t^j K \qquad j = 0,1, \ldots \tag{30}$$

$$y_t = \sum_{j=0}^{\infty} A_{jt} \mu_{t-j} \tag{31}$$

where A_{jt} is the $n \times n$ matrix.

The GIRF model describes the responses of all variables *j* to a shock in variable *i*. Hence, *H*-step-ahead forecast measures the shock in variable *i* as follows:

$$GIRF_t(H, \partial_{j,t}\rho_{t-1} = E\left(y_{t+H} \middle| d_j = \partial_{j,t}\rho_{t-1}\right) - E(y_{t+K}|\rho_{t-1}) \tag{32}$$

$$\omega_{ij,t}(H) = \frac{A_{H.t} \sum_t d_j}{\sqrt{\sum_{jj,t}}} \frac{\partial_{j,t}}{\sqrt{\sum_{jj,t}}} \partial_{j,t} = \sqrt{\sum_{jj,t}} \tag{33}$$

$$\omega_{ij,t}(H) = \sum_{jj,t}^{-1/2} A_{H.t} \sum_t d_j \tag{34}$$

Next, we measured the directional connectedness from *j* to *i* which further highlights the influence variable *j* has on variable *i* in terms of forecast variance share. Afterward, the variance shares are summed up in a way that they are equal to one. It indicates that all variables 100% explain the variable *i*'s forecast error variance. The GFEVD is computed as follows:

$$\tilde{\theta}_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \omega_{ij,t}^2}{\sum_{j=1}^{n} \sum_{t=1}^{H-1} \omega_{ij,t}^2} \tag{35}$$

where $\sum_{j=1}^{n} \tilde{\theta}_{ij,t}(H) = 1 \ and \ \sum_{i,j=1}^{n} \tilde{\theta}_{ij,t}(H) = n$. Moreover, the numerator identifies cumulative effect of shock in variable *i* and the denominator represents the aggregate effect of all the shocks. Hence, total connectedness is measured as:

$$T_t(H) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij,t}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij,t}(H)}{n} \times 100 \tag{36}$$

It is a general demonstration of risk transmission from one variable to another. Further, the analysis is divided into total directional connectedness 'TO' others, total directional connectedness 'FROM' others and NET directional connectedness.

'TO' connectedness defines the situation where variable *i* transmits risk to all other variables *j* as follows:

$$T_{i\rightarrow j,t}(H) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ji,t}(H)} \times 100 \tag{37}$$

'FROM' connectedness is the share of risk variable *i* receives from other variables *j* as follows:

$$T_{j\rightarrow i,t}(H) = \frac{\sum_{i,j=1, i\neq j}^{n} \tilde{\theta}_{ij,t}(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij,t}(H)} \times 100 \tag{38}$$

Finally, we subtract Eq. (38) from Eq. (37) in order to obtain the NET total directional connectedness .

$$T_{i,t} = T_{i\rightarrow j,t}(H) - T_{j\rightarrow i,t}(H) \tag{39}$$

The intuitive explanation of Eq. (39) is the influence of variable *i* on the estimated network where a positive (negative) value determines the net transmitter (recipient) role of variable *i* on the network and whether variable *i* drives (driven by) the network.

4. Empirical Results

4.1 Data and Descriptive Statistics

The current research aims to examine the risk transmission between green markets and commodities where green markets included in the study are S&P Green Bond (SPGB), Wilder Hill Clean Energy (WHCL), S&P Global Clean Energy (SPCL), World Renewable Energy (RENX), MSCI Global Green Building (MSGB), and MSCI ACWI Water Utility (MSWT). Meanwhile, commodities include Crude Oil WTI (CWTI), Natural Gas (NTGS), Gold (GOLD), Silver (SLVR), Copper (COPR), and Wheat (WHET). The data have been sourced from Datastream for the period encapsulating 3 January 2011 to 30 June 2021.

Table 1 illustrates the summary statistics of green markets and commodities. The average values of green markets demonstrate that RENX yields the highest mean value, followed by MSWT, MSGB, WHCL, and SPCL. However, SPGB yields a negative and lowest average return. Commodities show comparable average values of CWTI and GOLD, whereas NTGS, WHET, SLVR, and COPR yield negative mean returns. RENX, WHCL, and SPCL observe the pronounced variability in the returns of green markets, whereas MSGB and MSWT reveal parallel variability in the returns and SPGB indicates moderate variability in its returns. Out of commodities, CWTI and NTGS denote the highest, whereas SLVR exhibits moderate variability in the returns, WHET, COPR and GOLD. Slightly negative values of skewness of green markets and commodities indicate substantial losses experienced by respective markets during high volatility periods. However, NTGS and WHET showed positive values of skewness, indicating less exposure to market uncertainties. Jarque-Bera’s normality test indicates substantially high and abnormal values demonstrating that return series are not normally distributed.

[Table 1 about here]

Table 2 presents the correlation coefficients of green markets and commodities along with their p-values. Most of the correlations have significant p-values demonstrating that correlations between green markets and commodities are substantial and there is remarkable association between green and commodity markets. However, NTGS showed insignificant correlation with SPGB and MSWT; GOLD is insignificantly related to RENX, MSGB, and NTGS; SLVR revealed insignificant relationship with NTGS; finally, WHET demonstrated no correlation with RENX and MSWT. Overall, the correlation values depict that green markets and commodities are significantly correlated except for few reported variations in the commodity markets.

