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Dynamic interlinkages between carbon risk and volatility of green and renewable energy: A TVP-VAR analysis

Le Thanh Ha[a], Ahmed Bouteska[b], Taimur Sharif[c], Mohammad Zoynul Abedin[d,*]

[a] Faculty of Economics, National Economics University, Hanoi, Viet Nam
[b] Faculty of Economics and Management of Tunis, University of Tunis El Manar, Tunisia
[c] School of Management and Economics, University of Kurdistan Hewler, 30M Avenue, Erbil, Iraq
[d] Department of Accounting and Finance, School of Management, Swansea University, Bay Campus, Fabian way, Swansea SA1 8EN, Wales, UK

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ABSTRACT

Our paper applies a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach to investigate interlinkages among carbon emissions futures and the volatility of the renewable energy sector. The findings show that the system-wide dynamic connectedness realized a peak in early 2020 in the wake of the COVID-19 crisis. Net total directional connectedness proves that carbon emissions futures and wind energy play the roles of both net transmitters and net receivers of shocks in both periods – before and after the pandemic. The findings of this paper can support policy formulations to avoid rapid fluctuations in carbon prices, make the carbon price table, and limit the negative effect of carbon risk on the energy market, while promoting the protection of systemic financial risks in the renewable energy sector and ensuring a green energy supply.

1. Introduction

In the contemporary world of business, almost all industrial sectors of the global economy are affected by the detrimental effects of climate change in the form of natural disasters (World Finance, 2019). The continued increase in the frequency and intensity of natural disasters has cost millions of lives, destroyed capital stock and caused economic instabilities worldwide (IMF, 2020). The devastating natural disasters that have occurred recurrently over the years have awakened public conscience about global warming (The ASEAN Post, 2018), policymakers have made continued attempts to decarbonise the energy mix (Belaïd and Al-Sarihi, 2024) and many governments around the world have vowed to lower the rate of increase of temperature levels by reducing CO_2 emissions (IPCC, 2014). These developments have created numerous new financial opportunities in the forms of renewable energy, green bonds, carbon pricing (Sangiorgi and Schopohl, 2021; Chai et al., 2023; Chai et al., 2023; Reboredo, 2018; Zhang et al., 2019). The search for renewable energy sources has begun to replace fossil fuels. In addition to wind, water, solar, biomass, wave energy, among others, the energy industry faces many challenges in its quest to achieve sustainable development and reduce CO_2 emissions (Bouteska et al., 2023b; Chen et al., 2023; Yadav et al., 2023). The commitment to these goals is recognized in the 2015 Paris Climate Agreement and the UN Sustainable Development Goals (SDG), and this has fueled fierce competition among investors to secure their position among the leaders or the first movers in the renewable energy sector (Sharif et al., 2022; Uddin et al., 2021, 2024). In 2017, solar and wind

* Corresponding author.
E-mail address: m.z.abedin@swansea.ac.uk (M.Z. Abedin).

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energies witnessed record growth by 32% and 10% respectively (IRENA, 2018). Also, it is predicted that wind capacity will keep rising at a pace of approximately 14% per year, and that solar capacity will grow at a rate of around 18% per year (Statistical Review of World Energy, 2021). If the predicted growth rates sustain, the industry will require more green capital and this will lead to the growth in green economy (Wang et al., 2023). As a source of capital to fund the fledgling green economy, green bond has been increasingly used to fund or refund eco-friendly projects (ICMA, 2021) and to fasten the transformation of the conventional mix of energy consumption (Liu and Tang, 2022), since its launching during 2007–08 by the multilateral development banks (MDBs) such as the World Bank and the European Investment Bank (EIB) (Abedin et al., 2023; Azhgaliyeva et al., 2020). In 2019, total green bond sales reached a new record of US$258.9 billion, representing a 51% increase over 2018 (Climate Bonds Initiative, 2019). The majority of the revenues (38%) were used to fund renewable energy and energy efficiency (Azhgaliyeva et al., 2020) and the outcomes showed considerable signs of improvements in the environmental performance (Dhifaoui et al., 2022). However, due to the assertion that the successful mobilization of private funds to green bonds create scope of using financial markets to finance eco-friendly ventures (Reichelt, 2010), the effect of carbon risk on the renewable energy sector volatility appears as an associated issue of the green bonds. Given this backdrop, we investigate the nexus of carbon risk with the volatility of the energy sector.

The findings of this research highlight that crude oil and clean energy are the main net transmitters of shocks whereas solar energy, green bonds, and natural gas are the significant net receivers of shocks. The findings reveal that while green bonds do not represent an effective hedge for renewable energy equities, they minimize the uncertainty of the energy market. In particular, carbon emissions futures (CEF) and wind energy play the roles of both net transmitters and net receivers of shocks in both the period before and after the COVID-19 crisis. Carbon pricing becomes the principal transmitter of shocks to the renewable energy sector over the pandemic COVID-19, but the impact of carbon risk diminishes at the ending of the time series.

This paper makes some contributions to the extant literature. First, there are very few studies on the effects of carbon risk on global equity prices, green bonds, and nonrenewable and renewable energy stocks, particularly for the light of the COVID-19 crisis, or studies in positioning of carbon pricing in this connection. However, among the meagre amount of studies in this field, Balcılar et al. (2016) investigated the risk spillover among energy futures prices and carbon emission trading in Europe. Until now, especially under light of the pandemic COVID-19, no research has provided a detailed and comprehensive examination of the dynamic connectedness among the carbon price and the renewable energy sector. Our article fills this void, aiming to assess the volatility spillover among the carbon price and the renewable energy sector. Our goals are to avoid rapid fluctuations in prices of carbon, make the prices of carbons table, and limit the negative effect of carbon risk on the energy market. Simultaneously, it promotes the protection of systemic financial risks in the renewable energy sector and ensures a green energy supply. Second, the findings reveal the heterogeneity of dynamic interconnectedness between assets influenced by global Black Swan events (Bouteska et al., 2023a), e.g., the COVID-19, and make three methodological contributions to the literature: (a) we first examine the relationship among green bonds and renewable energy stocks employing the TVP-VAR and LASSO-DY methods; (b) we investigate the effect that carbon pricing has on the sector's volatility. Our study illustrates the robustness of these conclusions in the face of challenging market conditions, such as the COVID-19 crisis; (c) extant literature mostly analyzes the GARCH modeling to assess the spillover impact among carbon and energy sectors (Aristeidis and Elias, 2018; Samitas et al., 2022a). However, this method cannot effectively examine the directional features of the spillover impact. Moreover, many current literatures address the volatility spillover impact using static models, but there exists a paucity of research on the dynamic spillover impact (Bouteska et al., 2023c). Given this backdrop, our research concentrates on the spillover effect of carbon futures and particularly the impact of the pandemic COVID-19 on the volatility of the renewable energy sector and, in this way, delves into an issue that previous studies have not noticed.

