Dynamics Connectedness: TVP-VAR Insights into the Nexus between Selected Global Green Financial Instruments

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Research aims: This study investigates the dynamics of connectedness among global green financial instruments driven by low-carbon policies.
Design/Methodology/Approach: Employing the Time-Varying Parameter Vector Autoregressive (TVP-VAR) and Wavelet analysis, the researchers analyzed four primary variables derived from historical closing price indices, namely Global Carbon Efficient Index (SPGCEI), Global Clean Energy Index (SPGCE), Global Green Bond Index (SPGBI), and Global Sukuk Index (SPGSI). Daily data from January 2, 2015, to November 8, 2023, was considered. Data processing was then carried out utilizing E-Views 13 and R-Studio.
Research Findings: The findings demonstrated that a low-carbon policy stimulates green financing through the stock market and increases the bond and sukuk for carbon reduction. Moreover, the study revealed that the dynamic connectedness level of all variables was 45.25%. While the SPGCEI and SPGBI act as net pairwise transmitters, the SPGCE and SPGSI function as net pairwise receivers.
Theoretical Contribution/Originality: The study confirms that low-carbon policies drive green financing through stocks, promoting bond and sukuk activities for carbon reduction. By identifying the dynamic connectedness level and the roles of net transmitter and net receiver spillovers, it validates the impact of policies and introduces an innovative analytical framework for future research on the evolving dynamics of green finance.
Policy Implication: The study recommends regulatory efforts to enhance connectedness and liquidity in green financial instruments to foster an effective and sustainable low-carbon ecosystem.
Keywords: Carbon Policy; Dynamic Connectedness; Global Green Finance; Time-Varying Parameter Vector Autoregressive; Wavelet

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Introduction

The efforts to mitigate global warming have been underway since the inception of the Paris Agreement in 2015, aiming to limit global temperature increases to below 2°C, above pre-industrial levels (Michaelowa et al., 2022). Despite these efforts, current projections suggest a temperature rise exceeding 3°C by the century's end, emphasizing the urgency of addressing this gap (Schleussner et al., 2016). To narrow this disparity, industries, major energy consumers, and CO_2 emitters have committed to achieving carbon neutrality by the mid-21st century (Broadstock et al., 2021). Concurrently, both public and private sector entities have pledged to source renewable energy, adopt cleaner technologies, improve efficiency, and conserve resources (Kreibich & Hermwille, 2021).

In response to the growing climate change awareness, countries and financial institutions have embraced low-carbon policies as part of global efforts to reduce greenhouse gas emissions (Gozgor & Karakas, 2023). Green finance instruments, such as sustainable stocks and green bonds, have emerged to support sustainable projects and provide investment opportunities (Abakah et al., 2022; Chen et al., 2023). Governments and international organizations have played a pivotal role in promoting low-emission practices, creating financial trade indices that categorize environmentally friendly companies. This movement is facilitated through policies aimed at encouraging green financing for various sectors. Several studies, such as Yu et al. (2022), Cui et al. (2023), and Yadav et al. (2023), have confirmed that policy in low carbon driven the capitalization of these instruments and fostered low emission transition.

Two crucial stock indices in this context are the Global Carbon Efficient Index (SPGCEI) and the Global Clean Energy Index (SPGCE). The former provides an overview of global equity markets, representing approximately 70% of the total global market capitalization. It assesses carbon efficiency, reflecting efforts to reduce carbon emissions while considering the environmental impact of income sectors and fossil fuel investments (da Silva et al., 2019). It not only shows efforts for carbon efficiency but also underscores the environmental impact of the income sector and investment in fossil fuels. The S&P Global Carbon Efficient Index measures the performance of companies with relatively low greenhouse gas emissions. It excludes companies with the largest relative carbon-to-revenue footprints. In addition, the Global Clean Energy Index is designed to measure the performance of companies in global businesses related to clean energy in both developed and emerging markets, with a target number of 100 constituents. The index focuses on clean and low-carbon energy, with low or zero values on indicators of carbon emissions from fossil fuel reserves (Zhang & Umair, 2023). Both indices also demonstrate commitment to clean energy and environmental sustainability.

On the financing side, green financing, such as Green Bond and Sukuk (Islamic bonds), is becoming more popular to accelerate the emission transition. The green bonds index (conventional) is issued to fund sustainable projects, such as renewable energy or energy efficiency. It demonstrates engagement in sustainable finance and low-carbon development, focusing on green projects. Then, there is the Global Sukuk Index (SPGSI), which reflects ownership of a particular asset. This could include green or sustainable bonds supporting green development projects within the Islamic principles framework (Azhgaliyeva et al., 2020). This reflects a commitment to the principles of environment and sustainable development. Both indices show engagement in sustainable finance, focusing on green development (Bhuiyan et al., 2019). The Green Bond (SPGBI) is specifically for green projects, while the Global Sukuk Index includes sustainable sukuk that support environmental principles and sustainable development, creating funding for projects that support the shift to a low-carbon economy (Babu et al., 2022). The SPGCEI, SPGCE, SPGBI, and SPGSI are essential for the long-life green transition. Therefore, the study of these instruments related to the connectedness and sources of spillover became mandatory.

Within this context, this study addresses two main questions:

RQ$_1$*: Are the SPGCEI, SPGCE, SPGBI, and SPGSI interconnected?*
RQ$_2$*: Which markets are spillover's main transmitters/receivers to the other markets?*

Further, the dynamic connectedness among global green financial instruments is an underexplored area of research crucial for achieving sustainable carbon reduction goals. As such, this study investigates the dynamics of connectedness between stocks (SPGEI and SPGCE) and bond instruments (SPGBI and SPGSI) driven by low-carbon policies. The researchers employed the Time-Varying Parameter Vector Autoregressive (TVP-VAR) and Wavelet analysis to capture parameter changes over time, providing insights into fluctuations in the relationships between green finance instruments under the influence of low-carbon policies (Lu et al., 2023). This modeling approach was chosen for its capacity to account for time dynamics, reflecting changes in government policies, global market conditions, and other factors affecting these relationships (Balcilar et al., 2021a). The results of this study contribute to the literature on the complex connectedness between green financial instruments under low-carbon policies. Its implications for global financial sustainability can lay the foundation for better decision-making by stakeholders, including governments, financial institutions, and investors concerned with aspects of sustainability.

Literature Review and Hypotheses Development

Previous Research

The dynamics of connectedness among financial instruments have gained significant attention in the field of finance, especially in the context of sustainable and green finance. Several studies have explored the interconnectedness of various financial assets and indices, shedding light on the transmission mechanisms and spillover effects within these markets.

