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The nexus between global carbon and renewable energy sources: A step towards sustainability

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ABSTRACT

The energy transition is at the core of sustainable development as it helps to combat global warming and climate change. Similarly, carbon markets also support the climate change mitigation. Therefore, by realizing the potential role of clean energy and carbon markets in ensuring environmental sustainability, this study analyzes the spillovers and connectedness between the environment (global carbon) and renewable energy sources (wind, solar, geothermal, biofuel, and fuel cell). The empirical analysis is conducted by applying the novel "TVP-VAR" connectedness framework of Balcilar et al. (2021) on the daily data over the period from August 1, 2014, to February 4, 2022. The findings show that solar and biofuel appear as the highest net shock transmitter among alternative renewable sources while global carbon is shown as the net receiver of shocks. The largest transmission of shocks to global carbon is observed from wind followed by solar. Although these findings support the connectedness between renewable energy and the environment, however this connectedness is influenced by economic crises such as the oil crisis and pandemic crisis. During COVID-19, the fuel cell was the highest transmitter of shocks. The results are important for policy formulation, investment, and portfolio management as they provide insights into the interconnectedness and help in boosting climate actions.

1. Introduction

Climate change and global warming are the most pressing issues in the contemporary global economy. The effect of climate change differs within and across regions as "approximately 3.3–3.6 billion people are highly vulnerable to climate change" (IPCC, 2022). Climate change is exacerbating due to unsustainable development practices which adversely affect humans and the ecosystem. To limit global warming at 1.5 °C, global emissions must decline by 43% by 2030 (World Bank, 2022). Climate action is the urgent need of present time to cope with the risks associated with global warming and climate change. In effect, climate action is at the core of sustainability as it promotes climate-resilient development. In this respect, carbon pricing can prove to be an effective instrument in the transition towards low-carbon societies (IPCC et al., 2018) as it is a market-based solution to combat climate change and shifts economic incentives and supports investment in cleaner and efficient solutions in the energy sector (IHS Markit & CLIFI, 2020). It is a price on greenhouse gas emissions and creates financial incentives for emission reduction and removal. Carbon price incorporates climate change costs into decision making thereby changing investment, production, and consumption patterns to support low carbon growth. It also discourages investment in fossil fuels which are carbon intensive as emissions become expensive, thereby increasing investment in clean energy markets.

Carbon pricing sends financial signals to investors regarding the importance of low-carbon investment in the current period as well as in the future. In 2021 revenues of USD 84 billion were raised through global carbon pricing, 60% higher than the 2020 level (World Bank, 2022).

Along with carbon pricing that supports climate action, global carbon increases liquidity in carbon markets and bridges the gap between current and future investment. The global carbon index supports access

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to new assets class which is useful for hedging against the increasing costs of climate change (IHS Markit & CLIFI, 2020). Thus, carbon markets help to achieve carbon neutrality through the efficient allocation of resources (Xia et al., 2023).

For decarbonization of the global economy, measures have been taken to overcome emissions (Tiwari et al., 2022) by increasing the usage of renewable energy (Majeed and Luni, 2019). Non-renewable energy resources are the major sources behind emissions that inhibit efforts toward sustainable development and zero-carbon initiative. Renewable energy supports sustainability through the transformation of energy sector, remodeling energy supply, changing consumption patterns (Tang and Zhou, 2023), decreasing resource dependence (depletion), and ecological degradation (Zhao et al., 2022).

As global warming is increasing and threatening the sustainability of the earth through increasing frequency and intensity of natural disasters causing loss of lives, and capital and initiating economic instability (Le et al., 2023). Therefore, to limit global warming and support sustainability, measures are required at the global level. In this regard, carbon markets and renewable energy can play their roles. Carbon markets support emission reduction (decarbonization) and the development of low carbon technologies (Liu et al., 2023), and renewable energy development in a cost-effective manner (Nie et al., 2021). Besides renewable energy firms are affected by carbon prices because “renewable energy subsidies and emission allowance still account for a considerable portion of the firm’s revenue” (Chun et al., 2022). Not only this global carbon index aims at the convergence in carbon price variation. The convergence in carbon prices is necessary as fluctuating carbon prices adversely affect the use of clean technologies (Guo et al., 2023). Thus, it aims at harmonization of carbon prices across all markets that further supports resource integration (within the economies). Furthermore, different energy sources have varying effects and possess diverse problems regarding their deployment therefore it is important to examine the association between global carbon and various renewable energy sources. As future expectation about carbon constraints affects investment decisions (Trinks et al., 2022), therefore, it is of utmost importance to investigate the spillover and connectedness between renewable energy indices and global carbon to manage risk and optimize portfolios.

This study contributes to the literature in several ways. This is the first study, to the best of our knowledge, that investigates the spillover and connectedness between renewable energy sources (solar, wind, biofuel, fuel cell, and geothermal) and the environment (global carbon). The global carbon index is a better proxy of the environment as it tracks the underlying assets of the most liquid carbon markets and is constructed to be liquid, diversified, and well-suited as a basis for financial products (IHS Markit & CLIFI, 2020). Second, the study also analyzes a special connection between various sources of clean energy and the environment during economic fluctuations particularly the oil crises and COVID-19. Third, the study applies the novel time-varying parameter vector autoregression (TVP-VAR) extended joint connectedness framework to analyze joint connectedness between the environment and renewable energy sources. It is noteworthy that the TVP-VAR extended joint connectedness framework is a better approach as it is not affected by outliers employing the multivariate Kalman filter approach, the window size is not arbitrarily determined, no loss of observations, and accurately determine the values of parameters, VAR coefficients can change gradually and values immediately adjust to events (Antonakakis et al., 2020; Balcilar et al., 2021). Last, the study also conducts robustness analysis using Diebold and Yilmaz (2012) approach.

The remaining study is organized as follows: Literature review is provided in section 2 while data and methodology are explained in section 3. Empirical findings are presented in section 4, while robustness analysis is presented in section 5, and the conclusion is the last section.

2. Literature review

2.1. Theoretical linkages and empirical evidence

Renewable energy ensures the sustainability of the environment through the substitution of carbon-intensive fuels, thereby supporting decarbonization, and promoting climate action (Majeed and Luni, 2019) and resource conservation (Zhao et al., 2022). In 2021, more than 440 billion USD was spent on renewables in the power sector. Although investment in clean energy has increased by 12%, it is still not enough to meet the climate goal (IEA, 2022b) and it should increase threefold from the current rate of deployment (IRENA, 2022).

Uncertainty affects renewable energy markets (Ren et al., 2023), financial markets, assets (Hoque et al., 2022), investment decisions, and the decision about the use of green technologies in the operations of emission-generating industries (Mo et al., 2022). It also changes investor’s behavior in the financial markets thereby changing investment decisions in the renewable energy sector. Similarly, the COVID-19 uncertainty impacted renewable energy stocks (Liu et al., 2022) and increased volatility in energy markets (Salisu and Adediran, 2020). Stock indexes are important as it guides clean energy companies, track the industry’s progress, and its potential role in emission mitigation (Liu et al., 2022). According to Anke and Most (2021), renewable energy sources (RES) are at the core of decarbonization, and the EU emission trade system (ETS) also helps in carbon mitigation through efficient resource allocation. However, uncertainty associated with climate policies causes variability in demand for critical metals that are required for renewable energy (IEA, 2022a) thus adversely affecting clean energy deployment and climate action.

As most of the energy (80%) is produced from non-renewable resources, an increase in the price of non-renewable energy leads to an increase in renewable energy use (Atems et al., 2023). Among non-renewable resources, oil is an important source that affects all other sectors. An increase in the price of oil leads to the use of alternate energy resources particularly clean energy resources (Dogan et al., 2023; Bouoiyour et al., 2023; Dutta, 2017) which causes an increase in the prices of clean energy stocks. As a result, most of the researchers focused on the association between oil price fluctuations and stock market volatility, particularly clean energy stocks and their performance. In this regard, Dutta (2017) showed that a higher uncertainty in oil prices is associated with increased volatility in the returns of equity markets. Although volatility in crude oil prices impact clean energy stock returns but clean energy stock prices are not influenced by emission price volatility. The study of Balcilar et al. (2021) examined the connectedness between agricultural commodities and crude oil prices using the “TVP-VAR based extended connectedness technique”. They reported interconnectedness between the markets as crude oil not only affects these markets but also responds to changes in those markets.

As the use of oil and other fossil fuels contributes to environmental degradation different market measures such as carbon pricing have been introduced to penalize the externalities associated with the use of fossil fuels. Carbon pricing includes carbon taxes, emission trading systems (ETS), carbon crediting mechanisms, and result-based climate finances (RBCF). Carbon taxes are the taxes and excise duties that clearly state the price of carbon while ETS is a policy instrument where industries are obligated to decrease their emissions and can engage in emission trading to meet these emission obligations. The main types of ETS include cap-and-trade and baseline-and-credit. In a cap-and-trade system, a total cap on the emissions is set and emissions units are either “auctioned off or allocated” according to the criteria. An emission unit is surrendered by regulated emitters at each ton of emission. In a baseline-and-credit system, emitters with emissions above the baseline surrender their credits while emitters who can reduce emissions (below the baseline) can sell their credits to other emitters. The carbon crediting mechanism issues tradable emission units to those who voluntarily implement emission reduction activities while RBCF is a type of climate finance where funds are distributed by climate financers to those who achieve a pre-agreed set of climate results (World Bank, 2020).