The layout of our paper is developed following five steps: Section 2 presents a review of recent literature on the effects of carbon risk on the renewable energy sector volatility. Section 3 covers the dataset utilized in the analysis and the methods used for data analysis. Section 4 reveals the results and discussion, and Section 5 offers concluding comments.

2. Literature review

The volume of research-led investigations on carbon prices is rising significantly in the recent decades, focusing on carbon risk and green finance and investment, owing to the global movement against climate change (Bolton and Kacperczyk, 2021; Ezroj, 2020; Heinkel et al., 2001; Yadav et al., 2023). Although literature seems to have failed to develop a consensus on the influence of the utilization of renewable energy on growth of economy and carbon emissions, empirical investigations on green bonds and the interaction of carbon prices with nonrenewable and renewable energy equities and commodities in particular have occupied a centre of attention in finance research (e.g., S. Chai et al., 2023; N. Chai et al., 2023; Sangiorgi and Schopohl, 2021; Reboredo, 2018; Zhang et al., 2019; Apergis and Payne, 2012; Menegaki, 2011).

2.1. Interlinkages among fossil fuel stocks and products

The interconnectedness amid stock markets and products have been addressed by many studies in the forms of transmissions, volatility and correlations using multivariate models. Bollerslev (1990) pioneered the attempt by proposing the constant conditional correlation (CCC), followed by the proposition of the BEKK model by Engle and Kroner (1995), use of the CCC model and development of the dynamic conditional correlation (DCC) model by Engle (2002), use of copula functions by Rodriguez (2007), Durante and Jaworski (2010) and Bhatti and Nguyen (2012), and so on. In the recent times, literature has documented a number of studies on the interaction between fossil fuel stocks and products. For example, Onour and Sergi (2010) studied the oil price volatility and its influence on stock price and observed association between S&P500 index and the stock markets in the Gulf region. Filis and

Chatziantoniou (2014) investigated the connectedness of oil price with shocks in the stock markets and observed strong association between them. Likewise, Zhang and Asche (2014) investigated the stock markets in the Nordic region and noticed its connectivity with oil price. As for more recent time, Xiao and Wang (2020) check the dynamic linkage among the equity market and the price of crude oil and revealed a nonlinear bidirectional causative exchange between them. On the other hand, Asl et al. (2021) explored the spreads and returns between the S&P Global Clean Energy Index, the S&P Global Oil, Natural Gas, Crude Oil Indices, and other investment channels. The outcomes of their research suggested that the renewable energy and oil indices generally received the largest selection weights in the portfolio.

Literature documents some scholarly works on the green power market and the oil market. For example, Ferrer et al. (2018) employed the time-frequency connectedness method devised by Baruník and Krehlík (2018)) to evaluate the dynamic association among the green power market and the oil market in the US. Although the authors found evidence of significant association for the short run but none for the long run, their analysis showed no influence of crude oil prices on the results of green power stocks. The results corroborate the outcomes of an earlier study by Henriques and Sadorsky (2008), who applied a vector autoregression (VAR) framework and identified a weak link between oil markets and green power markets. On the other hand, Reboredo (2015) used a Conditional Value-at-risk (CoVaR) technique to discover the proportionality among the oil market and the green power market. Reboredo (2018) further verified the great variety of advantages of green bonds for stock and energy markets, but found only a small impact on firm and treasury market investors. Jin et al. (2020) assessed the hedging effect of green bonds and suggested the role of green bonds as a very useful hedging mechanism for carbon pricing volatility. In their study on the spreads and returns among various stock indices and products including the S&P Global Clean Energy Index, Asl et al. (2021) emphasised green power stocks as a resilient insurance against equity hazards with fossil fuel sectors.

2.2. Interlinkages among carbon and the energy sectors

The risk of spillover is one of the major concerns with the nexus amid the carbon and the energy sectors, and some of the studies have attempted to address this in the recent decades. For example, Arouri et al. (2012) investigated the volatility spillover of oil process with the financial markets in Europe and observed volatility connectedness in these markets. Balcılar et al. (2016) investigated the risks associated with future prices of energy and carbon emission trading in Europe and observed significant volatility and time-varying risk conduction from the carbon price and also time-varying correlations. They also found volatility hedging efficiency in the spot and futures items of the emissions market. Volatility spillover was more complicated in multi-renewable energy sector systems than it is between two sectors. Fuel cells and solar energy sectors were a crucial part of the risk distribution path, so they must be avoided. Zhu et al. (2020) used the price of carbon data of the European carbon futures market for the 2005–2017 period to assess the volatility spillover influence of carbon and electricity. The study suggested higher risk in high frequency models compared to the low and medium frequency models. Chenetal (2021)) found that the global carbon and energy sectors were dynamically intertwined. As an exception, the findings of Ji et al. (2018) revealed that the spillover impact between carbon and the energy sector varied over time and did not remain constant.

The contemporary literature has mostly employed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to explore the association between the carbon and the energy sectors (Ha et al., 2023). For example, Zhang and Sun (2016) used the GARCH modeling to examine the dynamics of volatility spillovers among Europe's carbon trading sector and the fossil energy market. Balcılar et al. (2016) used the MS-DCC-GARCH modeling to assess the risk spillover impact and connectedness between the European energy and carbon markets and suggested significant dynamic features of risk spillover of the energy market to the carbon market. Based on a bivariate VAR-GARCH model, Dutta et al. (2018) investigated the daily return and volatility relation among EU [carbon] Allowance (EUA) price and renewable energy equity returns. They found that EUA price changes had a positive impact on the renewable energy return. The findings revealed that emissions and green power prices in Europe had a substantial volatility connection. Wang et al. (2020) investigated the dynamic dependency among the global carbon price using the copula GARCH model and the general matching impact approach. They discovered a clear, dynamic connection among EUA and CER futures and spot. Moreover, a clear spillover impact between carbon and non-renewable energy, with a time-varying and asymmetric strength and trend, was reported by Gong et al. (2021). The oil market present the most influence on the carbon sector. Spillover effects between the carbon and fossil fuel industries lasted for approximately three weeks, and they gradually diminished overtime. Time-varying spillovers have the biggest impact, particularly when there is a one-week lag. Zou and Zhang (2022) employed a DCC-GARCH model to investigate the volatility spillover impact and dynamic linkage among China's emission quota and the fossil fuel industry. The dynamic connection among the fossil fuel industry and carbon price time-varying tendency was small in the period under consideration. They found the prohibition of emission limits flows, leading to ineffective dynamic relations among the two markets, and low-cost transmission. These findings imply a reduction in future volatility spillover impacts and dynamic correlations.