[Table 2 about here]

Figure 1 plots the time evolution histogram of the sampled green markets and commodities for the given time period. The evolution of return series exhibits that green markets and commodities have undergone substantial stress periods with traces of intense spillovers during the crisis. The initial intense spillovers are indicative of European Sovereign Debt Crisis (2012-2014) with subsequent crises of shale oil revolution (2014-2015), Chinese Crisis (2015-2016), Brexit Referendum (2016-2017), US interest rate hike (2017-2018) and the recent ongoing global pandemic of COVID-19 (2019-2020). We observe from the plots that green markets exhibit thinner spillover as compared to commodities, where the frequency of spillovers is higher. In this way, the evolution of return series unveils time-varying characteristics with significant ups and downs in the graph symbolizing crisis periods.

[Figure 1 about here]

4.2 Network Connectedness using DCC-GARCH

Figure 2 displays the volatility[3] network connectedness of green markets and commodities where a strong disconnection between green markets and commodities is observed. A connectedness sphere with two distinct hemispheres of green markets and commodities is manifested with higher intra-group connectedness and lower inter-group connectedness. However, a keener look at the hemispheres emphasizes that SPGB transmits strong spillovers to SLVR and weak spillovers to GOLD. The volatility connectedness of green and commodity markets into separate hemispheres corroborate Caporin et al. (2021) and Balli et al. (2019), who documented volatility clustering of various markets in their connectedness analysis. The connectedness between green markets and commodities is in line with Naeem et al. (2021a), who reported significant spillovers in the same class of green and commodity markets and stronger connectedness of gold and silver with green bonds.

Meanwhile, green markets such as WHCL, SPCL, and RENX show strong intra-connectedness, whereas SLVR and GOLD reveal moderate intra-connectedness among commodities. The strong interconnectedness among green markets embodies their similar features, which lead them to higher connectedness. Moreover, our findings oppose the findings of Elsayed et al. (2020), who reported weaker connectedness of green market with other markets. Further, COPR transmits weaker risk spillovers to RENX and MSGB and SPGB, which show slight risk transmission from precious metals to green markets, narrating the diversification potential of green markets when economic circumstances are unfavorable (Naeem et al., 2021a, 2021b).

Interestingly, a strong disconnection of NTGS, CWTI, WHET, and MSWT highlights their indifference from external shocks and volatility among various asset classes, ultimately leading

[3] Volatility and risk are used interchangeably based on prior literature.

them to diversify the risk of volatile investments. Thus, given the flight-to-safety of investors during economic downturns, NTGS, CWTI, WHET and MSWT can be useful diversifiers as they are less susceptible to shocks and uncertainty. The diversification avenues of commodities and green market are in line with Farid et al. (2021), Arif et al. (2021a) and Reboredo et al. (2020), who demonstrated a strong disconnection of commodities and green markets with other financial assets, which ensure their diversification capacities for various investment streams.

[Figure 2 about here]

Figure 3 represents total volatility connectedness using DCC-GARCH, which exhibits time-varying properties of the network structure. The significant leaps and bounces in the graph denote distressed economic events and recovery periods for each successive and intense risk spillover. The first spike in the graph points toward the European Debt Crisis (2010-2012), where balance sheet inaccuracies in the European Economy resulted in the high connectedness of global financial markets. The outbound resources were restricted from the central bank, ultimately intensifying the spillovers (Blundell-Wignall, 2012). In this financial turmoil period, the global financial markets show higher connectedness revealing varying attitudes of investors towards abrupt changes in the business cycles (Rufino, 2018). The consecutive jump in the graph (2014-2016) shows the occurrence of two major incidents, namely, Shale oil revolution and Chinese financial market crisis where the shale oil revolution is representative of risk transmission of energy and commodity markets (Arif et al., 2021a), and Chinese financial market crash symbolizes crash of the Chinese stock market in a single day (Womack, 2017). The higher connectedness during this period denotes that financial markets were forming stronger risk spillovers due to abnormal market conditions (Nguyen et al., 2020).

Similarly, the abrupt increase in the connectedness of financial markets during 2016-2017 represents Brexit referendum (Xiao et al., 2019), where risk spillovers were intense due to the exit of UK from the European Union. Successively, 2017-2018 signals a US interest rate hike. A sudden increase in interest rates shifted the financial markets into higher integration, reflecting uneven distressed economic conditions (Kang et al., 2021; Elsayed et al., 2020). Finally, a sheer rise in the system-wide connectedness during 2019-2020 shows the present global crisis of COVID-19, where emergency health issues raised serious economic concerns for investors, regulators, and financial market participants (Adekoya and Oliyide, 2020). Concurrent with Bouri et al. (2021), the financial contagion stimulates the financial markets towards higher connectedness. Overall, time-varying attributes in the risk transmission of green markets and commodities reveal that global financial markets are sensitive to crisis periods, uncertain economic conditions, and market volatility is driven by stress periods. In this way, system-wide volatility connectedness becomes high during abnormal market conditions, and connectedness becomes lower when markets return to a new normal.