Carbon prices influence “the stock prices of green energy companies by affecting corporate earnings”. Among various carbon pricing measures, the European Union ETS (EU ETS) results in a decline in emissions while increasing the profitability of renewable energy industries (Chun et al., 2022). Therefore, several studies focused on the connectedness between carbon prices, emission allowance, and green energy stock returns (Dutta et al., 2018; Guo et al., 2020; Hanif et al., 2021; Mo et al., 2022; Chun et al., 2022). By employing a bivariate “vector autoregressive–generalized autoregressive conditional heteroskedastic (VAR-GARCH)” approach, Dutta et al. (2018) documented the positive impact of EU allowance prices on clean energy stock returns, though the association was insignificant. They also reported connectedness between emissions and clean energy indices, but it was country specific. Guo et al. (2020) supported the positive association between firms trading profits and carbon abatement under the cap-and-trade system. They reported the Matthew effect (positive correlation between returns and profits of participants) in allowance trading as firms with higher abatements can have increased profits for carbon allowance however this effect was weak during phase 2 suggesting maturity of the EU ETS. Hanif et al. (2021) reported high spillover between European emission allowance (EEA) prices and clean and wind energy indices over the short run using “D&Y (2012, 2014), Barunik and Krehliks (B&K) and time-varying parameter copulas approach”. They also reported that EEA is the spillover receiver from clean energy. Mo et al. (2022) reported that carbon prices and green energy stock returns are dynamically correlated using quantile techniques and this connectedness is affected by events like COVID-19. According to their findings hedging between the carbon market and the clean energy stock market is beneficial in the short run. Chun et al. (2022) reported a negative association between the prices of carbon-concentrated fuel and clean energy companies, using wavelet methods while focusing on ETS. They also reported an opposite association between coal and carbon prices while a positive association between the price of carbon and clean energy firms. Rasoulinezhad and Taghizadeh-Hesary (2022) used the STRIPAT model to examine the relationship between carbon emissions and the green energy index for the top ten economies. Their findings support a decline in emissions from the green energy index. Although they constructed the energy index by using “Principal Component Analysis (PCA)” of renewable energy consumption from “nuclear, hydropower, solar, wind, and biofuel energy consumption” however they used carbon emissions to measure environmental quality which should have been more comprehensive. Wei et al. (2023) used the TVP-VAR approach to check the connectedness among climate change, carbon emission allowance, renewable energy, and crude oil markets. Their results reveal weak and fluctuating connectedness (during crises including COVID-19) among the examined series while climate change is the shock transmitter. However, their study used EU ETS for emission allowance which only covers EU nations. Not only this they used Wilder Hill clean energy index to represent renewable energy which measures performance of the 40 largest companies in the renewable energy sector including solar, wind, hydropower, and biofuel, and does not include geothermal which also supports decarbonization. Although they considered emission allowance and clean energy but did not focus on the association between these markets and their role in climate mitigation.

In contrast to these studies, Delarue and Van den Bergh (2016) highlighted the waterbed effect of EU ETS as renewable energy policies do not necessarily contribute to a further reduction in emission due to a shift in emissions from the power sector to other sectors in ETS. According to Kumar et al. (2012) an increase in the price of carbon will increase the investment in clean energy stocks however their findings suggest an insignificant impact of carbon prices on change in stock prices of clean energy while the change (increase) in oil prices has a positive impact on clean energy investment. While analyzing the goal of renewable energy sources (RES) and EU ETS for two future scenarios of 2030, Anke and Most (2021) reported that RES results in higher costs and does not contribute to decarbonization while carbon prices rise from 6EUR/t to 26-37EUR/t between 2017 and 2030. Higher carbon prices and coal phase-outs increase the feasibility of RES and thereby decreasing support costs.

Some studies also focused on the impact of economic events and crises on the association between clean energy and the environment. Although crises are unpredictable however they share certain similarities in transmission mechanism (Antonakakis et al., 2020). Dogan et al. (2022a,b) explored the spillover and interconnectedness between green finance and renewable energy indices using the “TVP-VAR extended joint connectedness model”. Their findings support dynamic connectedness being affected by economic events. According to their findings, wind behaved as a shock transmitter to green finances. However, during COVID-19 wind become the net receiver of shocks. Tiwari et al. (2022) analyzed spillover effects among green bonds, renewable energy stocks, and carbon markets during the pandemic period. Using the TVP-VAR framework they also reported the effect of economic events on connectedness among the green bond, renewable energy stocks, and carbon markets. They reported clean energy as the net transmitter of shocks to other markets. Another study by Liu et al. (2022) analyzed the effect of the pandemic’s economic uncertainty on renewable energy stock indexes using Diebold and Yilmaz (2012) and BK methodology for the US, Europe, and the world. Their findings support the significant influence of pandemic-induced unpredictability on renewable energy returns and volatilities. Similarly, Dogan et al. (2022a,b) reported that higher uncertainty caused by the pandemic affected the causal relationship between COVID-19, natural resources, and commodities. The pandemic affected prices and volatilities in the stock and commodity markets using the time-varying Granger causality approach.

Changes in policies affect the operations of industries and carry information regarding physical and transition risks (Diaz-Rainey et al., 2021). Therefore, investors consider climate-related policy changes into consideration while making investment decisions in the energy sector (Ren et al., 2023; Hoque et al., 2022). Uncertainty in climate-related policies causes delays in investments as changes in policies might affect the connectedness between assets. In this regard, another strand of researchers focused on policy changes and energy stock returns. The study of Monasterolo and De Angelis (2020) analyzed the effect of climate-related policies after the Paris Agreement (PA) on low-carbon and carbon-intensive assets in the US, EU, and the world using a multi-factor approach. Before PA low carbon assets were considered riskier however after the agreement the risk-return of these (low carbon) assets has reduced. Improvement in the performance of low carbon indices was observed suggesting a reduction in risk and an increase in mean returns. They reported a decline in connectedness (correlation) between low carbon indices after PA while it remained high for carbon-intensive indices. Similarly, the systematic risk associated with low carbon indices declined while their weights increased when compared to carbon-intensive indices. Hoque et al. (2022) examined the connectedness and spillovers between US climate policy uncertainty and energy stocks and carbon emission future prices before and after PA by employing D&Y (2012) and MGARCH approaches. They reported climate policy uncertainty and world energy indices to be shock transmitters while alternate energy and carbon markets as shock receivers. Dogan et al. (2023) reported a decline in renewable energy consumption in EU countries from environmental taxes, energy taxes, and carbon emissions while oil prices contribute to renewable energy consumption using FMOLS and DOLS techniques.

Although some studies examined the connectedness between oil prices and stock markets (Dutta, 2017), crude oil, agriculture and commodity markets (Balcilar et al., 2021), carbon prices, emission allowance, and clean energy (Mo et al., 2022; Chun et al., 2022; Anke and Most, 2021; Hanif et al., 2021; Guo et al., 2020; Dutta et al., 2018; Delarue & Van den Bergh, 2016; Kumar et al., 2012), carbon emission and clean energy (Rasoulinezhad and Taghizadeh-Hesary, 2022) while

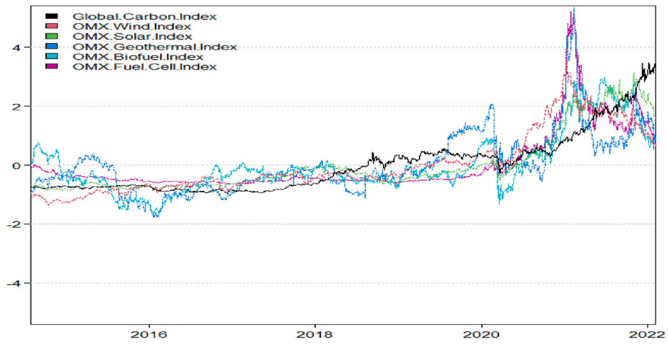

Fig. 1. Trends of the dataset.

others examined the impact of uncertainty caused by climate policy and events including the pandemic on the stock market and connectedness between various commodities including clean energy and green finance (Dogan et al., 2022a,b; Tiwari et al., 2022), natural resource and commodities (Dogan et al., 2022a,b), uncertainty and clean energy stocks (Liu et al., 2022), energy stock and carbon emissions (Hoque et al., 2022), PA on low carbon and carbon-intensive assets (Monasterolo and De Angelis, 2020), critical metals, clean energy and dirty energy (Ghosh et al., 2023), none of the studies examined the connectedness and shock transmission between renewable energy indices and global carbon index which is offered by this study.

2.2. Literature gaps

Although the study of Hanif et al. (2021) examined the spillovers and connectedness between carbon prices and clean energy, they did not consider the global carbon index which is a better proxy for the environment as it aims at convergence in carbon price variation. The convergence in carbon prices is necessary as fluctuating carbon prices in carbon trading adversely affect the use of low-carbon technologies (Guo et al., 2023). The variability in carbon prices hinders the potential of carbon markets in abating emissions and promoting low carbon technologies.

Furthermore, different renewable sources can have different effects and challenges in deployment therefore it is important to examine which sources are shock receivers/transmitters as it leads to a better approach in diversification of risk and can support government decisions related to supporting renewable energy sources under normal condition as well as under economic uncertainty. Thus, this study analyzed the connectedness between the environment and clean energy sources.

3. Data and methodology

3.1. Dataset

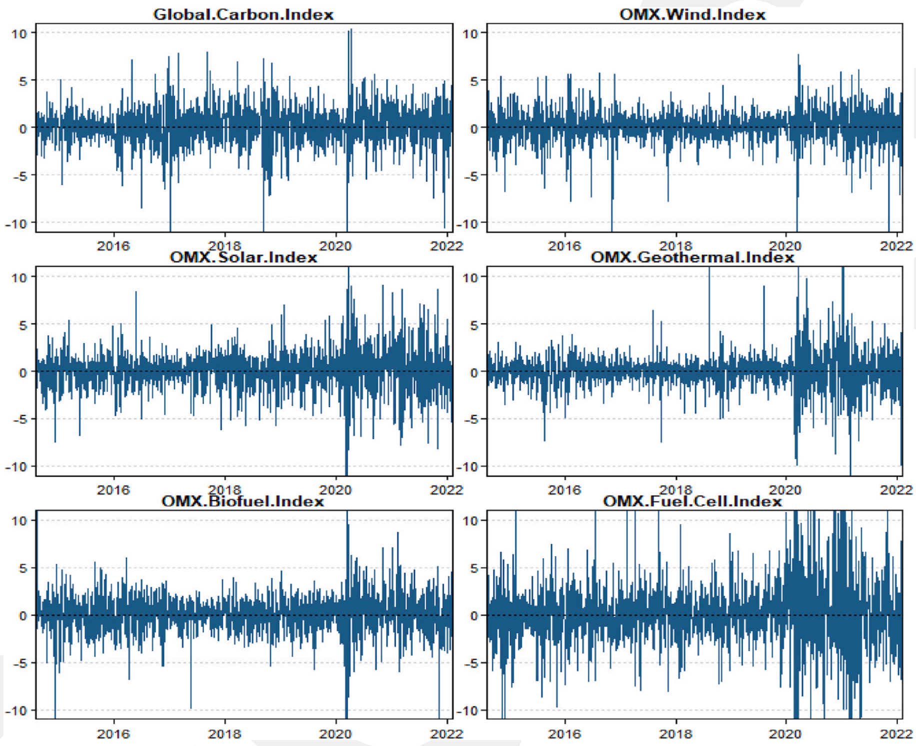

Fig. 2. Return trends of the dataset.