2.3. Interlinkages amid carbon, green and renewable energy markets in crisis periods

In the context of crisis periods associated with the recent Black Swan events, ranging from the global financial crisis (GFC) to the ongoing Russia-Ukraine war, a meagre volume of studies can be traced in literature, especially related to the very recent COVID-19 experience. For example, Ghorbel et al. (2014) studied the stock markets in Indonesia and Malaysia and noticed a positive temporal association of price of oil with the stock markets over the financial crisis period, 2008–09. Samitas (2022b) investigated the volatility spillovers amid various natural alternative investments including bonds, crude oil, gold, real estate, currency, and so on during 1 January 2010 – 30 September 2021 period, and revealed an escalating moderate market integration and total connectedness during the COVID-19 period. Samitas (2022c) investigated dynamic connectedness amid various natural alternative investments including bonds, crude oil, gold, real estate, currency, and so on during 1 January 2010 – 31 May 2021 period, and observed that volatility spillovers were moderate over time and that total connectedness reached its peak during crisis periods, i.e., COVID-19. In the context of the Russia-Ukraine conflict, two recent studies can be traced in literature. For example, using the newly developed quantile VAR (QVAR) model in China, Wu et al. (2023) observed bigger total spillovers between carbon and commodity markets in both tails than that at the middle quantile. Besides the Russia-Ukraine effects, the study also found evidence of the influence of monetary policy factors on the spillovers in the carbon-commodity system in both tails. Ha (2023) used multivariate wavelet analysis and explored the interlinks and frequency dimensions among green and renewable energy and carbon risk for the 7 February 2017 – 13 June 2022 period during the Russia-Ukraine conflict. The study found a significant nexus amid the solar energy index, envitec biogas, biofuels, geothermal energy, and carbon emission futures from early 2020 to middle 2022. Also, the partial coherencies observed among these indicators during the conflict from early April 2022 to the end of April 2022 implied an in-phase relationship of carbon emission futures with S&P global clean energy index pushing.

2.4. Summary of key findings

The aforementioned literature mainly demonstrates the interaction and links between green bonds, oil markets, commodities, and energy indices. The findings of the review of literature reveal that the renewable energy and oil indices receive the greatest ideal weights in their portfolio selection. The results also show that green power stocks could be strong insurance for equity hazards with fossil fuel industries. These findings have consequences about portfolio selection for the investors. Based on the investor's volatility in terms of portfolio choice and distribution, bio energy becomes a significant asset that could provide upside potential. However, the extant literature in general differs from our current analysis in that they assess the nexus among crude oil and renewable energy equities. As such, although extant literature provides information supporting greater investment in green initiatives to help counter climate change, we concentrate on exploring the suitability of green bonds and renewable energy stocks as a portfolio, and also the spillover effect of carbon futures, the impact of the pandemic COVID-19 on the volatility of the renewable energy sector, in particular. We also answer the question whether green bonds can function as a hedge for green power and carbon risk, especially in the wake of the COVID-19.

3. Database and method

3.1. Dataset

We use a daily dataset of carbon emissions futures (CEF), a market-based system aimed at reducing greenhouse gases (GHG), which would help to reduce global warming. The volatility of the energy sector is analysed through green bonds (*SPGB*), clean energy (*SPGTCLEN*), wind energy (*GWE*), solar energy (*SUNIDX*), natural gas (*NGF*), and crude oil (*OVX*). Our time series refers to the February 7, 2017- January 14, 2022 period. In the energy sector, we collect the S&P Green Bond Index (SPGB), a market-weighted index used to reflect the worldwide green bond market. The Macerich Company Global Solar Energy Index Net Total Return (*SUNIDX*) aims to measure the results of solar energy firms across the world. Moreover, we also employ the S&P Global Clean Energy Index (*SPGTCLEN*). The ISE Global Wind Energy Index (*GWE*) represents the information about the number of public firms involved in the wind power industry on the basis of an examination of their goods and services. In a natural gas futures (NGF) contract, the buyer is obligated to buy a particular quantity of natural gas at a future date and price. *NGF* is on the basis the delivery of global natural gas companies. The volatility index (*OVX*) of the CBOE crude oil ETF measures the volatility expected for crude oil in the coming 30days. The fund tracks the United States Oil Fund ETF (USO), which primarily holds short-term (1-month) New York Mercantile Exchange (NYMEX) futures contracts on West Texas intermediate crude oil (*WTI*). We obtain the first log-differenced series. These data may be considered as the growth rate of these indicators, as our researched indicators are more likely to create non-stationary systems. These systems are on the basis of the unit-root test statistic presented by Elliottetal. (1996).

All of the series in Table 1 have a positive average return. Specifically, the indicators with the biggest variance are CEF, natural gas, and crude oil. These appeared to be the riskiest assets in the data of Panel A as their variance was considerable, relative to that of the other assets. Significantly, all the series are found to be notably leptokurtic. These findings mean that their distributions have a larger tail than the normal distributions. Following Jarque and Bera (1980), all indicators are not normally distributed. With a 1% significance level, the ERS unit-root test of Elliott et al. (1996) indicate that the returns of all the indicators are stationary. Moreover, the weighted portmanteau testing from Fisher and Gallagher (2012) shows that both the returns and squared returns exhibit autocorrelation. These results support the use of our approach. We describe the series' interconnectivity using a TVP-VAR method with a time-varying variance-covariance structure. This article is the first attempt to comprehend the spillover impact of carbon futures on the volatility of the renewable energy sector, especially over the pandemic COVID-19. As a result, we investigate this linkage between different indicators that changed given the COVID-19 health crisis.

Moreover, Panel B and Panel C outline the general overview of these indicators in these two sample groups. Since the World Health Organization (WHO,2020) first officially declared the coronavirus disease of 2019 (COVID-19) to the world on December 31, 2019, this date divides our full sample into two subsample groups: pre-COVID-19 (from February 7, 2017 to December 31, 2019) and during-COVID-19 (from January 1, 2019, to January 14,2022). Table 1 represents the overall differences between the two eras of the used indicators. Except for SPGB, our included indicators have a higher average return in the COVID-19 time than in the pre-COVID-19 time. However, *NGF* and *OVX* have negative average returns in the pre-COVID-19 time. Further, after the financial system was rocked by the crisis of COVID-19 pandemic, the mean return of the carbon market in the world is higher. In the renewable energy sector, solar energy presents the highest mean return in the period of COVID. This shows that this indicator becomes the most suitable in times of crisis. It is remarkable that natural gas (*NGF*) and crude oil (*OVX*), which are fossil fuels, change from negative average returns to positive returns because of COVID-19. The fossil energy market becomes more attractive to investors when crises occur. More significantly, other indicators, with the exception of green bonds, become more volatile because all variances rise after COVID-19 appears. In other words, when the market experiences economic, political, and exceptional events like the COVID-19disease, green bond and natural gas are regarded as safe havens for asset managers because of their increased profits during the crisis (see Fig. 1). The findings of the ERS unit-root testing and the weighted portmanteau testing on these indicators throughout these two periods are probably similar to those offered by tests on the full sample. These results lead us to comprehend that modelling the interconnectedness of the series applying a TVP-VAR method with a time-varying variance-covariance schema is the best approach.