[Figure 3 about here]

Figure 4 illustrates the NET volatility connectedness using the DCC-GARCH technique for green markets and commodities. The graph's time-varying NET volatility connectedness reveals that volatile periods distinguish the green markets and commodities and spillovers are high when markets underscore the stress periods. The variation in the volatility spillovers, particularly during European Sovereign Debt Crisis (2010-2012), Shale oil crisis (2014-2015), Chinese market crash (2016), Brexit referendum (2016-2017), US interest rate hike (2017-2018), and COVID-19 (2019-2020) are in line with time-varying dynamics of earlier empirical studies (Naeem et al., 2021b,c; Arif et al., 2021a,b; Adekoya and Oliyide, 2020; Elsayed et al., 2020) who outlined the formation of strong risk spillovers during the crisis periods. The volatility NET connectedness reveals that spillovers moved upward (downward) for green markets (commodities), given that successive uncertainties appeared during the period. Moreover, the higher intensity of spillovers during COVID-19 indicates that the pandemic had a considerable impact in shaping the spillovers as the crisis was not primarily an economic backdrop but a worldwide health emergency that eventually influenced global businesses (Naeem et al., 2021c; Farid et al., 2021). In this way, markets shaped intense spillovers during the coronavirus pandemic.

[Figure 4 about here]

Overall, the DCC-GARCH estimates emphasize intra-group clustering (Caporin et al., 2021; Balli et al., 2019) with weaker inter-group connectedness. Green markets and commodities were mainly disconnected from the network. However, GOLD-SLVR exhibited stronger interconnectedness among commodities while WHCL-SPCL-RENX demonstrated pronounced intra-group connectedness among green markets. Meanwhile, time-varying attributes are exhibited in the net connectedness, signifying major events during the sample period.

4.3 Network Connectedness using TVP-VAR

This sub-section explains the network connectedness using the time-varying parameters vector autoregression (TVP-VAR) approach. Figure 5 displays the network connectedness of green markets and commodities where a sphere of disconnected green markets and commodities is formed. The strong connectedness between SLVR-GOLD and SPCL-WHCL is evident for commodities and green markets, respectively. SPCL and WHCL are interconnected and spillovers formed are stronger. Interestingly, it can also be observed that weaker risk spillovers from the network are received by both SPCL and WHCL in line with Elsayed et al. (2020), who also reported that clean energy markets are recipients of risk spillovers. Among commodities, the majority yet weaker spillovers are transmitted from CWTI and WHET to green markets and commodities, echoing Shahzad et al. (2018), who suggest a risk transmission mechanism from oil market to other markets. The strong connectedness between SLVR and

GOLD coincides with Kang et al. (2017) findings, where they reported sound dependence between precious metals. Parallel to our results in Figure 2, NTGS and WHET showed remarkable disconnection from the network with the weaker transmission of risk spillovers. Our findings reiterate that these markets are indifferent and less exposed to external shocks and volatilities that appeared due to unknown economic and financial circumstances. Overall, the results magnify the investors' pessimism during harsh economic conditions as they intuitively choose those investment streams which provide greater monetary benefits. In this vein, NTGS and WHET, due to their lower risk exposure, can offer diversification potential to the investors who want to reap the benefits of investments with high risk-absorbance, low volatility, and strong integration among financial markets. Given these facts, the findings are of high caliber for investors and portfolio managers to design their portfolios by including diversifiers for risk mitigation.

[Figure 5 about here]

Figure 6 presents total connectedness of green markets and commodities using the TVP-VAR approach. The graph displays substantial ups and downs, with each spike reflecting a stress situation with successive declines in the graph denoting recovery of markets to normal conditions. The first spike in the graph reaches 75% of total connectedness, revealing the European Sovereign Debt Crisis (2010-2012), where restriction to outbound resources created high inflation rates, resulting in intensified spillovers. Consequently, the connectedness tends to decline gradually, indicating that markets returned to normal operations, indicating the aftermath of ESDC. The graph gradually declines to 28% during 2015 and a sharp increase in the risk spillovers is documented during 2015, which echoes shale oil crisis (2014-2016), followed by Chinese market crash during 2016, where net connectedness reaches up to 55%. The spike during 2016 also symbolized Brexit referendum when UK exited the rest of the British states. This unexpected exit influenced the market operations with intensive risk spillovers, as Yoon et al. (2019) and Kang et al. (2021) documented. Finally, a sheer rise in the connectedness of networks that touched the maximum level until 76% during early 2020 signifies the onset of COVID-19 pandemic with its severe disruptions across the globe. In line with Zhang et al. (2020) and Adekoya and Oliyide (2020), the final sheer spike nominates COVID-19 pandemic with serious repercussions for the whole financial business world with severe policy and investment uncertainties.