To fill the contributions, our study uses IHS Markit Global Carbon Index as a representative of the environment and various sources of renewable energy; Bio Fuels Index, Fuel Cell Index, Geothermal Index, Solar Index, and Wind Index by NASDAQ OMX. We use daily data over the period from August 01, 2014 to February 04, 2022. The global carbon index is a better proxy of the environment as it tracks the underlying assets of the most liquid carbon markets and is constructed to be liquid, diversified, and well-suited as a basis for financial products. Moreover, RESs are at the core of decarbonization, for decarbonization of the global economy facing climate change measures have been taken to overcome emissions through an increase in the use of renewable energy (Majeed and Luni, 2019; Anke and Most, 2021; Tiwari et al., 2022). Non-renewable energy resources are the major source behind emissions and a hurdle towards sustainable development and zero-carbon initiative, to overcome this transition to RESs ("solar, wind, geothermal, hydropower, and biofuel") is required. The dataset can be obtained from DataStream.[1] Fig. 1 illustrates the time trends while Fig. 2 shows the

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[1] https://www.refinitiv.com/en/.

Table 1
Summary statistics.

	Global Carbon	Wind	Solar	Geothermal	Biofuel	Fuel Cell
Mean	0.113	0.04	0.08	0.02	0.01	0.05
Variance	4.129	2.81	4.77	3.53	4.46	12.42
Skewness	−0.448***	−0.74***	−0.63***	0.57**	−1.03***	0.52**
Kurtosis	5.005***	6.608***	7.552***	13.375***	10.842***	6.345***
JB	1967.122***	3490.658***	4458.963***	13709.575***	9263.159***	3143.695***
ERS	−16.800***	−11.363***	−18.641***	−9.018***	−13.458***	−17.658***
Q(20)	17.843**	17.680**	61.067***	43.714***	80.096***	23.260***
$Q^2(20)$	214.967***	151.333***	1110.718***	256.477***	1525.185***	401.719***

Notes: ***, **, and * depict the level of significance at 1%, 5% and 10%, respectively.

Table 2
Averaged Joint Connected Table – Full sample.

	Global Carbon	Wind	Solar	Geothermal	Biofuel	Fuel Cell	FROM
Global Carbon	89.61	2.62	2.50	1.47	2.12	1.68	10.39
Wind	2.10	76.08	7.72	4.20	5.46	4.44	23.92
Solar	2.30	7.55	60.33	8.00	11.71	10.11	39.67
Geothermal	1.44	4.13	7.84	75.96	6.24	4.39	24.04
Biofuel	2.06	5.56	11.77	6.16	67.94	6.51	32.06
Fuel Cell	1.59	4.08	10.41	4.36	6.53	73.03	26.97
TO	9.49	23.94	40.24	24.19	32.05	27.14	157.05
NET	−0.90	0.03	0.57	0.15	−0.01	0.17	TCI
NPDC	0.00	2.00	4.00	3.00	3.00	3.00	26.17

volatility in the returns. It can be seen from Figure (1) and Figure (2) that high volatility is observed during the oil crisis and COVID-19 pandemic.

3.2. *Methodology*

Antonakakis et al. (2020) proposed a time-varying parameter vector autoregression (TVP-VAR) framework which was recently adapted by Balcilar et al. (2021) and initiated the procedure helping from Lastrapes and Wiesen (2021). By and large, a scaling parameter λ_t estimated through $S^{gen,to}_{i\to\bullet,t}$ is established by Lastrapes and Wiesen (2021). The estimation of the scaling parameter λ_t is given by:

$$g\widetilde{SOT}_{ij,t} = \lambda_t gSOT_{ij,t} \tag{1}$$

$$\text{with } \lambda_t = \frac{jSOI_t}{\frac{1}{K}\sum_{i=1}^{K}\sum_{j\neq i}^{K} gSOT_{ij,t}} = \frac{jSOI_t}{gSOI_t} \tag{2}$$

Moreover, first, we calculate the total directional connectedness (TDC) and afterward the net total directional connectedness (NTDC):

$$TDC => S^{jnt,to}_{i\to\bullet} = \sum_{j=1,i\neq j}^{K} g\widetilde{SOT}_{ij,t} \tag{3}$$

$$NTDC => S^{jnt,net}_{i,t} = S^{jnt,to}_{i\to\bullet,t} - S^{jnt,from}_{i\leftarrow\bullet,t} \tag{4}$$

However, the above (equations (3) and (4)) models may not estimate the net directional pairwise spillovers. In order to eliminate this problem, Balcilar et al. (2021) calculated the TVP-VAR procedure via an extended joint connectedness approach and proposed the generalized scaling parameter λ_t which is given by:

$$\lambda_i = \frac{S^{jnt,from}_{i\leftarrow\bullet,t}}{S^{gen,from}_{i\leftarrow\bullet,t}} \tag{5}$$

$$\lambda = \frac{1}{K}\sum_{i=1}^{K}\lambda_i \tag{6}$$

Finally, the estimated net total and pairwise directional connectedness can be described as follows:

$$S^{jnt,net}_{i,t} = S^{jnt,to}_{i\to\bullet,t} - S^{jnt,from}_{i\leftarrow\bullet,t} \tag{7}$$

$$S^{jnt,net}_{i,t} = gSOT_{ji,t} - gSOT_{ij,t\bullet} \tag{8}$$

The TVP-VAR procedure can measure the system wide spillovers which was lacking in DY (Diebold and Yilmaz) generalized spillover index. The DY index provides misleading information regarding aggregate spillovers as it is bounded by 0 and 100 percent. Therefore, when a shock is introduced to an individual variable it leads to variation in other factors and leaves behind the factor to which the variation was introduced (Balcilar et al., 2021).

A first look of the variables is given in Table 1. The mean of all the series is positive with the highest mean recorded for global carbon (0.113) followed by OMX solar (0.080), OMX fuel cell (0.045), OMX wind (0.044), OMX geothermal (0.020) and OMX biofuel (0.010). OMX fuel cell represents the highest volatility (12.420) in the returns among all the series. The skewness values suggest that most of the series (global carbon, OMX wind, OMX solar, and OMX biofuel) are negatively skewed except for the few series (OMX geothermal and OMX fuel cell) which are positively skewed. The return followed the leptokurtic distribution (as the kurtosis value for most of the series is greater than 3). This suggests that the series are not normally distributed which is also evident from the JB statistics. The ERS test suggests that all series are stationary in their returns. Furthermore, Fisher and Gallagher (2012) weighted portmanteau test indicate that all the series are autocorrelated and have ARCH/GARCH errors. Thereby, justifying the need of using the TVP-VAR model.

4. Empirical findings

Table 2 presents averaged joint connectedness findings for the global carbon model (full sample). The elements in the main diagonal represent the contribution of the series while all off-diagonal elements represent the effect from or to other series. The rows in the table present the contribution of each index to the "forecast error variance" of other indexes in the network while the columns present the contribution of one index to other indexes individually (Dogan et al., 2022a,b; Balcilar et al., 2021). It can be noted from table (2) that OMX solar (40.24%) transmits the highest value of shocks followed by OMX biofuel (32.05%) while the

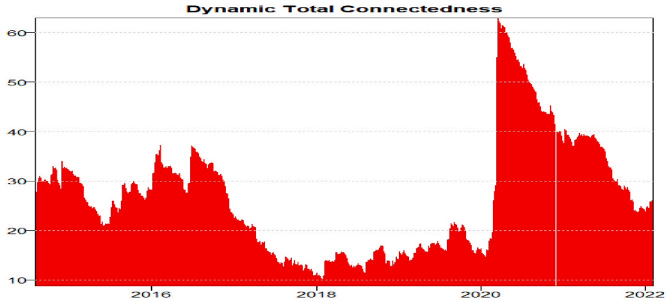

Fig. 3. Dynamic total connectedness-Global Carbon model (Full sample)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

lowest shocks are transmitted from the global carbon (9.49%) followed by OMX wind (23.94%) to other markets. The highest spillover shocks are observed from OMX solar to OMX biofuel (11.77%) followed by OMX biofuel to OMX solar (11.71%). While examining the impact of different renewable energy (clean energy) stocks on global carbon (environment) we observe that wind transmits the greatest impact to global carbon (2.62%) followed by OMX solar (2.50%), and OMX biofuel (2.12%). The shocks transmitted from the OMX fuel cell and OMX geothermal to global carbon stand at 1.68% and 1.47% respectively. The evidence suggests the connectedness between renewable energy and environment markets. Tiwari et al. (2022) also support connectedness and spillover between the environment (CO_2) and renewable energy markets.

While focusing on the shock transmission mechanism from the environment (global carbon) to renewable energy stocks, it is observed that global carbon transmits 2.10% shocks to OMX wind, 2.30% shocks to OMX solar, 1.44% shocks to OMX geothermal, 2.06% to OMX biofuel and 1.59% to OMX fuel cell. Thus, the least shocks from global carbon are transmitted to OMX geothermal. The transmission of shocks from renewable energy stocks to global carbon is greater than shocks transmitted from global carbon to renewable energy stocks suggesting the dominance of clean energy markets over the carbon markets. Tiwari et al. (2022) also reported similar results regarding the transmission of shocks from renewable energy markets to CO_2. Similarly, Nie et al. (2021) also reported the information transmission role of clean energy to carbon markets. They suggested a higher degree of information spillover to carbon markets as changes in price in the energy (clean) market will cause changes in returns in the carbon markets. This dominance of renewable energy is due to increased investment resulting from policy support (Tiwari et al., 2022). Similarly, environmental regulation policies also support renewable energy development use (Zhao et al., 2022). The TCI is 26.17% suggesting that on average 26.17% of the shocks from one variable spill to others. It is also worth mentioning that global carbon and OMX biofuel are the net receivers of shocks (0.90% and 0.01%) while OMX wind, OMX solar, OMX geothermal, and OMX fuel cell are the net transmitter of shocks (0.03, 0.57, 0.15, 0.17). The finding suggests the dominance of clean energy markets over the global carbon market.