In environmental sustainability and contemporary financial markets, the dynamics of connectedness between low-carbon policies and financial instruments play a central role in disseminating market capitalization. Low-carbon policies have emerged as a critical driver in shaping global responses to climate change (Yadav et al., 2023). Governments and regulatory bodies worldwide are adopting measures to reduce carbon emissions, promote renewable energy sources, and transition to a sustainable future. The connectedness between low-carbon policies and financial instruments is a dynamic and complex phenomenon affecting different sectors of the economy (Ehlers et al., 2020). The study conducted by Yu et al. (2022) examining the impact of green innovation in China confirms the high implementation of policies promoting green innovation, particularly among state-owned enterprises, firms, and medium-sized enterprises with lower financial constraints. This finding is also supported by Cui et al. (2023), who assert that policies promoting green financing play a primary role in driving low-carbon economic development. This is achieved predominantly by stimulating the upgrading of industrial structures and scaling up investments in science and technology.

Beyond investment considerations, low-carbon policies also contribute to sustainable outcomes by fostering transparency and incorporating social equity in green finance initiatives, aligning with sustainable development goals and promoting a greener future (Fu et al., 2023). The study of Abakah et al. (2022) highlighted the strong connectedness among green bonds at certain maturity levels and forms. Regarding the clean energy index and green bond, research by Hammoudeh et al. (2020) found limited causality between them. Chen et al. (2023) showed an interaction among green finance, renewable energy stock, and sustainable development in China, with varying degrees of influence and action direction at different points in time, exhibiting time-varying and heterogeneous characteristics. This research further explains the positive relationship between carbon efficiency index, clean energy, and green bonds. Additional connectedness has been explored by Zhang and Umair (2023), which investigated the connectedness between green bonds and renewable energy stocks and between carbon markets and renewable energy stocks. The study revealed that companies listed in the green energy index also tend to exhibit good financial performance in the global carbon efficiency index. Rozman and Azmi (2022) also uncovered a relationship between the sukuk index and the carbon efficiency index, suggesting that further empirical studies can provide deeper insights into the hypothesized connectedness.

Moreover, the study of Tiwari et al. (2021) focusing on the transmission pattern using Green Bonds, Solactive Global Solar, Solactive Global Wind, Global Clean Energy, and Carbon indicates that clean energy is seen to be the main net transmitter with Green Bonds and Solactive Global Wind emerging to be the major receivers. In contrast, research by Hanif et al. (2021) using the carbon market and various energy indexes underlined the dominant receiver of spillover of the clean energy index. According to Lu et al. (2023), the global carbon efficiency and clean energy indexes act as the main net transmitters of return spillover. Meanwhile, the green bond index receives more spillovers from others. The study indicates that changes in the SPGCEI components can significantly impact the performance of other indices, especially the SPGBI. This research characterizes SPGCEI as a spillover transmitter that can broadly affect financial markets through its impact on the green bond index. Another study by Wang et al. (2023) discovered that significant spillovers from energy, green bond, and carbon markets serve as valuable indicators for predicting uncertainties related to climate policy.

Gyamerah et al. (2022) further reinforce this view by showing that changes in the value of the renewable energy stock market can propagate and affect the performance of green bonds and sukuk.

Research Hypothesis

The hypotheses developed in the research study are as follows:

H_1: SPGCEI, SPGCE, SPGBI, and SPGSI exhibit significant interconnectedness.

Given the interconnected nature of financial markets, the researchers expect these global green financial instruments not to be isolated but interrelated.

H_2: SPGCEI and SPGBI act as transmitter spillovers, while SPGCE and SPGSI act as receiver spillovers.

Building on the concept of spillover effects, the researchers hypothesized that the SPGCEI and SPGBI play roles as transmitters of information and policy impact, while the SPGCE and SPGSI function as recipients of these effects.

Methodology

Data

This study employed the R-Studio application for data processing and focused on four variables extracted from the historical closing price index. The data were obtained from https://www.spglobal.com/ in the global green finance domain. These variables included the S&P Global Carbon Efficient Index (SPGCEI), S&P Global Clean Energy Index (SPGCE), S&P Green Bond Index (SPGBI), and S&P Global Sukuk Index (SPGSI). The dataset comprised daily data from January 2, 2015, to November 8, 2023, encompassing a total of 2.297 samples. The researchers transformed the closed price into a return through the formula $R = \frac{V_f - V_i}{V_i}$; R is return, V_f is final value, and V_i is initial value. Because the data indexes were non-stationary based on the unit-root test (Table 1), the data were transformed into a first log-difference d(1) $y_{it} = log\ (x_{it}) - log\ (x_{it}\text{-}1)$. The results of the transformation in the first difference can be seen in Figure 1.

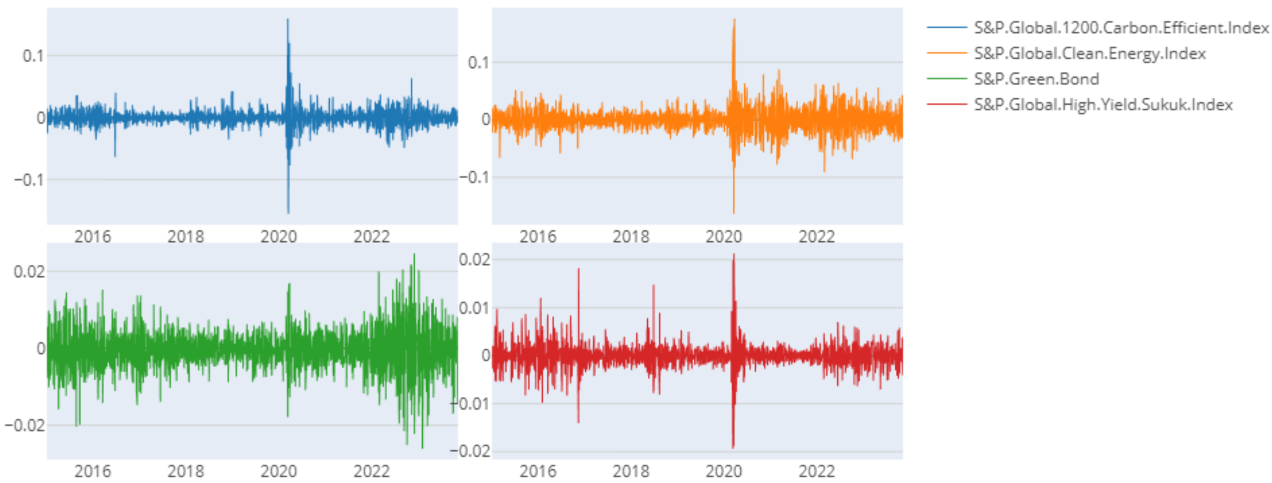

Figure 1 First Log-Difference Transformed Data

Based on the results of the normality test of Jarque and Bera (1980), it can be concluded that not all index data follow the normal distribution significantly. The ERS root unit test results from Elliott et al. (1996) show that all returns are stationary, at least at a significance level of 1%. Furthermore, Fisher and Gallagher's (2012) portmanteau test states that there is a correlation between return and the square of return, supporting the decision to apply the TVP-VAR approach in modeling the relationship of this index data, taking into account the structure of covariance that changes over time.