[Figure 6 about here]

Figure 7 presents the NET connectedness using TVP-VAR approach where green markets and commodities form overlapped spillovers during different time periods and significant events of economic shutdown. Green markets mainly form positive spillovers, whereas commodities shaped negative spillovers. The significant overlap between green and commodity markets highlights the mechanism of risk transmission during the European Sovereign debt crisis (2010-2012) and the recovery period after the shock event. During the normal circumstances, the positive spillovers of commodities dominated the negative spillovers of green markets, which intuitively highlight the string integration of commodities in the financial and economic system. Corroborating Kang et al. (2017) and Balli et al. (2019), the risk transmission of commodities during uncertain periods is pronounced, emphasizing the sound embeddedness of commodities as compared to green markets. During shale oil revolution (2014-2015), the graph illustrates a similar pattern of risk spillovers with significant dominance of commodities over green markets. However, during the Chinese market crash and Brexit referendum, dispersed volatility spillovers are formed by the two investment streams indicating that green markets and commodities equally faced the repercussions of these uncertain events. The pronounced risk spillovers with sharp incline in the connectedness during 2019 reiterate the comparable susceptibility of green markets and commodities to the external shocks. Hence, the NET connectedness describes whether green and commodity markets showed comparable exposure to the external shocks or the pattern varied for two unique financial assets.

[Figure 7 about here]

In summary, the network connectedness using TVP-VAR showed parallel system-wide connectedness, total connectedness of spillovers, and NET connectedness of markets as reported with the DCC-GARCH technique. We spot few variations in the network diagram with distinct hemispheres of green and commodity markets documenting substantial disconnection of NTGS and CWTI. The total connectedness exhibited time-varying attributes with sizable leaps and bounds in the graph. Similarly, NET connectedness showed distinct spillovers as estimated by DCC-GARCH while significant overlaps are reported in the NET connectedness as measured by TVP-VAR approach.

5. Conclusion

The current study investigates the risk transmission between green markets and commodities by adopting the two specific measures of connectedness: dynamic connectedness correlations (DCC-GARCH) and time-varying parameters vector autoregression (TVP-VAR) for the period encompassing 3 January 2011 to 20 June 2021. The estimation results are segregated into three categories network connectedness, total connectedness, and NET connectedness. The network connectedness between green markets and commodities signifies the formation of weakly knitted spheres where DCC-GARCH estimates reveal pronounced intra-group connectedness than inter-group connectedness where CWTI, NTGS and WHET mainly showed disconnection from the network. In the case of TVP-VAR, network connectedness exhibits the formation of two hemispheres where green markets and commodities are intricately interconnected but are weaker in magnitude. Meanwhile, there is a remarkable disconnection of CWTI, NTGS, and WHET among commodities and MSWT out of green markets, implying their indifference to external shocks when markets are undergoing severe downturns. The substantial disconnection of these markets from the network manifests their potential to offset the risk of uncertainty during turbulent times and provide diversification avenues for volatile investments. The total connectedness reflected time-varying attributes where intense spillovers indicate crises while recovery to normal circumstances represents gradual troughs in the graph. The major events with intense risk spillovers are European Sovereign Debt Crisis, shale oil crisis, Chinese stock market crash, Brexit referendum, US interest rate hike, and the COVID-19 pandemic. Similarly, NET connectedness validated the time-varying features of green markets and commodities, with green markets shaping positive risk spillovers and commodities fashioned in negative spillovers. However, we observe significant overlaps between spillovers of green markets and commodities during unfavourable market conditions.

Our findings illuminate several beneficial implications for policymakers, macro-prudential authorities, investors, portfolio managers, market participants and institutional investors. For policymakers, the study stipulates useful strategies to be adopted during normal as well as crisis periods. Given that markets are prone to unexpected economic circumstances, policymakers and macro-prudential authorities must re-formulate their existing policies of risk mitigation and encourage the institutional and individual investors to look for investment streams that offer low-risk and compensate the uncertain risks.

The present study sets a useful bar for investors for defining investments with high, moderate, and low risks. By carefully assessing the investment streams, investors can select and include those investments with the potential of providing diversification when markets are experiencing abnormal economic and financial circumstances. Portfolio managers and institutional investors can re-examine their portfolio design choices by employing appropriate risk mitigation tools and investments offering greater diversification and lower risk.

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Table 1: Descriptive statistics

Markets		Symbol	Mean	Max	Min	Std. Dev.	Skew	Kurt	J-B
Green Markets	S&P Green Bond	SPGB	-0.003	2.557	-3.091	0.382	-0.372	9.728	5226.845 [a]
	Wilder Hill Clean Energy	WHCL	0.022	13.399	-16.239	1.962	-0.523	9.760	5338.031 [a]
	S&P Global Clean Energy	SPCL	0.014	11.035	-12.498	1.467	-0.626	11.482	8387.058 [a]
	World Renewable Energy	RENX	0.043	42.217	-41.627	2.335	-0.523	127.434	1766576 [a]
	MSCI Global Green Building	MSGB	0.026	9.089	-11.740	1.035	-1.489	24.694	54704.28 [a]
	MSCI ACWI Water Utility	MSWT	0.028	9.750	-9.411	1.038	-0.355	15.662	18348.47 [a]
Commodities	Crude Oil WTI	CWTI	0.008	22.394	-28.221	2.601	-0.292	28.036	71547.53 [a]
	Natural Gas	NTGS	-0.007	26.749	-18.055	2.920	0.380	8.589	3629.043 [a]
	Gold	GOLD	0.008	5.775	-9.821	1.019	-0.660	10.338	6341.481 [a]
	Silver	SLVR	-0.006	8.948	-19.518	1.933	-1.021	11.656	9023.263 [a]
	Copper	COPR	-0.001	6.810	-7.591	1.330	-0.132	5.529	737.3963 [a]
	Wheat	WHET	-0.006	8.937	-9.223	1.795	0.285	4.976	482.6418 [a]

Note: ‘a’ indicates 1% level of significance.