Furthermore, the main diagonal values suggest that 89.61% of the index evolution of global carbon is caused by within-index shocks while 10.39% of the index movement is caused by network connections. As also highlighted by Lyu and Scholtens (2022) the dynamics of the carbon markets are explained by itself rather than others. In the case of renewable energy returns, it can be observed that 76.08% of OMX wind, 60.33% of OMX solar, 75.96% of geothermal, 67.94% of OMX biofuel, and 73.03% of the OMX fuel cell is caused by within index shocks, thus suggesting that most of the index movement in renewable energy is caused by network connections when compared to global carbon. However, Philips (2023) showed that most of the shocks in energy stocks are network driven.

The average connectedness results might mask the impact of economic events on the network (study model) under consideration, therefore, to overcome this it is worthwhile to examine the dynamic total connectedness of global carbon which is presented in figure (3). The dynamic total connectedness not only helps in understanding the changes in the total connectedness index (TCI) of the network over time but also explains the variation in the role of variables within the network over time, alternatively it examines the influence of variable changes within the network over time. The shaded region in figure (3) captures the changes in TCI. It can be observed that there is considerable variation in TCI values ranging between 10% and 63% over the study period, with the lowest TCI value being observed in 2018 and the highest value of TCI at the beginning of 2020 (COVID-19 period). The changes in TCI values support the responsiveness of the index to the major economic events suggesting an increase in connectedness in the face of uncertainty

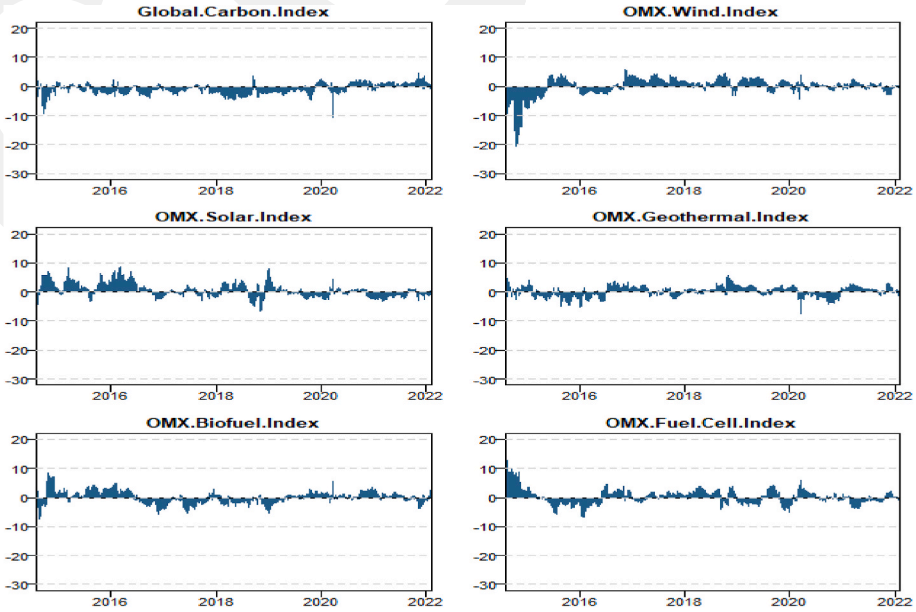

Fig. 4. Dynamic net total directional connectedness-Global Carbon model (Full sample)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

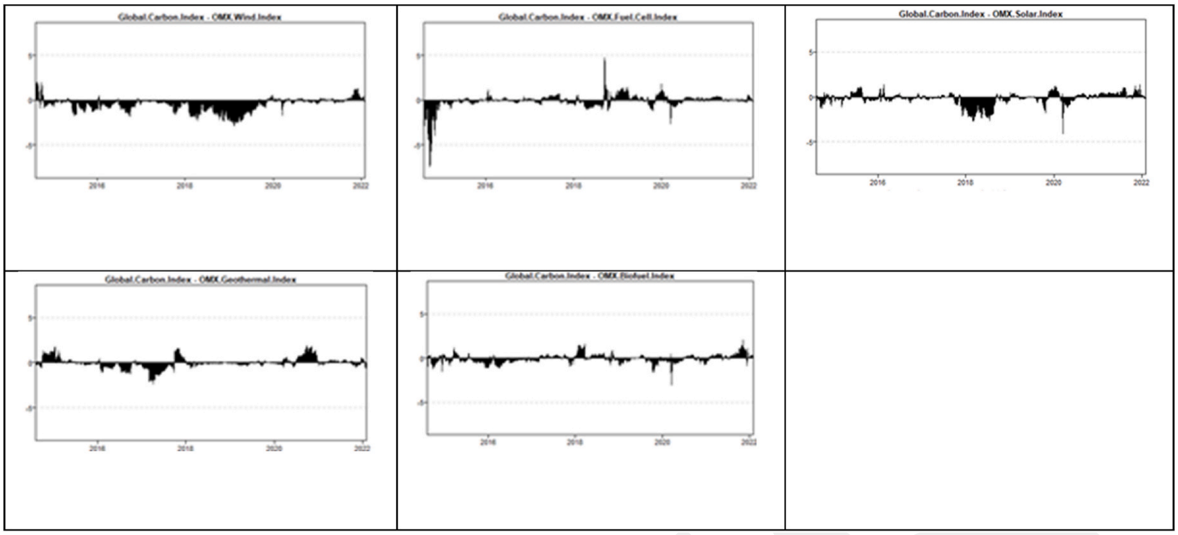

Fig. 5. Dynamic net pairwise directional connectedness-Global Carbon model (Full sample).

caused by economic events. These findings are also reported by Balcilar et al. (2021), Tiwari et al. (2022), and Dogan et al. (2022a,b) as they also supported higher connectedness during the crises (Oil crisis, Brexit referendum, and COVID-19) period when compared to normal periods. The higher connectedness during the crisis is because of the over-interpretation and transmission of information by the participants (Wei et al., 2023). This high TCI value shows a high spillover between renewable energy and the environment (global carbon) suggesting increased volatility fueled by the crisis.

The results obtained from dynamic net total directional connectedness for the full sample are presented in figure (4). This analysis depicts the role of indices as net shock receivers and transmitters and changes in these roles over the study period. The positive value suggests the role of indices as a net shock transmitter while the negative value suggests the role of indices as a net shock receiver. It can be observed from figure (4) that none of the indices solely act as a net shock receiver or transmitter. Global carbon and OMX wind index act as net shock receivers in the beginning while OMX solar, OMX geothermal, OMX biofuel and OMX fuel cell indices act as net shock transmitters during the same period. The global carbon index appears to be a net receiver for most of the period under consideration except for the beginning, with few spikes by the end of 2018 and the start of 2020. However, after the mid of 2020, global carbon seems to be a shock transmitter. OMX wind receives shocks during 2014 and mid of 2015 and between 2016 and 2017 while in the other periods, it is a net shock transmitter. In most of the periods, OMX wind is the shock transmitter. In the case of OMX solar, OMX geothermal, OMX biofuel, and OMX fuel cell, switching between the roles of net shock receiver and transmitter is observed. This switching behavior is like the findings of Tiwari et al. (2022) who also reported the constantly evolving role of the carbon and energy markets.

Now we examine the dynamic net pairwise directional connectedness for the full sample. It tells us about the role played by each market with respect to other markets in the network. Specifically, figure (5) highlights the impact of one market on the other within the network and tells us about both roles (receiver and transmitter) assumed by global carbon, suggesting that it impacts clean energy indices as well as is sensitive to the revolutions existing in those markets (renewable energy). The dynamic pairwise directional connectedness between global carbon and OMX wind indices suggests that global carbon is the shock receiver from OMX wind during the period (August 2014 to February 2022). While global carbon is the shock receiver from 2014 till 2019 and afterward is a shock transmitter to OMX fuel cell. In the case of pairwise directional connectedness between the global carbon and OMX solar, OMX geothermal, and OMX biofuel indices it is observed that there is quite a switching between the roles from receiver to the transmitter by global carbon. These findings support a relatively dominant interconnectedness between clean energy and the environment.

Although the crisis is unpredictable, they do share certain similarities in transmission mechanisms (Antonakakis et al., 2020) and affect investors risk behavior (Gosh et al. 2023). Therefore, to capture the connectedness between global carbon and renewable energy indices during the oil crisis an analysis has been conducted for the period between August 1st’ 2014, till December 29th’ 2016 (Table 3). It is noted from table (3) that OMX solar (48.98%) delivers the highest degree of shocks to others followed by OMX biofuel (36.50%) which is consistent with our previous findings and results of Caporale et al. (2022) as they also reported solar energy as the highest shock transmitter to other markets. However, the magnitude of shocks is higher during the crisis than during normal periods. The lowest shocks are transmitted from the global carbon (7.54%). Thus 48.98% of forecast error variance resulted from OMX solar while global carbon has a minimal impact on renewable energy markets as it transmits only 7.54% of “forecast error variance” to

Table 3
“Averaged Joint Connected” – Oil crisis.

	Global Carbon	Solar	Biofuel	Fuel Cell	Wind	Geothermal	FROM
Global Carbon	90.87	1.84	2.00	0.99	2.94	1.36	9.13
Wind	2.32	10.74	7.12	3.88	70.88	5.06	29.12
Solar	1.73	53.06	13.40	13.43	10.19	8.20	46.94
Geothermal	1.35	8.71	6.85	4.83	5.21	73.05	26.95
Biofuel	1.59	13.10	64.87	6.74	6.95	6.74	35.13
Fuel Cell	0.55	14.58	7.14	69.45	3.39	4.88	30.55
TO	7.54	48.98	36.50	29.88	28.68	26.24	177.83
NET	−1.59	2.04	1.38	−0.67	−0.45	−0.71	TCI
NPDC	0.00	4.00	5.00	2.00	2.00	2.00	29.64

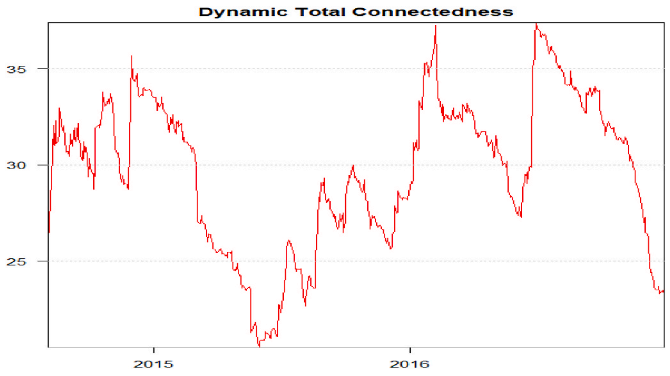

Fig. 6. Dynamic total connectedness-Global Carbon model (Oil crisis)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

other markets. The highest spillover shocks are observed from OMX solar to the OMX fuel cell (14.58%). While examining the impact of different renewable energy stocks on global carbon it is observed that OMX wind transmits the largest shocks to global carbon (2.94%). It is also observed that there is an increase in the intensity of shock transmission from 2.62% in the full sample model (Table 2) to 2.94% (oil crisis model) in the case of OMX wind to global carbon while shock transmission from other renewable markets has declined in magnitude. The evidence still suggests the connectedness between clean energy and the environment. Tiwari et al. (2022) supported connectedness and spillover between the environment and renewable energy markets however Kumar et al. (2012) reported an insignificant effect of carbon prices on clean energy stock prices.