3.2. Empirical method

The most widely utilized econometric methods for examining connectedness was suggested by Diebold and Yilmaz (2012). This approach is used by researchers to track contagions in a preset system. They resolve negative impacts caused by a certain economic shock. One drawback of the outstanding method is that it relies on a rolling window size determined by the time-variant of connectedness. The application of the mean squared prediction error of the utilized rolling window VAR to identify the ideal window-size (Antonakakis et al., 2020) and the mutual spillover index (Lastrapes and Wiesen, 2021) have both been proposed as solutions to this problem. Our method is expected to offer more accurate findings compared to approaches used previously in studies as they solve the drawbacks of the row sum normalization method, even the explications are same to those of the original connectivity methods by Caloia et al. (2019). In sum, this strategy resolves a number of issues with the priorly proposed connectedness technique, containing: (i) no arbitrary rolling size should be selected; (ii) the forecasted results are not influenced by outliers because of the multi-variate Kalman filter technique, that includes the Kalman gain; (iii) we let the VAR coefficients to fluctuate with time; (iv) variances and covariances a real so allowed to fluctuate with time to ameliorate the observation of volatility of energy market, that is valuable in portfolio and risk administrations; (v) the answer of Lastrapes and Wiesen (2021) to the row sum normalization issue has been established; and (iv) in a particular way, we have made large the joint connectedness methodology which is consistent with the directional joint connectedness study but provides higher flexibility for the measurements calculation of the net total and pairwise directional connectedness. The latter are one of the principal aspects of this strategy and they are very valuable due to the fact that they show the comparison in bilateral power of the indicators.

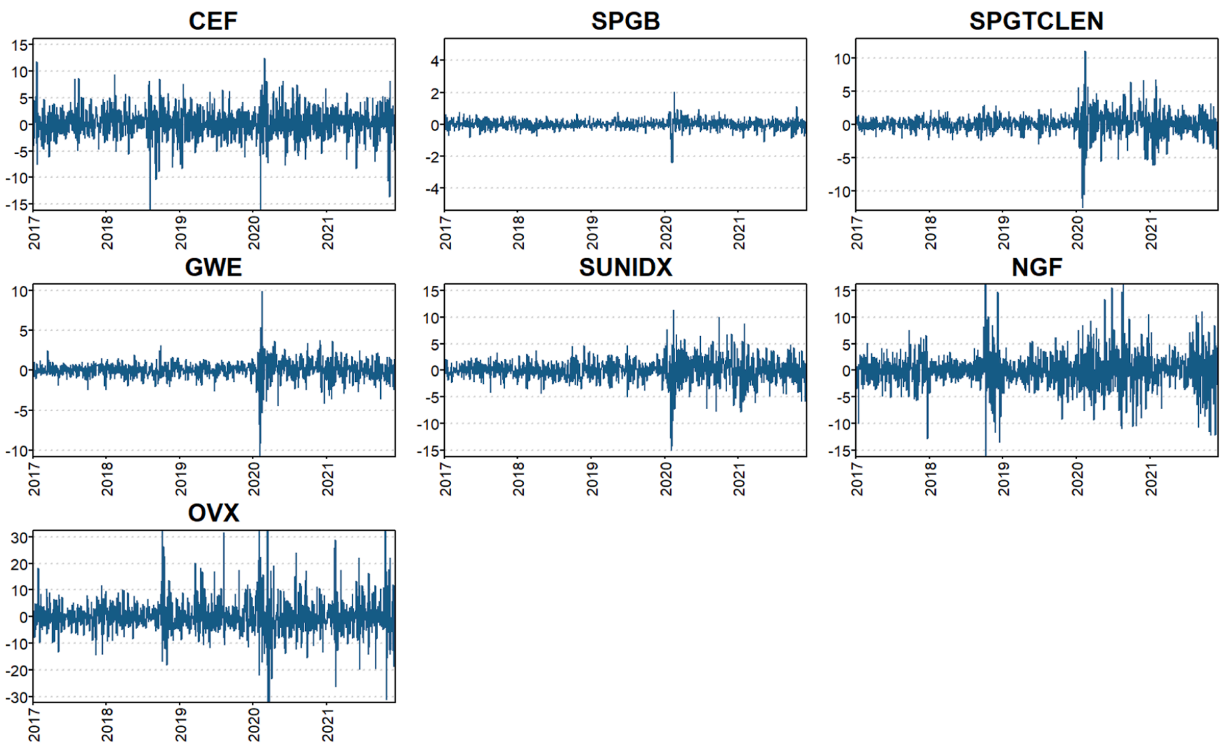

Fig. 1. Carbon emissions futures, green bond, clean energy, wind energy, solar energy, natural gas, and crude oil returns.

3.2.1. Time-varying parameter vector autoregression

For this step, we follow the approach of Samitas et al. (2022b) and accordingly employ Antonakakis et al.'s (2020) extended version of the time-varying vector autoregressive (TVP-VAR) connectedness method (originally developed by Koop and Korobilis, 2014), which is combined with the Diebold and Yilmaz (DY) (2012) model. Given this combination, TVP-VAR provides more precise parameter estimates and hence covers certain shortcomings of the DY model by allowing variances to vary over time and using multivariate Kalman filters to become less sensitive to outliers (Samitas et al., 2022c). The Bayesian information criterion (BIC) proposes that the TVP-VAR modelling be regressed by a lag length of order one in our study:

$$y_t = \mathfrak{Z}_t y_{t-1} + \psi_t \quad \epsilon_t \sim N(0, \Sigma_t) \tag{1}$$

$$vec(\mathfrak{z}\mathfrak{Z}_t) = vec(\mathfrak{Z}_{t-1}) + u_t \quad u_t \sim N(0, R_t) \tag{2}$$

Where $\mathfrak{Z}_t$ and Σ_t are $\mathrm{P} \times \mathrm{P}$ dimensional matrices, while y_t, y_{t-1} and ψ_t are $\mathrm{P} \times 1$ dimensional vectors. R_t is a $\mathrm{P}^2 \times \mathrm{P}^2$ dimensional matrix, where as $vec(\mathfrak{Z}_t)$ and u_t are $\mathrm{P}^2 \times 1$dimensional vectors. This methodology contains all indices $(\mathfrak{Z}_t)$ varying overtime, as well as the connection among series. Additionally, the Σ_t and $R_t$variance-covariance matrices are taken into account as being time-varying. Most previous studies have evidenced that variances and covariances vary with time, especially in the financial market, which indicates the altering market and risk ratio.