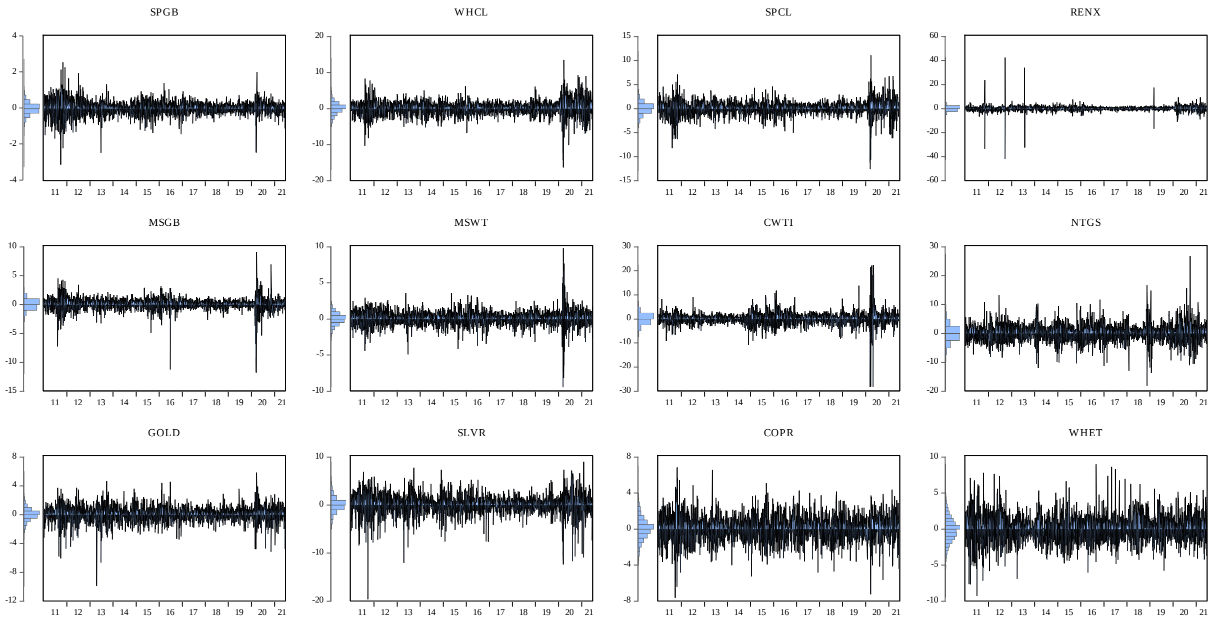
Table 2: Correlation matrix

	SPGB	WHCL	SPCL	RENX	MSGB	MSWT	CWTI	NTGS	GOLD	SLVR	COPR	WHET
SPGB	1											

WHCL	0.179	1										
	0	-----										
SPCL	0.313	0.810	1									
	0	0	-----									
RENX	0.079	0.436	0.508	1								
	0	0	0	-----								
MSGB	0.274	0.568	0.595	0.333	1							
	0	0	0	0	-----							
MSWT	0.332	0.371	0.490	0.222	0.551	1						
	0	0	0	0	0	-----						
CWTI	0.128	0.303	0.272	0.132	0.243	0.131	1					
	0	0	0	0	0	0	-----					
NTGS	0.012	0.049	0.052	0.045	0.045	0.033	0.111	1				
	0.5375	0.0099	0.007	0.0182	0.018	0.0837	0	-----				
GOLD	0.421	0.071	0.091	-0.005	0.023	0.132	0.111	-0.004	1			
	0	0.0002	0	0.798	0.22280	0	0	0.8299	-----			
SLVR	0.400	0.183	0.207	0.082	0.174	0.169	0.200	0.028	0.804	1		
	0	0	0	0	0	0	0	0.1449	0	-----		
COPR	0.321	0.327	0.337	0.178	0.328	0.190	0.299	0.046	0.258	0.389	1	
	0	0	0	0	0	0	0	0.017	0	0	-----	
WHET	0.112	0.067	0.062	0.022	0.078	0.029	0.102	0.053	0.098	0.117	0.126	1
	0	0.0004	0.0012	0.2504	0	0.1314	0	0.0051	0	0	0	-----