While focusing on the shock transmission mechanism from the global carbon to renewable energy stocks, it is observed that the highest shocks of 2.32% from global carbon are transmitted to OMX wind. The transmission of shocks from renewable energy stocks to global carbon is greater than shocks transmitted from global carbon to renewable energy stocks. The TCI is 29.64% suggesting an increase during the oil crisis when compared to the full model (26.17%). During the oil crisis, the global carbon, OMX wind, OMX geothermal, and OMX fuel cell are the net receiver of shocks while OMX solar and OMX biofuel are the net transmitter of shocks.

Furthermore, the main diagonal values suggest that 90.87% of the index evolution of global carbon is caused by within-index shocks while 9.13% of the index movement is caused by network connections. In the case of renewable energy returns, it can be observed that 70.88% of OMX wind, 53.06% of OMX solar, 73.05% of geothermal, 64.87% of OMX biofuel, and 69.45% of the OMX fuel cell is caused by within index shocks, thus suggesting that most of the index movement in renewable energy is caused by network connections when compared to global carbon. It can be observed that the index movement caused by network connections in renewable energy is greater during the oil crisis when compared to the normal period (full sample). Likewise, Caporale et al. (2022) also reported higher connectedness of renewable energy indices because of climate change policies.

The dynamic total connectedness of global carbon during the oil crisis is presented in figure (6). The shaded region in figure (6) suggests considerable variation in TCI values ranging between 1% and 40% over the study period, with the lowest TCI value being observed in mid of 2015 and the highest value of TCI in the beginning and mid of 2016. The changes in TCI values support the responsiveness of the index to the oil crisis suggesting an increase in connectedness between the markets. These findings are also reported by Balcilar et al. (2021), Tiwari et al. (2022), and Dogan et al. (2022a,b) as they also supported higher connectedness during the crises period (Brexit referendum and pandemic period) when compared to normal periods. This high TCI value shows a high spillover between the environment and renewable energy.

The results obtained from dynamic net total directional connectedness during the oil crisis are presented in figure (7). It can be observed from figure (7) that only the global carbon index acts as a net shock receiver while renewable energy assumes both roles (net shock receiver and transmitter). Carbon prices act as net receiver of shocks from clean energy indices (Hanif et al., 2021) and electricity companies (Ji et al., 2019). OMX wind and OMX fuel cell indices act as net shock transmitters in the beginning while OMX solar, OMX geothermal, and OMX biofuel indices act as net shock receivers during the same period. OMX solar is the shock transmitter for most of the period when compared to other indices. OMX geothermal receives shocks for most of the period from the beginning while transmitting shocks during the last few months of 2016. OMX biofuel transmits shocks for most of the period except for the beginning and end of the period where it receives shocks from the other markets. OMX fuel cell index transmits shocks during the start and end of the period while receiving shocks during the mid (most of the) period under consideration.

The dynamic net pairwise directional connectedness between renewable energy and the environment during the oil crisis is presented in figure (8). The dynamic pairwise directional connectedness between global carbon and OMX wind and global carbon and OMX fuel cell index suggests that global carbon is the shock receiver from both OMX wind and OMX fuel cell. While in the case of OMX solar, OMX geothermal,

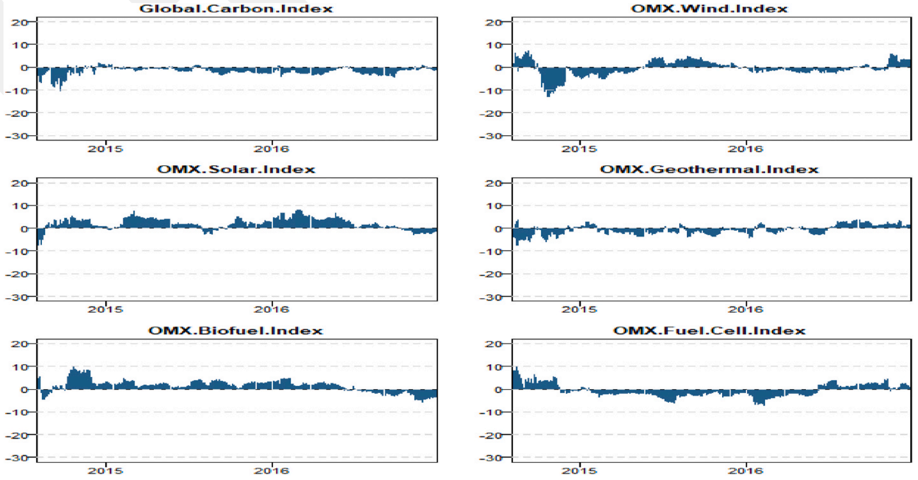

Fig. 7. “Dynamic net total directional connectedness”-Global Carbon model (Oil crisis)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

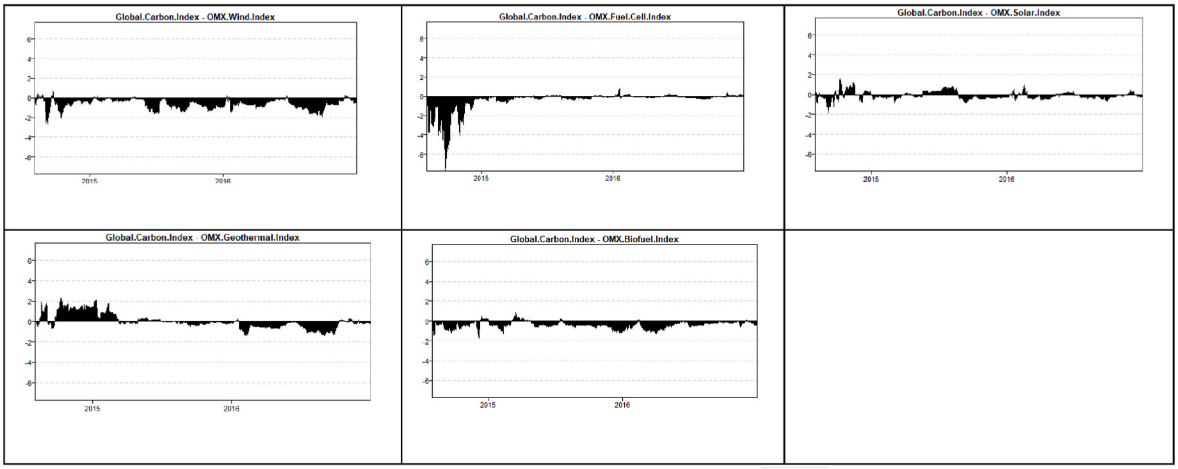

Fig. 8. Dynamic net pairwise directional connectedness-Global Carbon model (Oil crisis).

Table 4
“ble – COVID-19”

	Global Carbon	Wind	Solar	Geothermal	Biofuel	Fuel Cell	FROM
Global Carbon	91.97	1.32	1.80	1.28	2.05	1.58	8.03
Wind	1.63	77.23	7.50	2.56	2.16	8.92	22.77
Solar	2.10	7.00	65.26	7.70	7.55	10.39	34.74
Geothermal	0.99	2.23	8.07	66.13	9.28	13.31	33.87
Biofuel	1.97	2.20	7.65	9.28	66.85	12.06	33.15
Fuel Cell	1.34	7.14	11.12	13.78	12.15	54.47	45.53
TO	8.03	19.89	36.14	34.60	33.19	46.25	178.09
NET	0.00	−2.88	1.40	0.73	0.03	0.72	TCI
NPDC	2.00	1.00	4.00	4.00	2.00	2.00	29.68

OMX biofuel, and global carbon the pairwise directional connectedness suggests the change in roles from receiver to transmitter over time suggesting the interconnectedness between the global carbon and renewable energy markets.

As extreme events affect investment decisions (Ghosh et al., 2023), therefore the study also captured the connectedness between renewable energy indices and global carbon during the COVID-19 crisis (Table 4) between January 5th’ 2021, till February 4th’ 2022. Table (4) suggests that OMX fuel cell (46.25%) delivers the highest value of shocks to other markets followed by OMX solar (36.14%), during COVID-19 while OMX solar (40.24%) followed by OMX biofuel was the highest transmitter of shocks in the full sample. Furthermore, OMX wind become a receiver and OMX biofuel acted as a shock transmitter (Table 4) during COVID-19 while in the full sample (Table 2) OMX wind was a net transmitter and OMX biofuel was a shock receiver. It is noteworthy that during the pandemic period, TCI increased to 29.68% which is higher than reported in table (2), (26.17%). The higher TCI shows an increase in dependence between the network members suggesting a higher level of risk in the market (Akyildirim et al., 2022). Table (4) reports a decline in main diagonal values in most of the cases when compared to table (2) suggesting an increase in index movement in global carbon and renewable energy caused by network connections during the pandemic. Akyildirim et al. (2022) also reported shocks in energy markets to be network driven during the pandemic. Mo et al. (2022) also reported the effect of the pandemic on the connectedness between carbon prices and green energy stock returns. Similarly, higher connectedness was reported between metal and energy markets and between commodity markets during COVID-19 by Ghosh et al. (2023) and Ghazani et al. (2023). The increased connectedness during the pandemic is because of the transmission of financial stress to the markets caused by lockdowns as these measures affect economic activities by postponing investment and consumption decisions (Akyildirim et al., 2022).