Based on the Wold representation theorem, we transform TVP-VAR into a TVP-VMA modelling in the coming step: $y_t = \sum_{h=0}^{\infty} N_{h,t}\psi_{t-1}$where $N_0 = I_Z$ and ψ_t is a vector of white noise shocks with (symmetric but not orthogonal) with $\mathrm{P} \times \mathrm{P}$ time-varying covariance matrix $E(\psi_t \psi_t^{'}) = \Sigma_t$. Consequently, the η-step estimate error is denoted as:

$$\beta_t(\eta\eta) = y_{t+\eta} - E(y_{t+\eta}|y_t, y_{t-1}, \ldots) \tag{3}$$

$$= \sum_{l=0}^{\eta-1} N_{l,t}\psi_{t+\eta-l} \tag{4}$$

With a forecast error covariance matrix is equal to:

$$E((\beta_t(\eta)\beta'_t(\eta)) = N_{l,t}\Sigma_t N'_{h,t} \tag{5}$$

The proposed technique follows Koop et al. (1996) and Pesaran and Shin's (1998) η-step forward generalized forecast error variance decomposition (GFEVD). The (scaled) GFEVD,

$q\mathfrak{d}\mathfrak{z}_{ij,t}$,maybe considered like the effect of a shock in indicator j on indicator i and is specified as follows:

$$\beta\beta_{ij,t}^{gen}(\eta) = \frac{E\left(\beta_{i,t}^2(\eta)\right) - E[\beta_{i,t}(\eta) - E(\beta_{i,t}(\eta))|\psi_{j,t+1}, \ldots, \psi_{j,t+1}]^2}{E(\beta_{it}^2(\eta))} \tag{6}$$

$$= \frac{\sum_{l=0}^{\eta-1}(e_i^{'}N_{lt}\Sigma_t e_j)^2}{(e_j^{'}\Sigma_t e_j).\sum_{l=0}^{\eta-1}(e_i^{'}N_{lt}\Sigma_t N'_{lt}e_i)} \tag{7}$$

$$q\mathfrak{d}\mathfrak{z}_{ij,t} = \frac{\beta_{ij,t}^{gen}(\eta)}{\sum_{j=1}^{\eta}\beta_{ij,t}^{gen}(\eta)} \tag{8}$$

Wheree_i is a $\mathrm{P} \times 1$zero selection vector with unity on its ith location and $\beta_{ij,t}^{gen}(\eta)$ is the decline degree of indicator i's η-step forecasting error variance owing to the control of the unexpected shocks of indicator j.

Diebold and Yilmaz (2012) proposed standardizing the $\sum_{j=1}^{\mathrm{P}}\beta_{ij,t}^{gen}(\eta) \ddagger 1$ to unity utilizing the row sum, conducting to the generalized spillover panel, $gST_{ij,t}$.

The generalized spillover table is the foundation for numerous spillover summary estimates of the total directional connectedness from others to indicator i and the total directional connectedness from a shock in indicator i to others. This statistical feature can be written as:

$$rrr_{i\leftarrow\bullet,t}^{gen,from} = \sum_{j=1,i\neq j}^{\mathrm{P}} q\mathfrak{d}\mathfrak{z}_{ij,t} \tag{9}$$

$$rrr_{i\rightarrow\bullet,t}^{gen,to} = \sum_{j=1,i\neq j}^{\mathrm{P}} q\mathfrak{d}\mathfrak{z}_{ij,t} \tag{10}$$

The net total directional connectedness of indicator I indicates if indicator i impacts the system more compared to that is impacted by it, between the core metrics of the connectedness technique: $rrr_{i,t}^{gen,net} = rrr_{i\rightarrow\bullet,t}^{gen,to} - rrr_{i\leftarrow\bullet,t}^{gen,from}$.If$rrr_{i,t}^{gen,net} > 0\left(rrr_{i,t}^{gen,net} < 0\right)$, indicator i is a net transmitter (receiver) of shocks, implying that indicator $i$is driving (driven by) the system.

The significant component of the connectedness centre is the total connectedness index (TCI), that plots the interconnections within

Table 1
Summary statistics.

Panel A: Whole sample

	Whole sample						
	CEF	SPGB	SPGTCLEN	GWE	SUNIDX	NGF	OVX
Mean	0.22	0.0131	0.0686	0.0495	0.1121	0.025	0.0267
Variance	7.9107	0.0853	2.4967	1.3687	4.5023	11.1285	53.9363
Skewness	-0.480 * **	-0.829 * **	-0.853 * **	-1.155 * **	-0.602 * **	0.104	2.023 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.135)	(0.000)
Kurtosis	4.005 * **	9.940 * **	11.664 * **	19.983 * **	6.590 * **	4.479 * **	28.028 * **
JB	874.036 * **	5234.038 * **	7162.450 * **	20857.096 * **	2313.220 * **	1036.125 * **	41332.231 * **
ERS	-14.220 * **	-5.954 * **	-10.513 * **	-7.196 * **	-12.754 * **	-16.965 * **	-14.311 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	37.184 * *	87.452 * **	102.405 * **	87.502 * **	64.568 * **	33.804 * *	34.573 * *
	(0.011)	(0.000)	(0.000)	(0.000)	(0.000)	(0.028)	(0.022)
$Q^2(20)$	95.197 * **	506.826 * **	955.487 * **	739.368 * **	508.853 * **	189.455 * **	128.111 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B: Pre-COVID-19 Pandemic

	Whole sample						
	CEF	**SPGB**	**SPGTCLEN**	**GWE**	**SUNIDX**	**NGF**	**OVX**
Mean	0.2104	0.0166	0.0479	0.0391	0.0787	-0.0494	-0.0063
Variance	7.2953	0.054	0.681	0.4997	1.91	7.7271	24.6269
Skewness	-0.351 * **	0.020	-0.064	-0.176 *	-0.103	-0.301 * **	1.317 * **
	(0.000)	(0.826)	(0.477)	(0.053)	(0.254)	(0.001)	(0.000)
Kurtosis	3.831 * **	0.314 *	0.628 * **	1.131 * **	0.495 * *	7.219 * **	7.218 * **
JB	457.574 * **	3.024	12.390 * **	42.288 * **	8.672 * *	1582.848 * **	1780.859 * **
ERS	-11.326 * **	-3.804 * **	-5.472 * **	-3.542 * **	-8.434 * **	-12.145 * **	-9.139 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	21.265	35.121 * *	27.232	47.595 * **	31.771 * *	30.922 *	29.041 *
	(0.382)	(0.020)	(0.129)	(0.000)	(0.046)	(0.056)	(0.087)
$Q^2(20)$	48.166 * **	8.605	44.233 * **	47.274 * **	68.538 * **	197.736 * **	88.321 * **
	(0.000)	(0.660)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel C: During-COVID-19 Pandemic