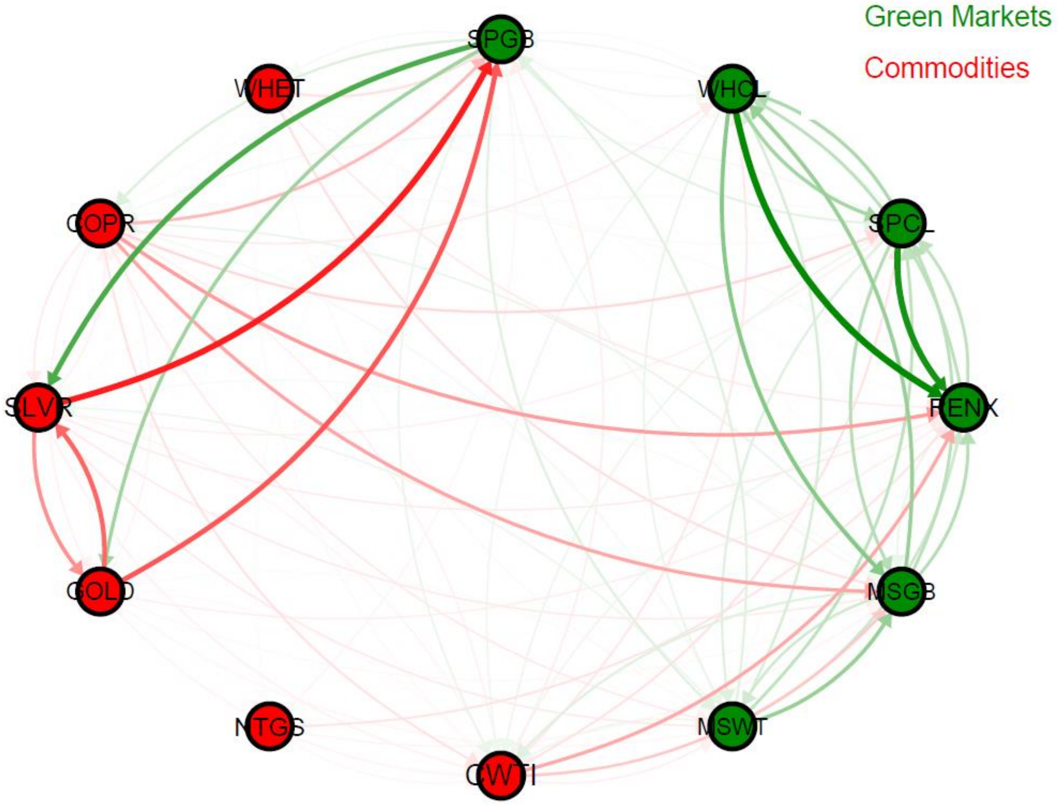
Note: This table indicates the correlation and respective p-value.

Figure 1: Time evolution of sample data



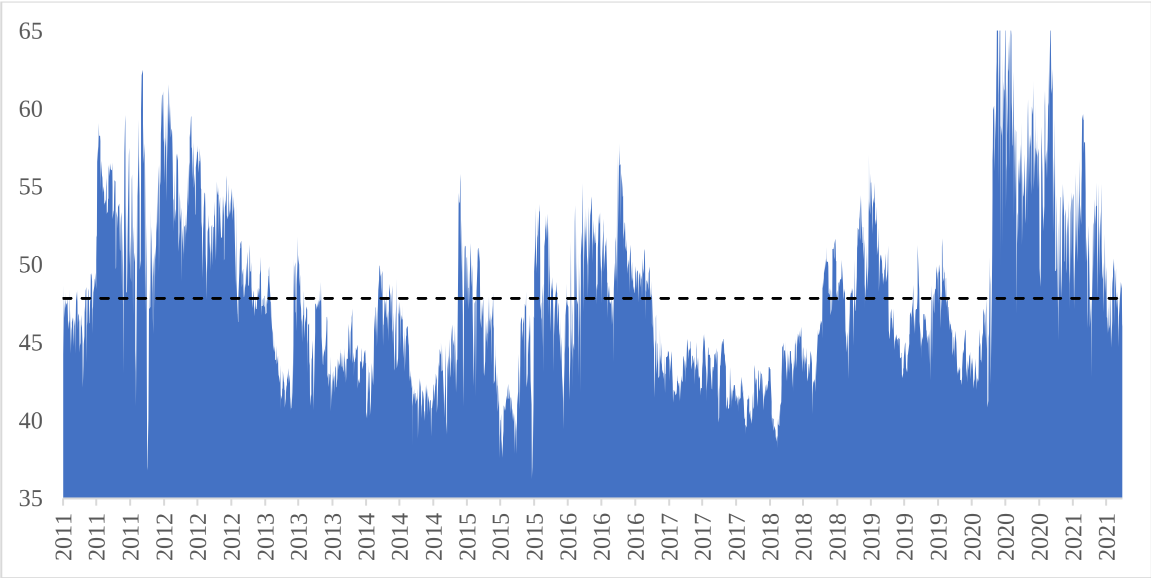
Note: This figure shows the time evolution along with histogram for the sampled data from 3/01/2011 to 30/06/2021.