Methodology

This research applied two quantitative analysis techniques, namely TVP-VAR, and continued with Wavelet Coherence Analysis (WCA). The first technique used was a VAR toolkit. This method allows comparison of the relative impact of shocks on one variable against another and considers the feedback loop from across the network. The study also combined methodologies by Diebold and Yilmaz (2012, 2014), Antonakakis et al. (2020), and Lastrapes and Wiesen (2021) to obtain a TVP-VAR-based shared connectedness approach.

$$y_t = A_t y_{t-1} + u_t \; u_t|F_{t-1} \sim N(0, V_t) \quad \text{..(1)}$$

$$vec\,(A_t) = vec\,(A_{t-1}) + v_t \; v_t|F_{t-1} \sim N(0, S_t) \quad \text{....................................(2)}$$

Based on Equation (1) and (2), F_{t-1} represents the information available until time t-1, while yt, y_t–1, and ut are defined as m×1 vectors (with K as the data sample size). Additionally, A_t and V_t are characterized as m×m matrices. Furthermore, vec (At) and vt are specified as m_2×1 vectors, while S_t is a m_2×m_2 matrix.

The TVP-VAR methodology, in isolation, lacks completeness and requires an approach that investigates the interdependence among variables, relying on time-varying parameters and error variances. To address this, two parameters were introduced: generalized impulse response functions proposed by Koop et al. (1996) and generalized forecast error variance decompositions by Pesaran and Shin (1998). The computation of these parameters involves a transition from TVP-VAR to its vector moving average (TVP-VMA), utilizing the relationship outlined in Equation (3):

$$z_t = \sum_{i=1}^{k} A_t y_{t-1} + u_t = \sum_{i=1}^{\infty} A_{j,t} u_{t-j} \quad \text{...(3)}$$

The strength of employing generalized impulse response functions is denoted as $\psi_{j,t}(K)$. A given forecast horizon (K) lies in its robustness when interpreting VAR models, which is attributed to its independence from the order of errors. Generalized Impulse Response Functions effectively capture variations in dynamics both within individual variables and across variables. This is formally expressed in Equation (4):

$$GIRF\left(K, \sqrt{H_{jj,t}}, F_{t-1}\right) = E(y_{t-k}| \in_{j,t} = \sqrt{H_{jj,t}}, F_{t-1}) - E(y_{t-k}|F_{t-1}) \text{..........(4a)}$$

$$\psi_{j,t}(K) = H_{jj,t}^{-1/2} A_{k,t} H_t \in_{j,t} \quad \text{...(4b)}$$

Subsequently, Generalized Forecast Error Variance Decomposition plays a role in revealing the individual contributions of each variable concerning the forecast error variance of a specific variable. In simpler terms, it quantifies the extent to which the forecast variance of one variable influences the forecast error variances of other variables. This is formally expressed in Equation (5):

$$\psi_{ij,t}(K) = \frac{\sum_{t=1}^{k-1} \psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{k-1} \psi_{ij,t}^2} \quad \text{...(5)}$$

With $\sum_{j=1}^{m} \psi_{ij,t}(K) = 1, \sum_{ij=1}^{m} \psi_{j,t}(k) = m$, the connectedness metrics obtained from Generalized Forecast Error Variance Decompositions were generated in the following Equation:

$$TO_{jt} = \sum_{i=1, i\neq j}^{m} \psi_{ij,t} \ (K) \text{..........}(6)$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{m} \psi_{jt,t} \ (K) \text{..........}(7)$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \text{..........}(8)$$

$$TCI_{t}^{g}(K) = \sum_{i,j=1, i\neq j}^{m} \psi_{ij,t}^{g} \ (K) \text{..........}(9)$$

$$NPDC_{ij,t} = \psi_{ji,t}(K) - \psi_{jt,t}(K) \text{..........}(10)$$

$$PCI_{ijt}(K) = 2\left(\frac{\psi_{ij,t}^{g}\ (K) + \psi_{ji,t}^{g}(K)}{\psi_{ii,t}^{g}\ (K) + \psi_{ij,t}^{g}\ (K) + \psi_{ji,t}^{g}(K) + \psi_{ij,t}^{g}\ (K)}\right) \text{..........}(11)$$

The impact of a shock on variable i is denoted by $\psi_{ij,t}^{g}$ (K) with Equation (6) providing an overview of the overall impact of a shock on variable j, considering all other variables (total connectedness). Meanwhile, Equation (7) defines the collective influence of all variables on j (total directed connectedness from others to j). Subtracting Equation (7) from Equation (6), the researchers got a net total directional connectedness, indicating whether j is a net receiver or transmitter of the shock (Equation 8). Subsequently, Equation (9) introduces the total connectedness index, illustrating the influence of j on other variables. It is crucial to emphasize that all connectedness measures encapsulate the combined impact, while Equations (10) and (11) elucidate net pairwise directional connectedness, delineating a bilateral relationship between two variables and the pairwise connectedness index between them (i and j) (Ashraf et al., 2023).