	Whole sample						
	CEF	**SPGB**	**SPGTCLEN**	**GWE**	**SUNIDX**	**NGF**	**OVX**
Mean	0.2363	0.0079	0.095	0.0642	0.1532	0.1362	0.0702
Variance	8.8084	0.1297	5.07	2.6033	8.1654	15.9451	95.6083
Skewness	-0.619 * **	-1.051 * **	-0.739 * **	-1.067 * **	-0.614 * **	0.246 * *	1.821 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)
Kurtosis	4.056 * **	9.663 * **	5.552 * **	12.207 * **	3.820 * **	2.379 * **	19.923 * **
JB	383.617 * **	2086.327 * **	704.242 * **	3276.231 * **	343.497 * **	125.912 * **	8750.670 * **
ERS	-5.078 * **	-8.658 * **	-7.915 * **	-6.172 * **	-9.095 * **	-11.386 * **	-3.875 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	36.622 * *	78.286 * **	58.571 * **	48.405 * **	42.591 * **	19.170	21.883
	(0.013)	(0.000)	(0.000)	(0.000)	(0.002)	(0.511)	(0.347)
$Q^2(20)$	59.216 * **	207.795 * **	297.218 * **	270.601 * **	138.638 * **	37.894 * **	46.269 * **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Source: Authors' own work

a system, the market risk in our case. It is thus a significant signal for portfolio and risk administrators. The TCI is seen as the average total directional connectedness from(to) others, and it is computed as:

$$\text{qɖʒ}_t = \frac{1}{\mathrm{P}}\sum_{i=1}^{\mathrm{P}} rrr_{i\leftarrow\bullet,t}^{gen,from} = \frac{1}{\mathrm{P}}\sum_{i=1}^{\mathrm{P}} rrr_{i\rightarrow\bullet,t}^{gen,to} \tag{11}$$

where a large value indicates large market risk and therefore a large level of system spillovers, while a small value indicates small market risk and hence that shocks *i* no indicator generally influence its proper volatility without affecting others, which is informative from the perspective of portfolio diverseness.

Finally, the connectedness methodologies supports the pairwise interrelations of two indicators via the idea of net pairwise directional spillovers, which are given by: $rrr_{i,t}^{gen,net} = \text{qɖʒ}_{ij,t}^{gen,to} - \text{qɖʒ}_{ij,t}^{gen,from}$.If$rrr_{ij,t}^{gen,net} > 0\left(rrr_{ij,t}^{gen,net} < 0\right)$, indicator *i* present a larger impact on indicator *j* compared with vice versa, implying that indicator *i is the* dominant over indicator *j*. Table 1.

3.2.2. Extended joint connectedness approach

The main aim is to find the $\text{qɖʒ}_{ij,t}$ equivalence for the mutual connectedness methodology, known as $\text{jɖʒ}_{ij,t}$, which meets these criteria:

$$rrr_{i\leftarrow\bullet,t}^{jnt,from} = \sum_{j=1,i\neq j}^{\mathrm{P}} \text{jɖʒ}_{ij,t} \tag{12}$$

$$rrr_{\bullet\leftarrow i,t}^{jnt,to} = \sum_{j=1,i\neq j}^{\mathrm{P}} \text{jɖʒ}_{ji,t} \tag{13}$$

$$\text{jɖʒ}_i = \frac{1}{z}\sum_{i=1}^{\mathrm{P}} rrr_{i\leftarrow\bullet,t}^{jnt,from} = \frac{1}{\mathrm{P}}\sum_{i=1}^{\mathrm{P}} rrr_{i\rightarrow\bullet}^{jnt,to}$$

In order to do so, we should opt for the technique of Lastrapes and Wiesen (2021). Consequently, there commended computation of Eq. (12) should be correct. As the row total of the original and joint connectedness tables should equal 1, the joint connectedness stable's diagonal components should also still the same. Consequently, the scaling factor changes per row, yielding the current formulation:

$$\eta_i = \frac{rrr_{i\leftarrow\bullet,t}^{jnt,from}}{rrr_{i\leftarrow\bullet,t}^{gen,from}} \tag{14}$$

$$\eta = \frac{1}{\mathrm{P}}\sum_{i=1}^{\mathrm{P}} \eta_i \tag{15}$$

The only distinction among our η soaring and the one that comes from the joint connectedness approach is that our methodology gives higher flexibility since each row has its unique soaring item. So, the steps should be organized as follows:

- $\text{jɖʒ}_{ij,t} = \eta_i \text{qɖʒ}_{ij,t}$
- $\text{jɖʒ}_{ii,t} = 1 - rrr_{i\leftarrow\bullet,t}^{jnt,from}$
- $rrr_{i\rightarrow\bullet,t}^{jnt,to} = \sum_{j=1,j\neq i}^{\mathrm{P}} \text{jɖʒ}_{ij,t}$

In addition, through varying the soaring parameter by row, the net total and pairwise directional connectedness metrics may be computed from the following:

$$rrr_{i,t}^{jnt,net} = rrr_{i\rightarrow\bullet,t}^{jnt,to} - rrr_{i\leftarrow\bullet,t}^{jnt,from} \tag{16}$$

$$rrr_{ij,t}^{jnt,net} = \text{qɖʒ}_{ji,t} - \text{qɖʒ}_{ij,t} \tag{17}$$

4. Results and discussion

The average and dynamic results for the connectedness metrics in our analysis are shown in the following section. The average value of the TCI is based on the full sample data. The TCI is presented first, followed by a dynamic evolution of the TCI overtime. The latter approach is critical for understanding the TCI's response to various economic variables. Within our proposed system, we additionally evaluated at a for net total connectedness and net pairwise connectedness. This relationship enables us to understand in depth the economic and environmental implications of carbon emissions, and the renewable and non-renewable energy markets. It is valuable to mention that each indicator might act as a net shock transmitter or a net shock receiver. Lastly, following Lastrapes and

Wiesen (2021), we calculate the joint spillover index. These results may be used to investigate the reasons for variations in the relationships of various indicators under the network.

4.1. Time-variant of average dynamic connectedness

Table 2 shows the average results for the interlinkages of various indicators inside the network of varied indicators using the whole set of data from February 7, 2017 to January 14, 2022. The diagonal part in the table reports the fluctuation of a single indicator, which is estimated through its own shocks, while the off-diagonal components describe the impact of this indicator on the fluctuation of others (FROM) and of others on this indicator's fluctuation (TO). Specifically, in Table 2, the rows show each individual indicator's impact on a given indicator's prediction error variance, but the columns represent the impact that one specific type of indicator has on all the other indicators independently.

The TCI average value for the full set of data is 41.06%. This signifies those changes within this network can explain 41.06% of the variation in our network of investigated indicators. This indicates that idiosyncratic influences consider for almost 59% of the system's error variation. The contribution of each indicator is indicated in the last row of Table 2. This analysis implies that clean energy and crude oil have a significant role in transferring shock impacts and volatility to other indicators under the system. Tiwari et al. (2022) reveal that clean energy is the dominant than all other markets and that it is the principal net transmitter of shocks in the full network. It is remarkable that the price of carbon is a receiver of shocks in the network. Ji et al. (2018) and Creti et al. (2012) also document that the carbon price is the net receiver of spillover. We find that CEF are transmitting the largest shock to solar energy–around 2.66%. Moreover, the renewable energy sector, including clean energy, wind energy, solar energy, and green bond, is more volatile when it

Table 2
Averaged Joint Connectedness.