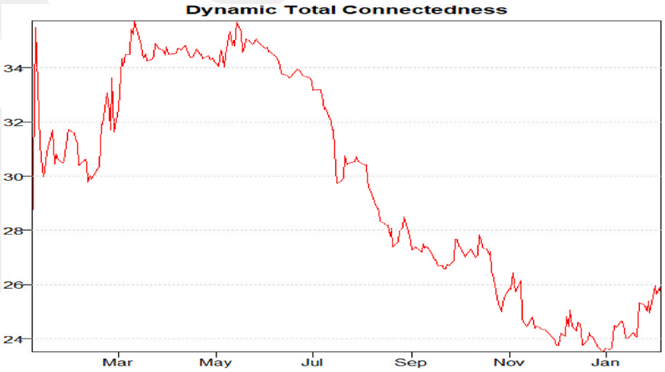

Fig. 9. “Dynamic total connectedness”-Global Carbon model (Covid-19 period).

The dynamic total connectedness of renewable energy and global carbon during the COVID-19 pandemic is presented in figure (9). Figure (9) presents the considerable variation in TCI values ranging between 23% and 36% during the pandemic period, with the lowest TCI value being observed in January 2022 while the highest value of TCI is observed in March and May 2021. The changes in TCI values support the responsiveness of the index to the pandemic period suggesting an increase in connectedness among the considered markets. Similarly, Balcilar et al. (2021), Tiwari et al. (2022), and Dogan et al. (2022a,b) also reported higher connectedness during the crises period when compared to normal periods. Similarly, Bouoiyour et al. (2023) also reported increased connectedness between clean energy and oil markets during the COVID-19 crisis.

The results in figure (10) show that only OMX wind is a net shock receiver during the pandemic period. Global carbon is a net shock receiver from January to June 2021 while is a net shock transmitter from

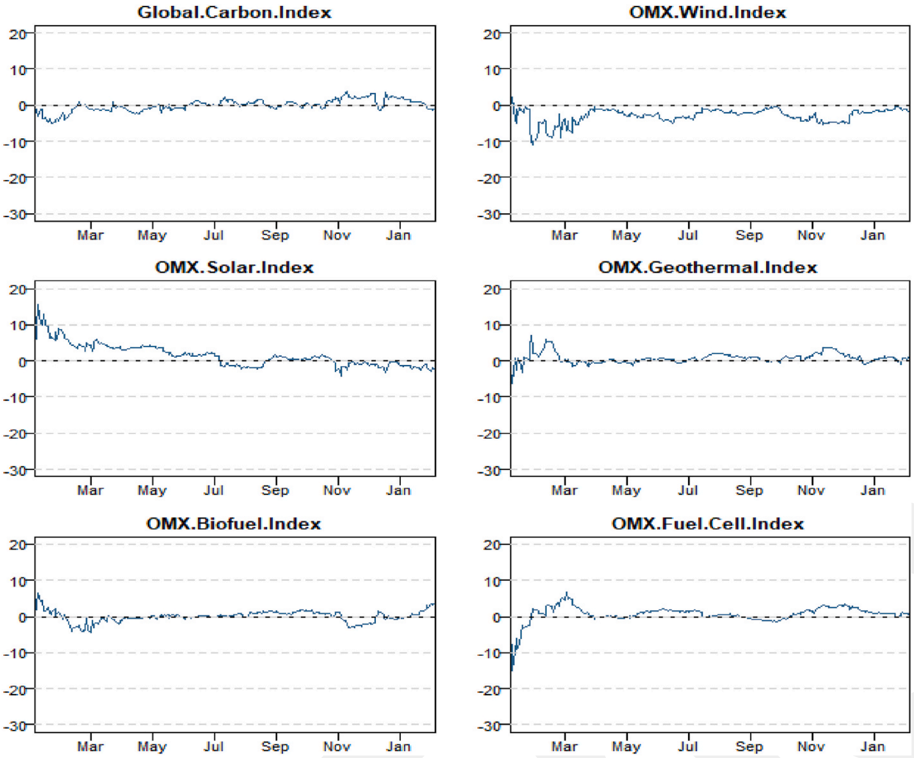

Fig. 10. "Dynamic net total directional connectedness"-Global Carbon model (Covid-19 period).

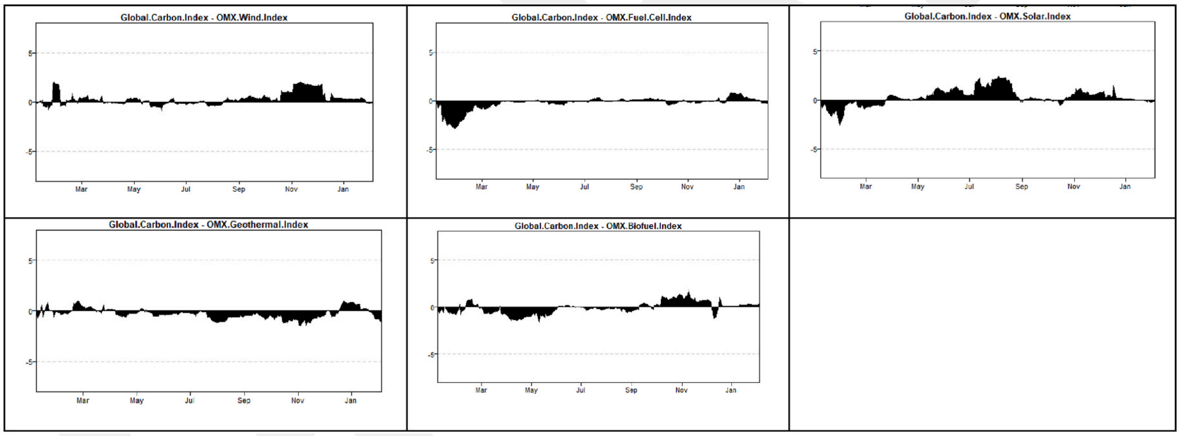

Fig. 11. "Dynamic net pairwise directional connectedness"-Global Carbon model (Covid-19 period).

June to February 2022. OMX solar, OMX geothermal, OMX biofuel, and OMX fuel cell act as net transmitter and net receivers, and these roles changes during the analyzed period.

Figure (11) presents findings for the COVID-19 crisis. The dynamic pairwise directional connectedness between global carbon and OMX wind index suggests that global carbon is the shock transmitter to OMX wind. While global carbon is the shock receiver from OMX fuel cell between January till July and October till December (2021) while behaving as a shock transmitter between July and August, and December till February (2022). Similarly, in the case of pairwise directional connectedness between the global carbon and OMX solar, OMX geothermal, and OMX biofuel indices it is observed that there is quite a switching between the roles from receiver to the transmitter by global carbon. Thus, supporting interconnectedness among the markets.

5. Robustness analysis

To check the robustness of our findings we applied the connectedness approach by Diebold and Yilmaz (2012) which can capture returns and volatility spillover effect (Hoque et al., 2022). It helps to measure interdependence across variables helping in analyzing the idiosyncratic and influence of others. Furthermore, it provides results for aggregate, directional, and net interdependence (Antonakakis et al., 2020). In simple words, it helps in the quantification of "*the intensity and direction of spillovers across different asset markets*" (Liu et al., 2022) thereby distinguishing between net shock transmitter and receiver and helping in understanding the underlying changes. The generalized averaged joint connected table (5) provides the findings of multiple spillover summary measures.

The lower diagonal in Table 5 presents the values for stocks. When compared to the findings reported in Table 2 the TCI value is higher (32.39%) than reported in Table 2 (26.17%) suggesting the increase in

Table 5
Robustness Averaged Joint Connected Table (Full sample).

	Global Carbon	Wind	Solar	Geothermal	Biofuel	Fuel Cell	FROM
Global Carbon	81.80	4.54	4.20	2.55	4.18	2.73	18.20
Wind	2.97	69.18	9.45	5.42	7.09	5.90	30.82
Solar	2.71	8.15	58.48	8.36	12.24	10.06	41.52
Geothermal	2.08	5.94	10.03	67.14	8.71	6.10	32.86
Biofuel	2.63	7.03	13.05	7.32	62.47	7.51	37.53
Fuel Cell	2.32	5.74	11.80	5.50	8.05	66.58	33.42
TO	12.70	31.41	48.53	29.14	40.27	32.29	194.34
NET	−5.49	0.58	7.01	−3.72	2.74	−1.12	TCI
NPDC	0.00	2.00	5.00	1.00	4.00	3.00	32.39

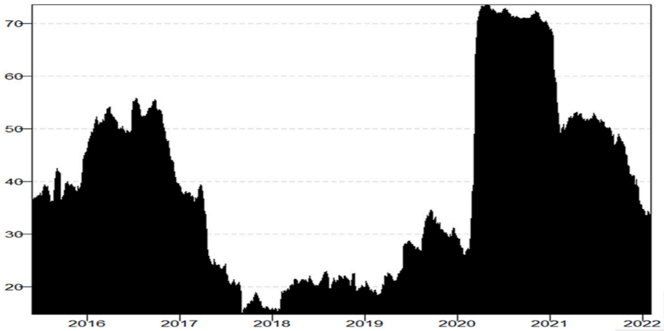

Fig. 12. Dynamic total connectedness-Global Carbon model (Full sample)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

explanation of development in the network by a network of indices (global carbon and renewable energy) under consideration. Alternatively, 32.39% of the forecast error variance within the network of the variable under consideration is the "product of cross-market innovation". The idiosyncratic effect is almost 67% of the "forecast error variance" of the network. This leads to the conclusion that co-movement in future contracts of these markets will be observed. While examining the contribution to other assets from each specific asset, the total guiding spillover sent to others from each specific asset ranges from 12.70% from global carbon to 48.53% for OMX solar. The highest forecast error variance of about 48.53% and 40.27% is attributed to OMX solar and OMX biofuel while global carbon transmits the lowest forecast error variance of about 12.70% to other markets.