Next, this study follows the order from Kartal et al. (2023) o examine the process of Wavelet analysis. Wavelet denoted as ψ can be embodied as $\psi\ (t) = \pi^{-\frac{1}{4}} e^{-iw0^{t}} e^{-\frac{1}{2}t^{2}}\ , p(t), t = 1, 2, 3, \dots, T$; Next, symbol (f) is frequency, *(k)* is position and time horizontal. The equivalent of the reduction of the Wavelet was achieved by associating position and density coefficients, as outlined in Equation (12)

$$\psi_{k,f}\ (t) = \frac{1}{\sqrt{h}}\ \psi\ \left(\frac{t-k}{f}\right), k,\ f\ \in \mathbb{R}, f \neq 0 \text{..........}(12)$$

After annexing the time series data p(t), the equivalence of the steady Wavelet function was found in Equation (13):

$$W_{P}\ (k,f) = \int_{-\infty}^{\infty} p\ (t) \frac{1}{\sqrt{f}} \psi\ \left(\frac{t-k}{f}\right) dt \text{..........}(13)$$

Equation (13) was stimulated as Equation (14) after annexing the parameter ψ to the equivalence:

$$p(t) = \frac{1}{C_{\psi}} \int_{0}^{\infty} \left[\int_{-\infty}^{\infty} |W_{P}(a,b)|^{2}\ da\ \right] \frac{db}{b^{2}} \text{..........}(14)$$

The Wavelet power spectrum (WPS) was employed in this paper to find out the sensitivity of t_1 to t_2. WPS offers the opportunity to recognize the affected areas with the highest sensitivity during economic and financial crises.

$$WPS_{p}\ (k,f) = |W_{P}(k,f)|^{2} \text{..........}(15)$$

The reduction of time series factors was accomplished through the cross Wavelet transform (CWT) aspect in the subsequent phase, as indicated in Equation (16):

$$W_{pq}\,(k,f) = W_p(k,f)\, W_q\,(k,f) \ldots\ldots \quad (16)$$

where W p(k,f) and Wq(k,f) show the CWT of two-time series factors (Alola & Kirikkaleli, 2019). The Equation of the squared Wavelet coherence is shown in Equation (17)

$$R^2\,(k,f) = \frac{\left|C(f^{-1}W_{pq}(k,f))\right|^2}{C(f^{-1}\left|W_p(k,f)\right|^2 \, C\,(\,f^{-1}\,\left|W_q(k,f)\right|^2)} \ldots\ldots (17)$$

$$\emptyset_{pq}(k,f) = tan^{-1}\left(\frac{L\{C(f^{-1}\,W_{pq}\,(k,f))\}}{O\,\{C(f^{-1}W_{pq}\,(k,f))\}}\right) \ldots\ldots (18)$$

Finally, the Wavelet coherence approach was formulated in Equation (18), where L represents a hypothetical operator, and O denotes the real part of the operator.

Results and Discussions

Empirical Result

Table 1 provides statistical results for four financial indices: SPGCEI, SPGCE, SPGBI, and SPGSI. Here is an interpretation of those statistical results:

Table 1 Statistical Summary

	SPGCEI	SPGCE	SPGBI	SPGSI
Mean	0.027	0.024	-0.003	0.018
Variance	0.0093	0.0233	0.0014	0.00037
Skewness	0.707***	0.406***	-0.168***	0.497***
	(0.000)	(0.000)	(0.001)	(0.000)
Ex.Kurtosis	25.968***	9.840***	2.646***	14.212***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	64704.173***	9326.576***	680.633***	19416.342***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-4.014***	-5.089***	-24.898***	-6.094***
	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	882.654***	598.244***	503.510***	512.984***
	(0.000)	(0.000)	(0.000)	(0.000)
Q2(10)	2574.893***	2399.683***	414.598***	1069.217***
	(0.000)	(0.000)	(0.000)	(0.000)

Note: SPGCEI = S&P Global Carbon Efficient Index; SPGCE = S&P Global Clean Energy Index; SPGBI = S&P Green Bond Index; SPGSI = S&P Global Sukuk Index; *Denote significance at 10%; **Denote significance at 5%; ***Denote significance at 1%.

The SPGCEI had the most significant average return of 0.027%, while the SPGBI tended to have a negative return. The largest variance in return was the Global Clean Energy Index of 0.23%, indicating that the fluctuation or volatility of returns was relatively high. At the same time, the Global Sukuk Index tended to fluctuate lower and was more stable. A positive value on the skewness test indicates a rightward slope, while a negative value on the Global Bond suggests a leftward slope (D'agostino, 1970). All indices showed significant values (p-value = 0.000) on the Ex-Kurtosis test, implying that the return distribution tends to have a thicker tail than the normal distribution (Anscombe & Glynn, 1983). In addition, the test on Jarque and Bera (JB) (Normality Test) assesses whether the distribution of returns follows the normal distribution. All indices revealed a very high significance level (p-value=0.000), signifying that the returns distribution was statistically not normally distributed (Jarque & Bera, 1980). All indices in the Unit-Root Test uncovered statistically significant results, indicating that returns were stationary, at least at a significance level of 1% (Elliott et al., 1996). Q(10) and Q2(10) Weighted Portmanteau Tests demonstrated statistically significant results (p-value= 0.000), signaling an autocorrelation in return (Fisher & Gallagher, 2012).

Averaged Dynamic Connectedness Results

Table 2 presents information on the average dynamic connectedness of index variables. The values in the matrix cells represent the percentage of connectedness between the index of the corresponding row and the index of the corresponding column. For instance, the 26.22% in the row of the Global Carbon Efficient Index and column of the Global Clean Energy Index denotes the percentage of connectedness between both indices.

Table 2 Average Dynamic Connectedness Table

	SPGCEI	SPGCE	SPGBI	SPGSI	FROM
Global Carbon Efficient Index	64.69	26.22	5.66	3.43	35.31
Global Clean Energy Index	27.30	64.07	5.09	3.53	35.93
Green Bond	4.45	4.44	84.03	7.08	15.97
Global Sukuk Index	5.80	4.17	5.56	84.46	15.54
TO	37.56	34.83	16.32	14.04	102.75
Inc. Own	102.25	98.91	100.34	98.51	TCI
NET	2.25	-1.09	0.34	-1.49	45.25%
NPT	2.00	1.00	2.00	1.00	

Note: SPGCEI = S&P Global Carbon Efficient Index; SPGCE = S&P Global Clean Energy Index; SPGBI = S&P Green Bond Index; SPGSI = S&P Global Sukuk Index.

The Total Connectedness Index (TCI) provides an overall connectedness index. The TCI value of 45.25% shows the total connectedness between variables. A positive value in NET indicates that the corresponding index is a net transmitter of spillovers to another index, while a negative value denotes a net receiver from another index (Balcilar et al., 2021b). Positive NET values for the Global Carbon Efficient Index (2.25%) and Global Green Index (0.34%) indicated that they were sending shocks to other indices, while negative NET values for the Global Clean Energy Index (-1.09%) and Global Sukuk Index (-1.49%) suggested that they were spillover receiver. Net Position Taking (NPT) indicates the net position of each index. A positive value indicates the net transmitter position, while a negative value indicates the net receiver position.