Panel A: Whole sample

Whole sample	**CEF**	**SPGB**	**SPGTCLEN**	**GWE**	**SUNIDX**	**NGF**	**OVX**	**FROM**
CEF	87.58	1.35	2.56	2.69	2.31	1.37	2.14	12.42
SPGB	1.97	79.31	4.40	8.49	2.97	0.77	2.09	20.69
SPGTCLEN	2.41	2.57	12.92	32.06	44.28	0.88	4.87	87.08
GWE	2.35	6.32	34.53	32.74	19.20	0.76	4.11	67.26
SUNIDX	2.66	1.68	50.49	19.55	20.61	1.00	4.01	79.39
NGF	1.56	0.68	1.20	1.01	1.27	91.56	2.72	8.44
OVX	1.24	0.65	3.86	2.94	2.90	0.58	87.84	12.16
TO	12.18	13.25	97.04	66.74	72.92	5.37	19.95	TCI
NET	-0.24	-7.44	9.96	-0.52	-6.47	-3.08	7.79	41.06

Panel B: During-COVID-19 Pandemic

	CEF	**SPGB**	**SPGTCLEN**	**GWE**	**SUNIDX**	**NGF**	**OVX**	**FROM**
		Whole sample						
CEF	92.57	1.76	0.81	1.63	0.93	0.54	1.75	7.43
SPGB	2.02	83.23	2.53	7.88	1.50	0.95	1.89	16.77
SPGTCLEN	0.63	1.79	20.52	27.19	43.49	0.91	5.48	79.48
GWE	1.13	6.11	31.33	45.10	12.14	0.68	3.51	54.90
SUNIDX	1.37	1.03	50.76	11.31	30.76	0.86	3.92	69.24
NGF	0.77	0.55	1.10	0.76	1.15	92.37	3.30	7.63
OVX	0.68	0.40	3.98	2.26	2.78	0.72	89.18	10.82
TO	6.60	11.63	90.50	51.03	62.00	4.66	19.84	TCI
NET	-0.84	-5.13	11.02	-3.87	-7.24	-2.97	9.03	35.18

Panel C: Post-COVID-19 Pandemic

	CEF	**SPGB**	**SPGTCLEN**	**GWE**	**SUNIDX**	**NGF**	**OVX**	**FROM**
	Whole sample							
CEF	79.96	0.85	4.98	4.13	4.40	2.61	3.07	20.04
SPGB	2.91	71.78	6.86	9.74	5.37	1.08	2.26	28.22
SPGTCLEN	5.56	3.52	6.31	34.70	43.30	1.55	5.07	93.69
GWE	4.62	7.32	35.53	21.09	25.81	0.87	4.76	78.91
SUNIDX	5.43	2.37	47.57	27.14	10.71	1.98	4.80	89.29
NGF	3.44	0.72	1.38	1.11	1.40	90.12	1.83	9.88
OVX	2.37	0.63	3.77	3.11	3.18	0.37	86.57	13.43
TO	24.34	15.41	100.09	79.91	83.46	8.46	21.80	TCI
NET	4.30	-12.81	6.40	1.00	-5.84	-1.42	8.36	47.64

Source: Authors' own work

receives shocks from carbon emissions, including natural gas and crude oil. In the opposite direction, CEF is also affected by the shocks from other energy indicators, namely (in descending order), wind energy, clean energy, solar energy, crude oil, natural gas, and green bond. Likewise, green bond, wind energy, solar energy, and natural gas are also net receivers of several shocks. Solar energy and green bond are the most important net receivers when there are fluctuations in the network system (Ha et al., 2023).

This research focuses on the idea that each indicator plays a distinct role at various times by dividing the elements of the observations by the COVID-19 crisis period. The system containing all the indicators, specifically, can only explain a medium amount of the system's history before the outbreak of COVID-19 (TCI = 35.18%). Nevertheless, by the time the pandemic of COVID-19 swept the world, this proportion has risen significantly to 47.64%. Similarly, idiosyncratic impacts can consider for roughly 52% of the system's forecast error variation during the crisis time of-COVID-19. These data support the theory that these indicators tend to move in lockstep, specifically in periods of uncertainty, such as the COVID-19 pandemic outbreak. During the whole of our observation period, CEF takes on two very distinct responsibilities. In regular times, CEF is more likely to be a net shock receiver in the network, but CEF looks to be a net transmitter in this unstable situation. This means that the carbon market is extremely sensitive and heavily impacted by other indicators. It can be seen that CEF transmits more shock to green energy than fossil fuels. Clean energy, the indicator that receives the least shocks from carbon emissions before the COVID-19 outbreak, receives the most shocks from CEF after the COVID-19 pandemic. We have empirical data to back up our claim that the carbon market is playing a role in the fluctuation of the energy market. This study confirms Wang et al.'s findings (2021), which suggest that energy market efficiency decreases during uncertain times. They also reveal the risk transmission between coal and WTI crude oil markets. Despite this, their study is still quite limited since they only demonstrate the correlation between coal and oil. Since we suggest that interconnectedness between markets as well as between these markets and environmental issues can vary over time, our method approach is more advantageous. Alternatively, each market's role may be exchanged at a certain time.

4.2. *Total dynamic connectedness*

It is worth noting that the average results are most relevant as an overview of the underlying interconnectedness. In the wave of the pandemic COVID-19, average findings are restricted to allow the examination of interconnectedness across a network of factors. As a result, a more dynamic framework of analysis is required. It not solely accounts the change in the TCI through time, but also how the functions of certain indicators under the research network may vary through time. Changes from net transmitting to net receiving, for example, must be taken into account. The reporting of results begins by the total dynamic connectedness results, which show the TCI's intertemporal development in Fig. 2.

The TCI values vary significantly during our sample period. The TCI values reach a peak of around 60% at the beginning of each sample. In particular, the bigger the TCI values, the higher the level of connectedness between the indicators. It is noticeable that the TCI values tend to be stable at around 40%. The TCI values surge to a peak of more than 60% when there is a shock from the COVID-19 pandemic. Past research has also shown that during times of uncertainty, such as the GFC (2007–2009), the interconnectedness of various commodities markets increases (Balcilar et al., 2021; Zhang and Broadstock, 2020). On that basis, the TCI's value falls into a declining trend near the end of 2021. The lowest value is nearly 10%. According to Balcilar et al.'s study (2021), total connectedness values have reached a new remarkable peak as a result of the COVID-19 pandemic. Ji et al. (2020) also recommend that certain commodity markets should be considered safe havens for investors during uncertain periods, such as the COVID-19 pandemic. Our results, as well as those of previous studies, show that the TCI's dynamic development is responsive to COVID-19 shocks. The connectedness grows as uncertainty increases. Finally, all of the above-mentioned peaks and troughs may be checked using the Diebold and Yilmaz (2012, 2014) methodology.