Figure 2: Network connectedness using DCC-GARCH method



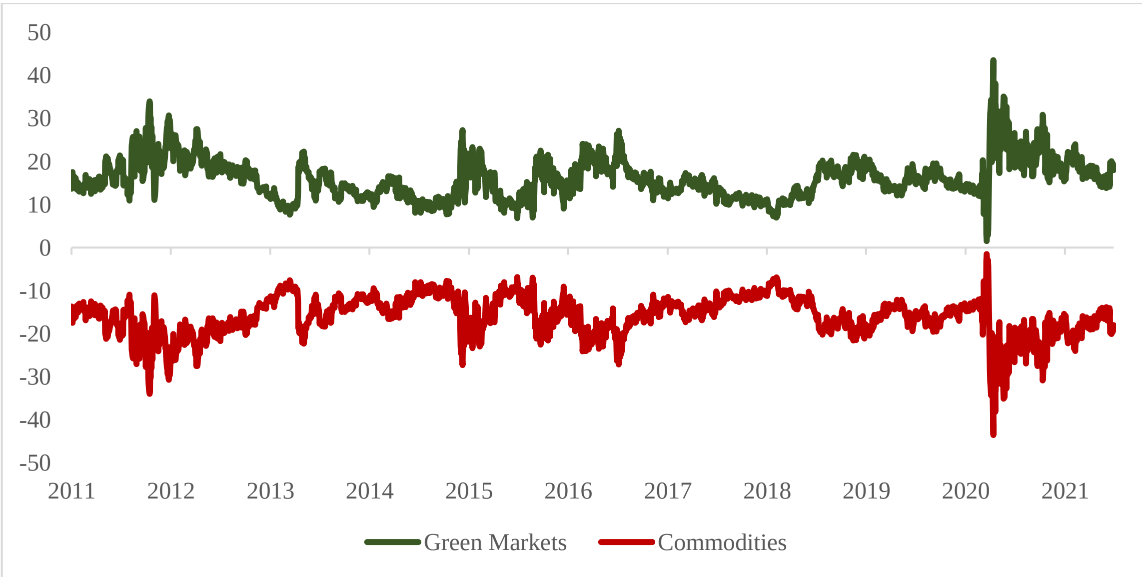
Note: This figure presents the network connectedness between green markets and commodities using DCC-GARCH connectedness framework.

Figure 3: Total connectedness using DCC-GARCH method



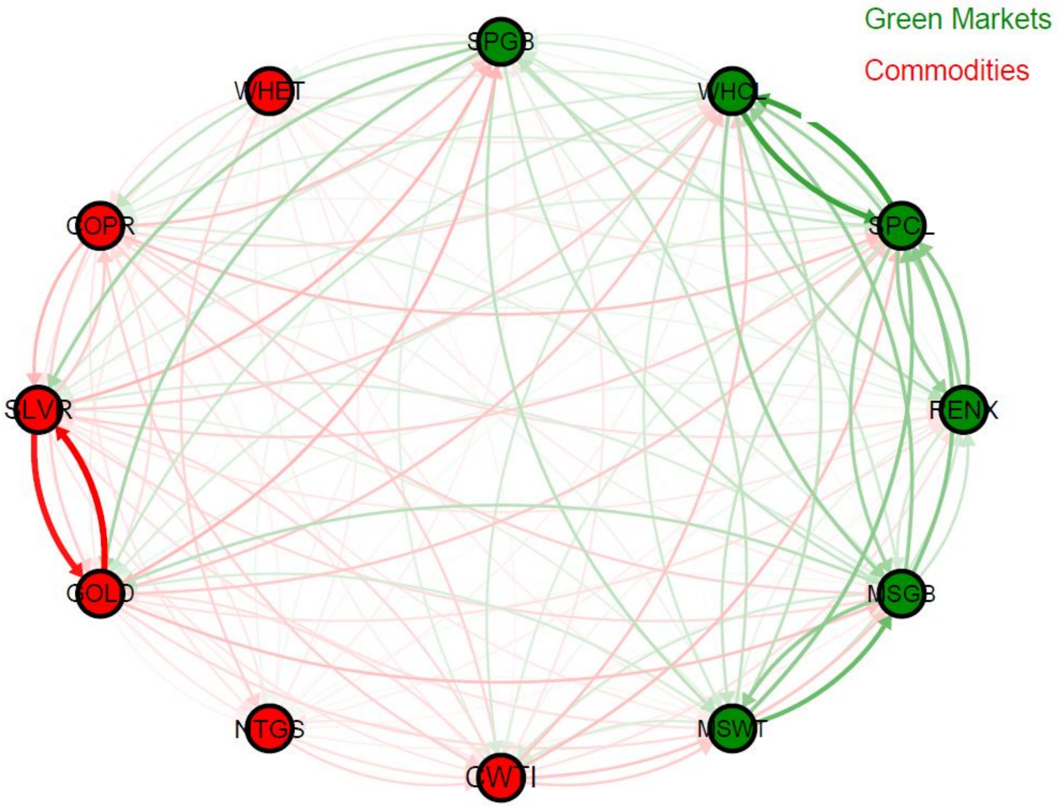
Note: This figure presents the total connectedness between green markets and commodities using DCC-GARCH connectedness framework.