Dynamic Total Connectedness

It is crucial to emphasize that the average result primarily functions as a concise representation of the underlying interconnectedness. This analytical framework examines the changes in the TCI over time and demonstrates how the significance of specific variables in the research network may vary over time.

Figure 2 portrays the evolution of the TCI over time. It can be seen that TCI values varied and fluctuated during the observation period, with large values indicating a significant impact between indices. In particular, the TCI range was high, especially in 2015, reaching a peak above 80%. After that, TCI fluctuated until early 2020, and a new upward trend began, reaching substantial values (around 65–70%) between 2020 and 2021. This increase may be related to significant changes during the COVID-19 pandemic. Post-pandemic, the level of connectedness has decreased but has increased since the beginning of 2022. This may be related to the uncertain global conditions caused by the Russia-Ukraine and Israeli-Palestinian War. The dynamic evolution of TCI in Figure 2 exposes a response to a particular event, with connectedness increasing during periods of high uncertainty.

Figure 2 The Dynamic Total Connectedness

Net Total and Pairwise Directional Connectedness

Examining this specific layer enables the categorization of net transmitter and receiver indices. The dynamic methodology outlined in this section enables the detection of potential transitions between these roles. To clarify, within a given time frame, each index in this study's network could alternate between functioning as a net transmitter and a net receiver of shocks within the system (Gabauer et al., 2023).

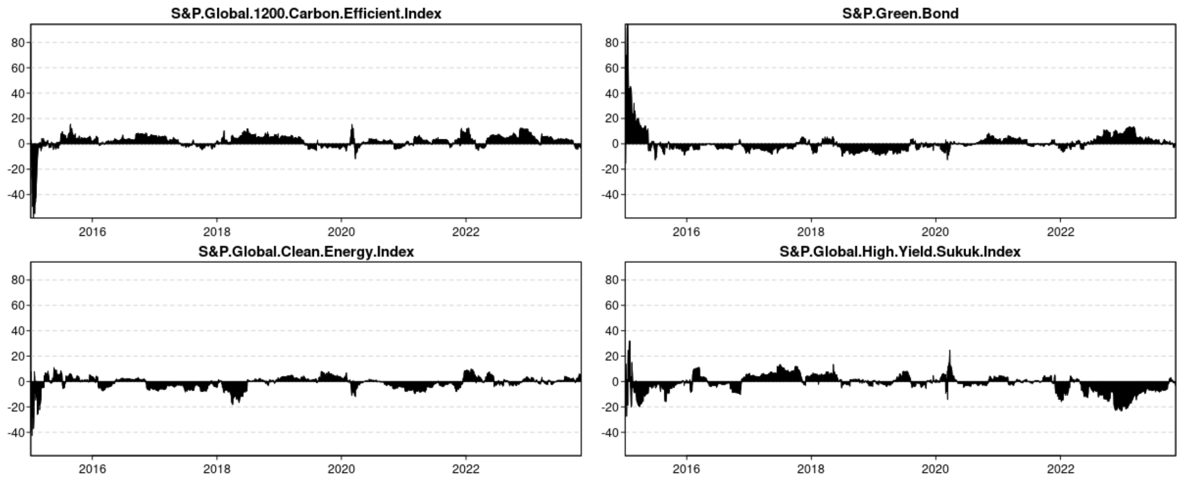

Figure 3 Net Total Directional Connectedness

Figure 3 illustrates the volatility received, impacting the variables used in this study. In line with the results presented in Table 2, the variables of SPGCE and SPGSI typically received Volatility Spillovers. In contrast, the SPGCEI and SPGBI were variables whose volatility impacted the others. There was a large degree of volatility in 2015 and after 2022. 2022 is a period of the Russia-Ukraine war and the Israeli-Palestinian conflict. This creates increasing global uncertainty. In the mid-period from 2016-2022, volatility levels varied for all four variables.

In Figure 4, the SPGCEI acted as a volatility transmitter to the SPGCE with a positive contribution. However, this index was more of a recipient of volatility than the green bond index, with a negative contribution. The SPGCEI also functioned as a volatility sender to the SPGSI with a positive contribution. Thus, the Net Total Pairwise Directional Connectedness for the Global Carbon Efficient Index was 2.25. On the other hand, the SPGCE was more of a recipient of volatility than the SPGCEI, which had a negative contribution. This index also acted as a transmitter of volatility to the green bond index with a positive contribution. However, the Global Clean Energy Index was more of a volatility receiver than the Sukuk index, with a negative contribution.

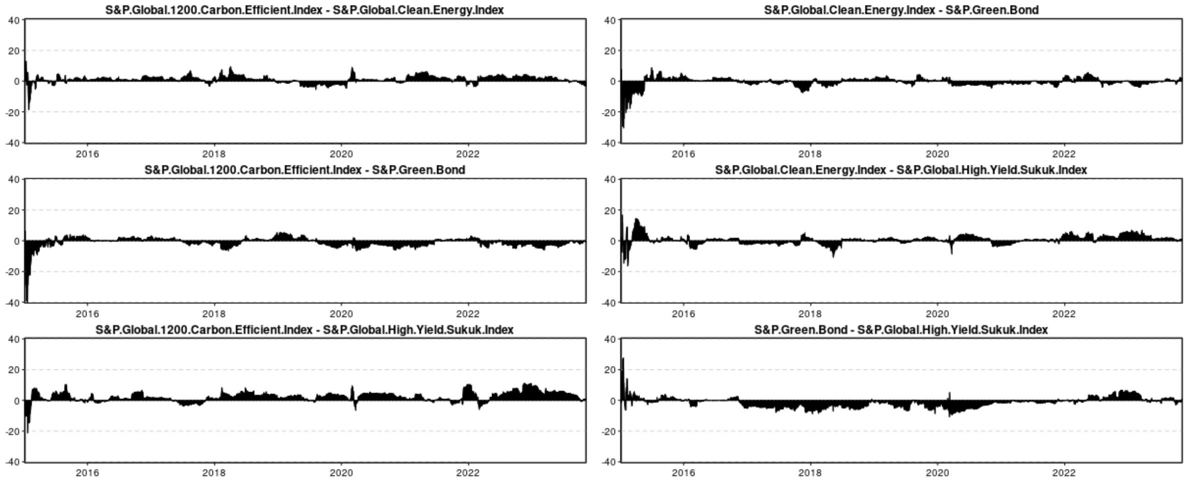

Figure 4 Net Total Pairwise Directional Connectedness

Network of Net Pairwise Directional Connectedness

The Net Pairwise Directional Connectedness network is depicted in graph form in Figure 4. Following that, Figure 5 gives a picture of the network with blue areas signifying net transmitters of volatility spillovers, suggesting a higher likelihood of influencing other assets in the network. Conversely, the yellow circle denotes the variable that net receives volatility spillover. The size of each node corresponds to the connectedness effect, with larger nodes indicating a more substantial connectedness effect. Arrows in the graph depict the direction of Network of Net Pairwise Directional Connectedness (NPDC), and the width of the lines indicates the intensity of connectedness.