Furthermore, table (5) shows that on net terms OMX solar (7.01%), OMX biofuel (2.74%), and OMX wind (0.58%) act as net shock transmitters in the system (on net terms they affect other markets instead of

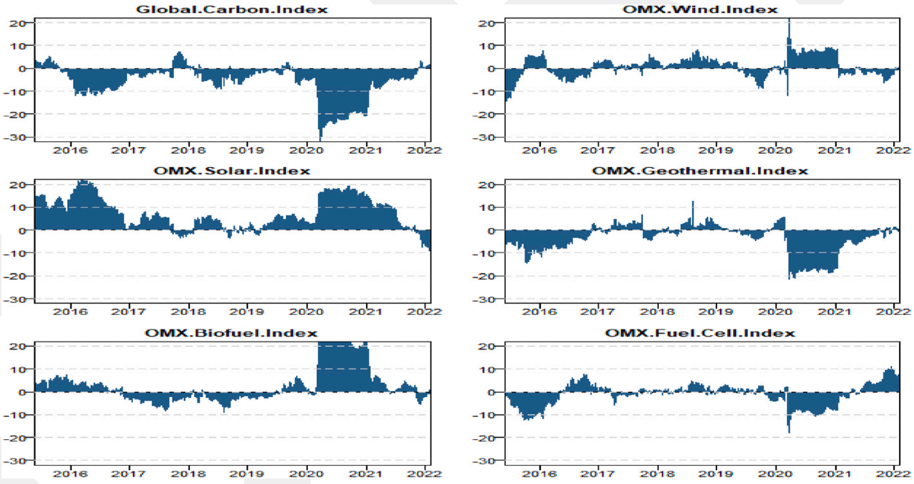

Fig. 13. Dynamic net total directional connectedness-Global Carbon model (Full sample)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

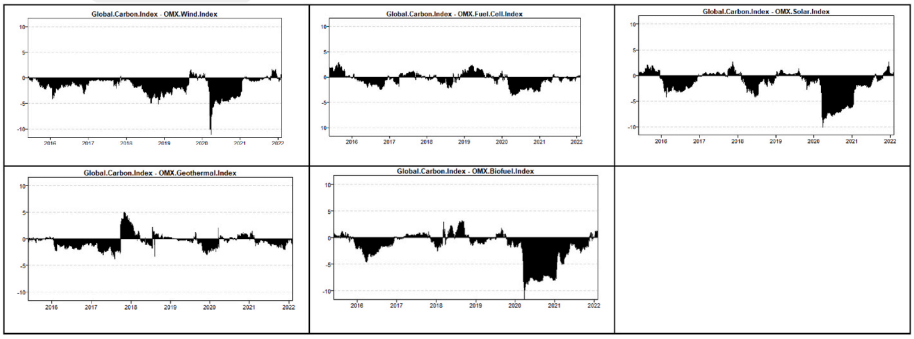

Fig. 14. Dynamic net pairwise directional connectedness- Global Carbon model (Full sample).

Table 6
Robustness Averaged Joint Connected Table – Oil crisis.

	Global Carbon	Wind	Solar	Geothermal	Biofuel	Fuel Cell	FROM
Global Carbon	84.06	5.18	3.42	2.75	3.51	1.07	15.94
Wind	3.60	61.09	13.88	7.00	9.60	4.83	38.91
Solar	2.55	10.64	52.62	8.37	13.26	12.56	47.38
Geothermal	2.05	7.32	11.81	61.76	9.40	7.66	38.24
Biofuel	2.36	8.87	15.18	8.28	56.76	8.54	43.24
Fuel Cell	0.85	4.20	16.32	6.56	9.24	62.82	37.18
TO	11.41	36.20	60.61	32.97	45.02	34.66	220.88
NET	−4.52	−2.71	13.24	−5.27	1.79	−2.52	TCI
NPDC	0.00	2.00	5.00	1.00	4.00	3.00	36.81

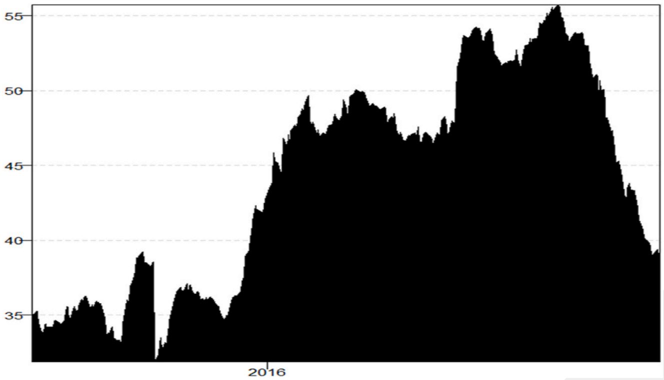

Fig. 15. Dynamic total connectedness-Global Carbon model (Oil crisis)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

being affected by other markets). On average OMX solar is the most important net transmitter of shocks. OMX fuel cell (1.12%), OMX geothermal (3.72%), and global carbon (5.49%) act as net shock receivers, and on average global carbon is the most important net receiver of shocks in the network.

The outcomes obtained from dynamic total connectedness (Fig. 12) suggest higher volatility in connectedness when compared to the normal period (2018) as TCI approaches a high peak at 75% between 2020 and 2021. Similarly, during the oil crisis, the connectedness increased to 55% (2014–2016) as suggested by higher TCI value. Thus these (two) high peaks (higher TCI) support higher connectedness between the markets during uncertain periods.

Figure (13) presents dynamic net total directional connectedness for the global carbon model using D&Y (2012) approach. None of the series examined behaved solely as either net receivers or transmitters of shocks in the full sample.

Furthermore, figure (14) reports the findings from dynamic net pairwise directional connectedness for the global carbon model for the full sample. The results reveal that none of the series solely behave as the net shock transmitter or receiver for the considered period.

The robustness of our findings is also examined by analyzing the connectedness between renewable energy and the environment during the oil crisis, using D&Y (2012) approach (Table 6). It is noted from table (6) that the highest value of shocks to other markets is transmitted from

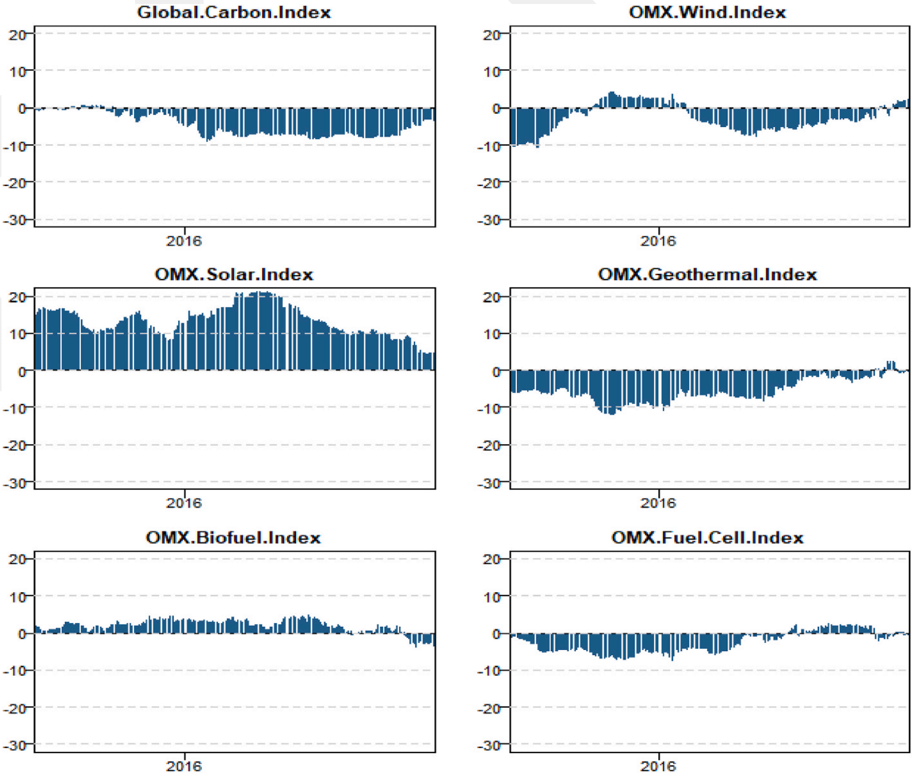

Fig. 16. Dynamic net total directional connectedness- Global Carbon model (Oil crisis)
Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

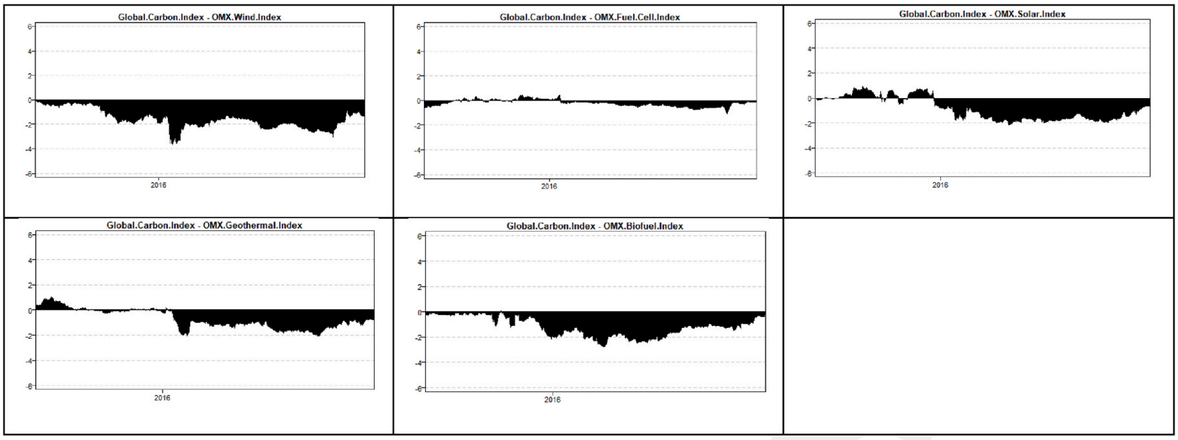

Fig. 17. Dynamic net pairwise directional connectedness- Global Carbon model (Oil crisis). Notes: Findings are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Table 7
Robustness averaged joint connected table – COVID-19.

	Global Carbon	Wind	Solar	Geothermal	Biofuel	Fuel Cell	FROM
Global Carbon	93.63	1.12	1.18	1.38	1.81	0.87	6.37
Wind	1.66	71.80	7.50	3.08	2.00	13.96	28.20
Solar	1.92	8.49	62.90	10.36	6.55	9.79	37.10
Geothermal	0.50	2.27	10.21	64.44	9.80	12.78	35.56
Biofuel	1.94	2.36	5.78	9.47	63.57	16.87	36.43
Fuel Cell	0.62	11.31	8.28	11.10	14.58	54.10	45.90
TO	6.64	25.55	32.96	35.39	34.74	54.27	189.55
NET	0.28	−2.65	−4.15	−0.16	−1.68	8.37	TCI
NPDC	3.00	2.00	0.00	3.00	2.00	5.00	31.59

OMX solar (60.61%). On average OMX solar is the most important net transmitter of shocks. OMX fuel cell (2.52%), OMX wind (2.71%), global carbon (4.52%), and OMX geothermal (5.27%) act as net receivers of shocks. The TCI value is 36.81%, higher than the TCI value of 32.39%, reported in table (5). It suggests the increase in explanation of development in the network by the network of renewable energy markets under consideration.