Figure 4: NET connectedness using DCC-GARCH method



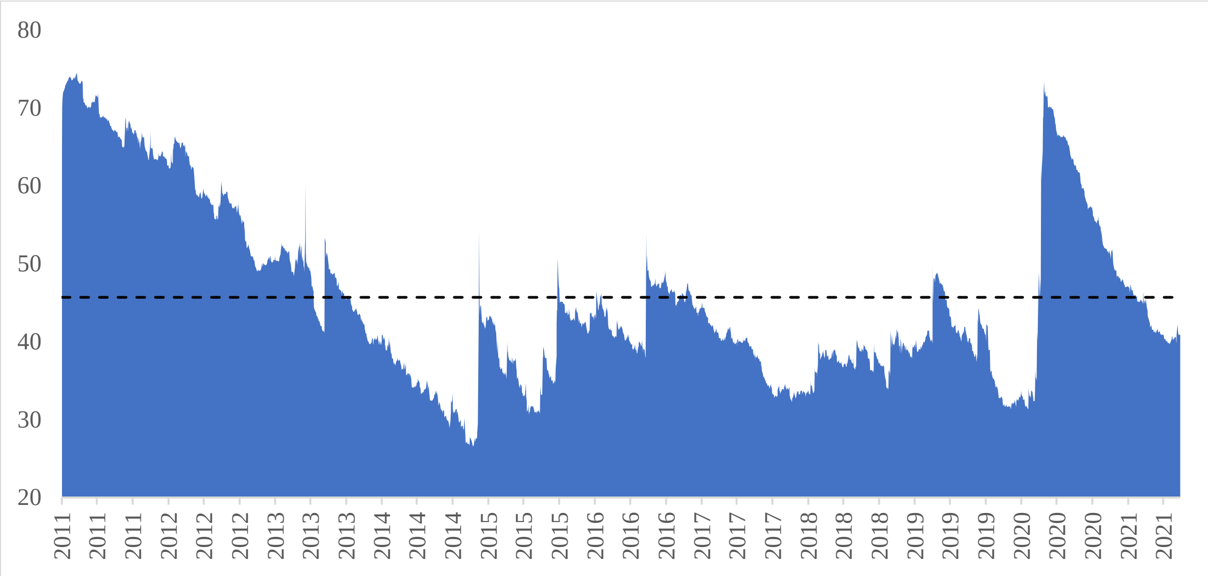
Note: This figure presents the NET connectedness of green markets and commodities using DCC-GARCH connectedness framework.

Figure 5: Network connectedness using TVP-VAR method



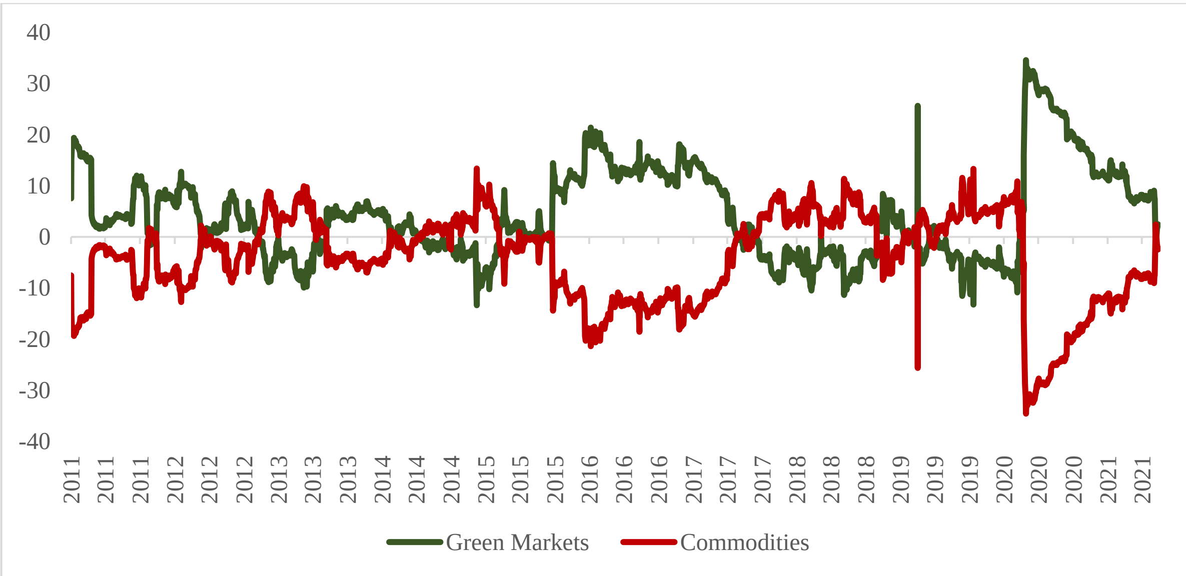
Note: This figure presents the network connectedness between green markets and commodities using TVP-VAR connectedness framework.

Figure 3: Total connectedness using TVP-VAR method



Note: This figure presents the total connectedness between green markets and commodities using TVP-VAR connectedness framework.

Figure 4: NET connectedness using TVP-VAR method



Note: This figure presents the NET connectedness of green markets and commodities using TVP-VAR connectedness framework.