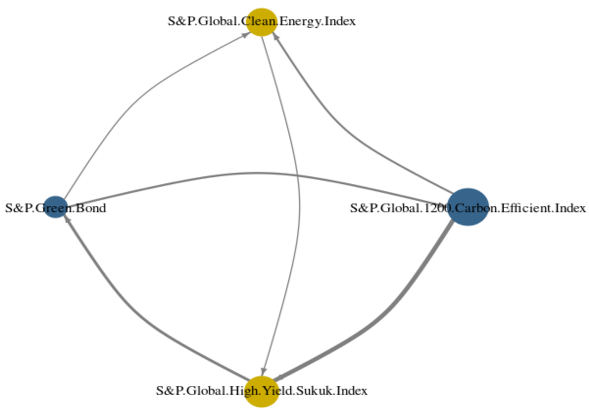

Figure 5 Network of Net Pairwise Directional Connectedness (NPDC)

The SPGCEI and SPGBI were net transmitters with immense potential to influence other assets in the network. These transmitters are important in sender impacts or shocks to other indexes. The SPGCE and SPGIS are net receivers influenced by net transmitters. The size of the node reflects the magnitude of the impact. The size of the SPGCEI is the largest, indicating that the index has the greatest impact on movement or change in the network. The size and direction of the chart give a visual idea of how strongly interconnected assets are in the network.

Time-Frequency Domain Analysis Using Coherence Wavelet

Before delving into the Wavelet analysis, it is essential to grasp their classification to ensure informed judgment. The horizontal axis represents time (observation period), while the vertical axis depicts frequency (with lower frequency indicating a higher scale). Wavelet coherence identifies regions in time-frequency space where two-time series co-vary. In this representation, warmer colors (such as red) indicate areas with significant connectedness, while colder colors (blue) signify lower dependence between the series. Cold regions outside the significant areas represent time and frequencies with no observed dependence between the series (Thaker & Mand, 2021). Next, the black contour delineates the region at a 5% significance level. Arrows within the Wavelet coherence plots indicate the lead/lag phase relations between the analyzed series. A zero-phase difference implies that the two-time series move synchronously at a specific scale. Arrows are directed to the right (→) or to the left (←) to denote in-phase or anti-phase relationships between the time series. In-phase signifies movement in the same direction, while anti-phase indicates movement in opposite directions. Arrows pointing right-down (↘) or left-up (↖) indicate that the first variable leads, while arrows pointing to the right-up (↗) or left-down (↙) show that the second variable takes the lead or become transmitter (Rijanto, 2023).

Figure 6 shows Wavelet coherence and distinct phases in the Global Green index instruments. If observed more closely, Wavelet coherency between SPGCEI and SPGCE dominated by warm colors (red) showed much coherent movement that occurred quite strongly (more in medium scale 8-64). The direction of the dominant arrow to the right (→) led to a return in phase. There is also an arrow to the right-down (↘), showing that SPGCEI led market movements more than SPGCE.

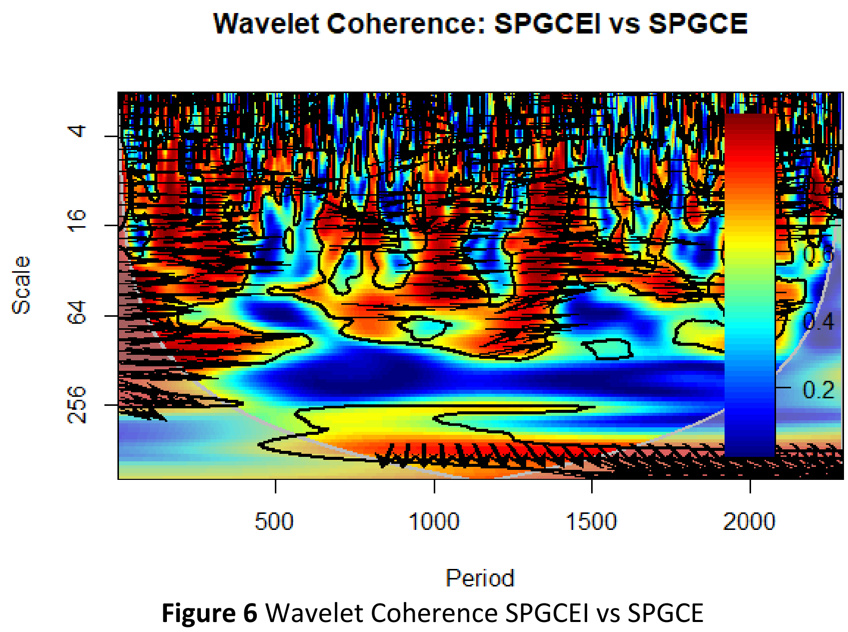

Figure 6 Wavelet Coherence SPGCEI vs SPGCE

In blue area dominance, Wavelet coherency in the SPGCEI and the SPGBI indicated a lack of joint movement (Figure 7). Suppose the researchers look at the TVP-VAR results in Table 2, which show that SPGCEI and SPGBI acted as transmitters for other indices. However, the blue color (indicates low connectedness) was dominant in short and medium scales (0-8 and 8-64 scale), and the long scale was dominated by a warm color (red). Then, if looking at the direction of the arrow that dominated the left-up direction, it can be interpreted that SPGBI (second variable) led to SPGCEI.