The results obtained from dynamic total connectedness (Fig. 15) during the oil crisis suggest higher volatility in connectedness as TCI approaches a high peak at 56%. This TCI value is higher when compared to TCI in the normal period of 2018 which is 10% (Fig. 12). Thus, supporting higher connectedness between the markets during the oil crisis.

Figure (16) presents dynamic net total directional connectedness during the oil crisis using D&Y (2012) approach. Global carbon and OMX geothermal behaved as net receivers while OMX solar behaved as net shock transmitters during the oil crisis, while other series (OMX wind, OMX biofuel, and OMX fuel cell) exhibit both behaviors.

Furthermore, figure (17) reports the dynamic net pairwise directional connectedness during the oil crisis. The results reveal that global carbon is the net shock recipient from OMX wind and OMX biofuel while in the case of other indices, it assumes both roles. The net receiver role of global carbon is more prominent.

For the robustness purpose, D&Y (2012) approach is used to examine the impact of the COVID-19 crisis on connectedness between the renewable energy markets and the environment (Table 7). It is noted from table (7) that the highest value of shocks to other markets is transmitted from OMX fuel cell (54.27%) during the pandemic while OMX solar (48.53%) during normal periods. During the pandemic (normal period), global carbon, and OMX fuel cell become net shock transmitters (net shock receivers) while OMX wind, OMX solar and OMX biofuel were net shock receivers (net shock transmitters). Furthermore, when compared to the findings reported in table (5) the TCI value is lower (31.59%) suggesting a decrease in the explanation of development in the network by the network of renewable energy markets.

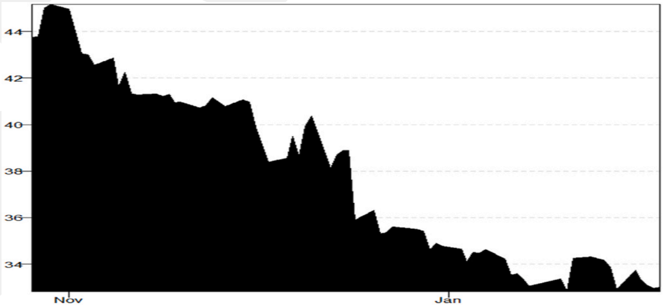

Fig. 18. Dynamic total connectedness-Global Carbon model (Covid-19 period) Notes: Findings are based on a TVP-VAR model with a lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

The results obtained from dynamic total connectedness (Fig. 18) during COVID-19 suggest higher volatility in connectedness as TCI approaches a high peak at 45%. This TCI value is higher when compared to TCI in the normal period of 2018 where it stands at 10% (Fig. 12). Thus, supporting higher connectedness between the markets during the COVID-19 crisis which is also supported by Akyildirim et al. (2022).

Figure (19) presents dynamic net total directional connectedness for the global carbon model during COVID-19 using D&Y (2012) approach. OMX fuel cell act as a net transmitter while OMX wind and OMX solar (after November) act as a net shock receiver during the pandemic. While other series (global carbon, OMX geothermal, and OMX biofuel) exhibit both behaviors.

Furthermore, figure (20) presents the dynamic net pairwise directional connectedness during the pandemic. The results reveal that global carbon is the net transmitter of shocks to OMX solar while the net

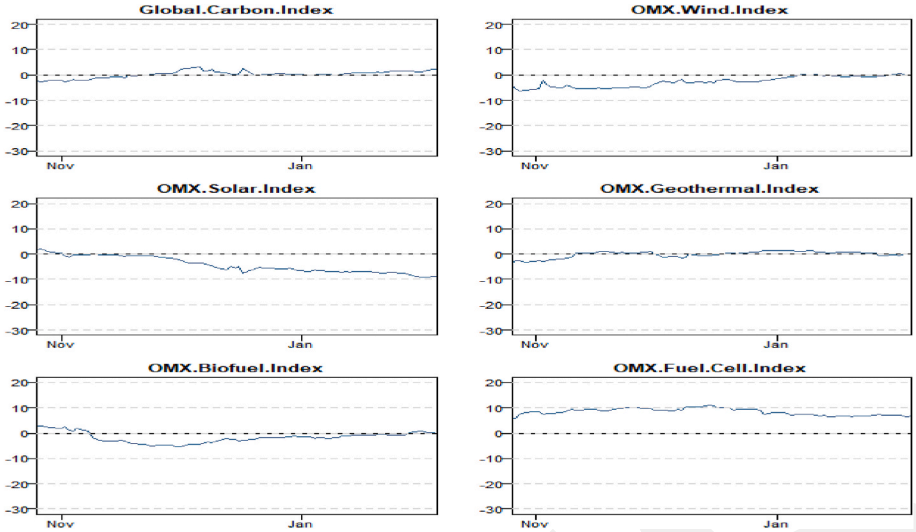

Fig. 19. "Dynamic net total directional connectedness"-Global Carbon model (Covid-19 period).

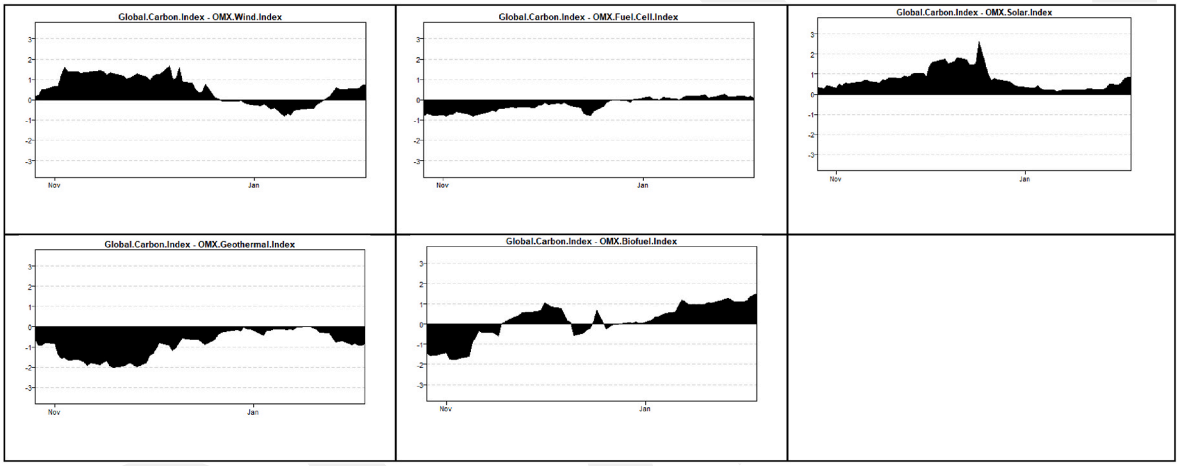

Fig. 20. "Dynamic net pairwise directional connectedness"- Global Carbon model (Covid-19 period).

receiver of shocks from OMX geothermal, while in other considered cases it assumed both roles.

6. Conclusions and policy implications

This study examined the connectedness between renewable energy and global carbon by applying a time-varying parameter vector autoregression (TVP-VAR) extended joint connectedness framework introduced by Balcilar et al. (2021) on the daily data from August 1, 2014, to February 4, 2022. The study also examined the connectedness between renewable energy and global carbon during the oil crisis and the COVID-19 crisis. Furthermore, to examine the robustness of our findings D&Y (2012) approach is used. The full sample, oil crisis, and COVID-19 results reveal that OMX solar is the highest transmitter of shocks to other markets in the full sample and oil crisis while OMX fuel cell transmits the highest shocks to other markets during COVID-19. The transmission of shocks from renewable energy to global carbon is greater (in magnitude) than shock transmission from global carbon to renewable energy stocks (in the full sample and oil crisis).

Most of the movements in the global carbon index are caused by within-index shocks while it is caused by network connections in the case of renewable energy (full sample and during the oil crisis). The robustness results obtained from D&Y (2012) approach also support previous findings. The impact of COVID-19 is greater when compared to the oil crisis.

6.1. *Policy suggestions*

This analysis helps and guides investors in portfolio diversification and risk management. Furthermore, our outcomes promote a crucial stream for constituting carbon policies through renewable energy sources investments. Accurately, investing in wind and biofuel renewable energy sources would influence the global carbon index since both of them are net transmitters. In other words, the decreasing of subsidies for wind and biofuel renewable energy sources could negatively impact the price of the global carbon-credit market. Regarding the renewable energy market, policymakers could take our findings into account since solar and fuel cells (but only during COVID-19) are the highest transmitter of shocks to other renewable energy sources markets. Therefore, endorsement policies for solar and fuel cell markets can be interlinked assets for policymakers.

The policy of carbon pricing can help to swing the pendulum to renewable energy stocks. An increase in carbon price escalates the production costs based on non-renewable energy sources while making clean energy attractive, thereby increasing investment in the renewable sector and its stocks. The policy of renewable portfolio standards (RPS) can enhance the role of carbon markets by setting a certain percentage of energy supply to come from renewable sources, such as wind or solar power. It remains imperative that policy makers seek global cooperation through international agreements on global carbon pricing systems and emissions reduction targets. Since results have shown that economic/pandemic crises are correlated with higher connectedness and spillovers, specific and short-term policies need to be devised during the crisis period.

6.2. Limitations and future study directions

The current study has certain limitations: Our period does not consider Russia's invasion of Ukraine, which can be included in future studies by expanding the time period. As COVID-19 induced uncertainty resulted in supply chain (raw material) disruptions with adverse impacts on renewable energy deployment, therefore, it is important to analyze the impact of these disruptions on clean energy indices and carbon markets to overcome these challenges in the future. Furthermore, the country-specific analysis provides insights about the policies for climate mitigation and achieving renewable energy deployment targets due to differences in development levels, resource allocation, and nationally determined contributions towards achieving environmental sustainability and should be focused on by future studies. Political will is another important determinant of renewable energy deployment and achieving environmental sustainability therefore future studies should focus on its role in determining the environment-energy nexus. Most importantly this study did not consider the possible connectedness between global carbon and hydropower which can be examined by future research studies.

CRediT authorship contribution statement

Eyup Dogan: Supervision, Model. **Tania Luni:** Writings, Data. **Muhammad Tariq Majeed:** Writings, Literature review. **Panayiotis Tzeremes:** Methodology, Writings.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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