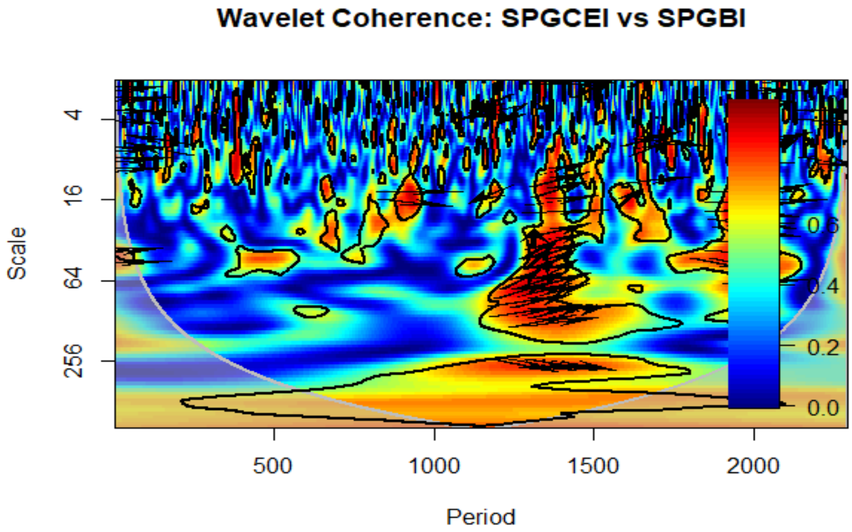

Figure 7 Wavelet Coherence SPGCEI vs SPGBI

Wavelet Coherence on the SPGCEI and the SPGSI disclosed very similar results to SPGCEI and SPGBI (Figure 8), but for this case, the blue domain covered the entire cone with a small area of red in the middle of the observation period. This implies that the rate of joint movement was still very low even as time went on. Red color can be observed on a scale of 0.2 to 0.6 and dominant on the long scale (more than 256). On the other hand, most of the arrows point right-up (↗) when looking at the lead lag connectedness, meaning that SPGCEI was leading (acting as a transmitter) to SPGSI.

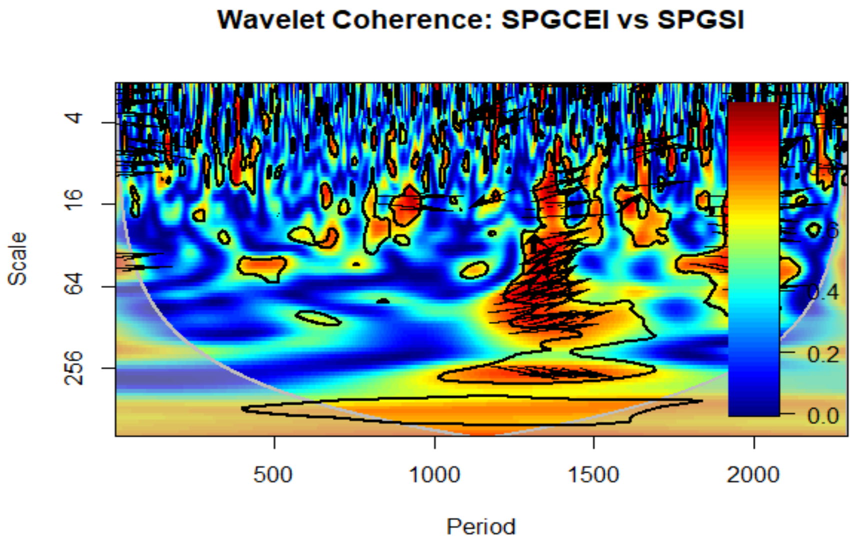

Figure 8 Wavelet Coherence SPGCEI vs SPGSI

The Wavelet coherence analysis for the SPGCE and the SPGBI revealed a predominant blue area covering most of the cone (Figure 9), suggesting generally weak joint movement in the time domain. Notably, the prevalence of blue areas was more pronounced at lower scales (higher y-axis levels), indicating that joint movement was more significant in the long term (above 64 scales) than in the short term (below eight scales). Additionally, the arrow direction was predominantly left up, signifying that SPGBI (the second variable) dominated the market.

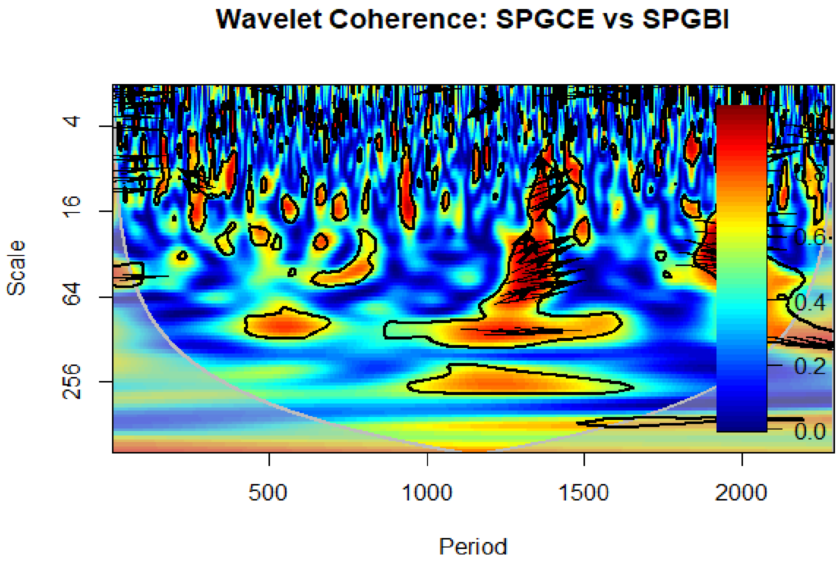

Figure 9 Wavelet Coherence SPGCE vs SPGBI

Examining the Wavelet coherence for the SPGCE and the SPGSI depicted a dominant blue area covering most of the cones (Figure 10), indicating relatively low joint movement. However, there is an observable increase in the dominance of red at the beginning and middle of the observation period, indicating a strengthening joint movement. These findings were statistically significant at a 5% level, particularly in the scale range of 0.3 to 0.6. The majority of arrows pointed to the top right and to the right (→), suggesting a lead-lag relationship where SPGSI was leading.

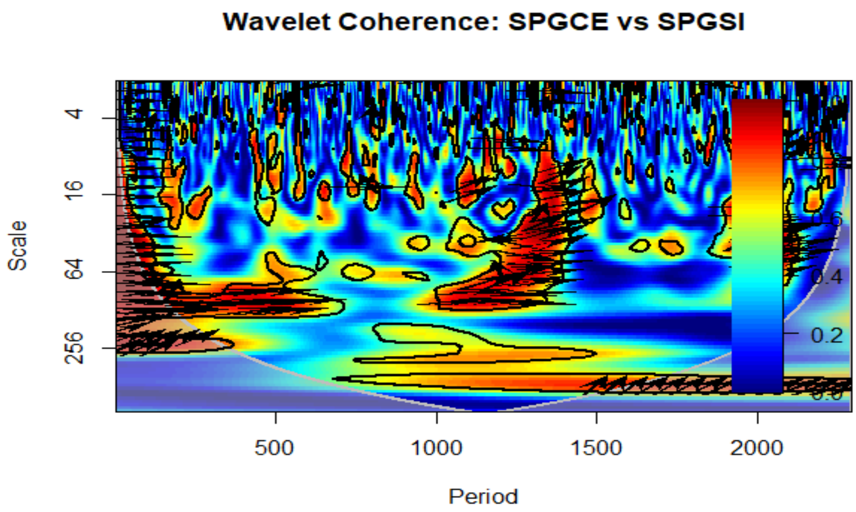

Figure 10 Wavelet Coherence SPGCE vs SPGSI

Additionally, analyzing the Wavelet coherency between the SPGBI and the SPGSI highlighted a predominance of blue covering most cones in both indices, suggesting relatively low joint movement (Figure 11). However, an increasing dominance of red in the middle of the observation period indicates a strengthening joint movement. These results were statistically significant at a 5% level, particularly in the scale range of 0.2 to 0.6. Most arrows pointed to the right (→), indicating a lead-lag relationship, with SPGBI leading.

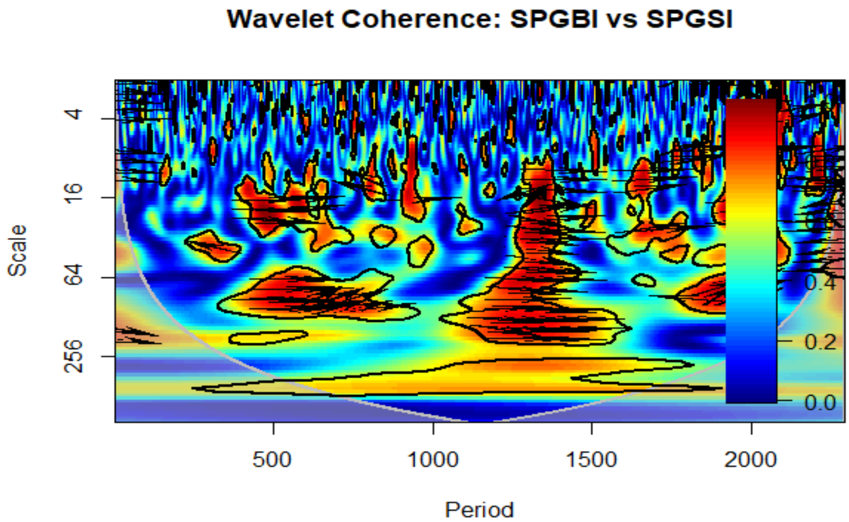

Figure 11 Wavelet Coherence SPGBI vs SPGSI

Discussion

This paper undertakes a comprehensive investigation into the dynamics of connectedness among global green finance instruments driven by low-carbon policies. TVP-VAR and WCA, the researchers delved into the intricate interconnectedness among the SPGCEI, SPGCE, SPGBI, and SPGSI. This section discusses the implications and significance of two crucial research findings.

First, the findings of this study revealed a substantial level of dynamic connectedness among variables. The TCI of 45.25% demonstrates the complex interplay of forces in the global green finance landscape (see Table 2). **Despite this, the level of connectedness remains relatively low and not supported by the first hypothesis. The hypothesis expects these global green financial instruments not to be isolated but interconnected (represented by high TCI). We anticipated the hypothesis that the level of the total connectedness index would be high exceeding 50%. The TCI of 45% represents spillover on one instrument and should not have much effect on other instruments.** This unveils that green instruments are still independent and not yet strongly connected, underscoring the non-interdependence of critical indicators in the global green finance ecosystem. Basically, connectedness among financial instruments has two sides of interpretation. A high level of interconnectedness in a system can provide benefits in the form of fast information exchange, high liquidity, effective coordination, resilience to change, innovative collaboration, operational efficiency, increased security, and better decision-making. However, this needs to be balanced with sound risk management to avoid potential systemic risk (Raddant & Kenett, 2021; Wu et al., 2021). According to the results of this study, low interconnectedness could have benefits in terms of risk management. However, it also poses challenges in creating a more integrated and interconnected network of green projects, which is crucial for comprehensively addressing complex environmental issues. As the green finance sector develops, there may be ongoing discussions about optimizing the balance between project independence and overall interconnectedness.

Second, the research findings highlighted the role of specific indices as either net transmitters or net receivers of spillover effects (Figure 4). **The result of this study confirms the second hypothesis in identified the net transmitter and net receievers. The SPGCEI and SPGBI have emerged as crucial net transmitters of spillover**, showcasing their ability to influence and shape other market dynamics. This is consistent with the findings of Lu et al. (2023), which indicate that the SPGCEI plays a more significant role in influencing other indices. **In contrast, the SPGCE and SPGSI function as net receivers of spillover, signifying their sensitivity to external influences (shock).**

These findings underscore the importance of implementing appropriate policy interventions. The positive impact of low-carbon policies underlines the need for sustainable regulatory efforts to support and enhance green financing instruments. The high level of connectedness among key indices emphasizes the significance of adopting a holistic approach in policy formulation, recognizing the interdependence of these indicators. Furthermore, understanding the dynamics of net transmitters and receivers provides valuable insights for policymakers in developing strategies to strengthen the resilience of the green financial ecosystem.

Conclusion

In conclusion, this research's findings emphasize the pivotal role of low-carbon policies in stimulating green financing, mainly through stocks, while fostering increased activities in bonds and sukuk for carbon reduction. Importantly, the researchers have quantified the level of dynamic connectedness among these variables, revealing it to be at 45.25%. The SPGCEI and SPGBI emerged as net pairwise transmitters, amplifying the transmission of effects to other indices. Meanwhile, the SPGCE and SPGSI both functioned as net pairwise receivers, absorbing these effects from other indexes.

The implications of these findings underscore the importance of advocating for strengthened regulations to augment the connectedness of green finance instruments. Supportive regulatory frameworks focused on low carbon can be a robust foundation for expanding global green finance markets. Moreover, proactive measures are imperative to enhance the liquidity of green financial instruments.

Additionally, this research underscores the significance of international cooperation in developing and implementing green finance policies, as it has the potential to magnify the positive effects of connectedness on global markets. In light of these insights, this study makes a theoretical contribution by confirming the driving force of low-carbon policies in shaping green financing dynamics and introducing an innovative analytical framework for future research. Importantly, it emphasizes the need for a regulatory push to fortify the connectedness of green finance, ultimately fostering high levels of liquidity for these instruments. Recognizing the interconnectedness and liquidity in green financial instruments as crucial elements, this research positions them as key factors in creating an effective low-carbon environment.

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Conflicts of interest

The author declares no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.