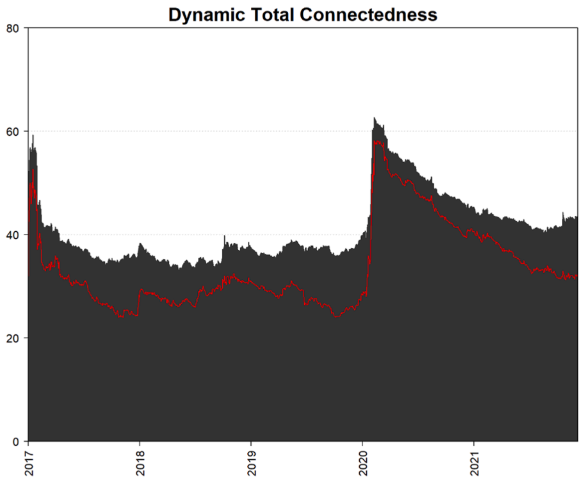

Fig. 2. Dynamic total connectedness.

4.3. Net total and pairwise directional connectedness

The coming section examines the net connectedness results. These results classify various kinds of markets as either net transmitters or net receivers. The present dynamic method contrasts with the categorization established in Section 4.1, which allows us to spot probable shifts among the two roles under consideration. In another way, depending on the study period and the specific i types of indicators, the role of indicators will change among net transmitters and receivers of shocks in the renewable energy sector.

Our article uses net total connectedness. It is implied that an indicator's function in relation to all the other indicators is consistent throughout time. The next sections detail our results on pairwise net connectedness, which involves looking at pairs of indicator types. Our goal is to see how their relationship has changed overtime, related to different prospective functions. These results are shown in Fig. 3. The values that are positive and negative show the net transmitting and receiving roles of each indicator under examination. Carbon emissions futures seem to be a net receiver in early 2017. This indicator changes to a net transmitter of shocks in late 2017 because of the historic agreement at COP21to reduce world warming to better situation below2°C, preferably to 1.5°C, in comparison with pre-industrial degrees. This result is also affected by Gulf economic instability, the resultant diplomatic tension and the Brexit crisis. The political upheaval in the global leading countries, and the diplomatic crisis in key fossil energy-exporting countries all have a direct impact on CEF. Prices of carbon, in late 2018, became a net receiver and changed to a net transmitter of shocks because of the COVID-19 outbreak. In both the time before and after the health crisis, the indicators for OVX and SPGTCLEN are net transmitters of shocks. The trend of SUNIDX, SPGB, and NGF are diametrically opposed to those of OVX. In contrast, the GWE expects observe both roles over time. In summary, crude oil and clean energy are net long-term transmitters of shocks inside our network during these crises. Meanwhile, CEF account for a significant percentage of the fluctuation in the energy market, and their position is only temporary.

It is worth noting that the special technique's normalizing procedure is not supported by any theories, and it therefore reflects an unpredictable manner of connectedness normalization. In consequent, it is preferable to use Lastrapes and Wiesen's (2021) theoretically given measurements. Following that, we are interested in the net pairwise connectedness results, which are shown in Fig. 4. Our

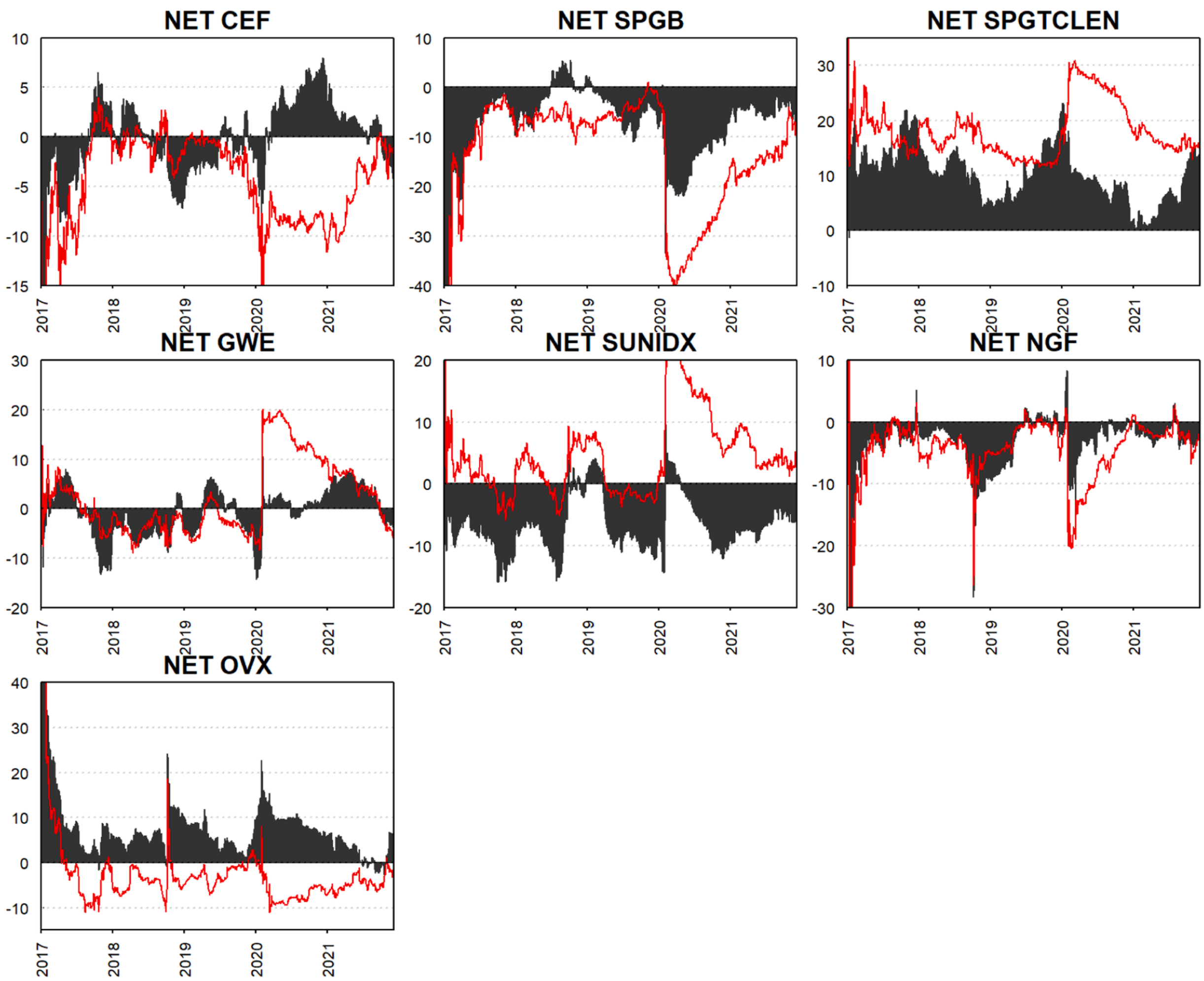

Fig. 3. Dynamic net total directional connectedness.

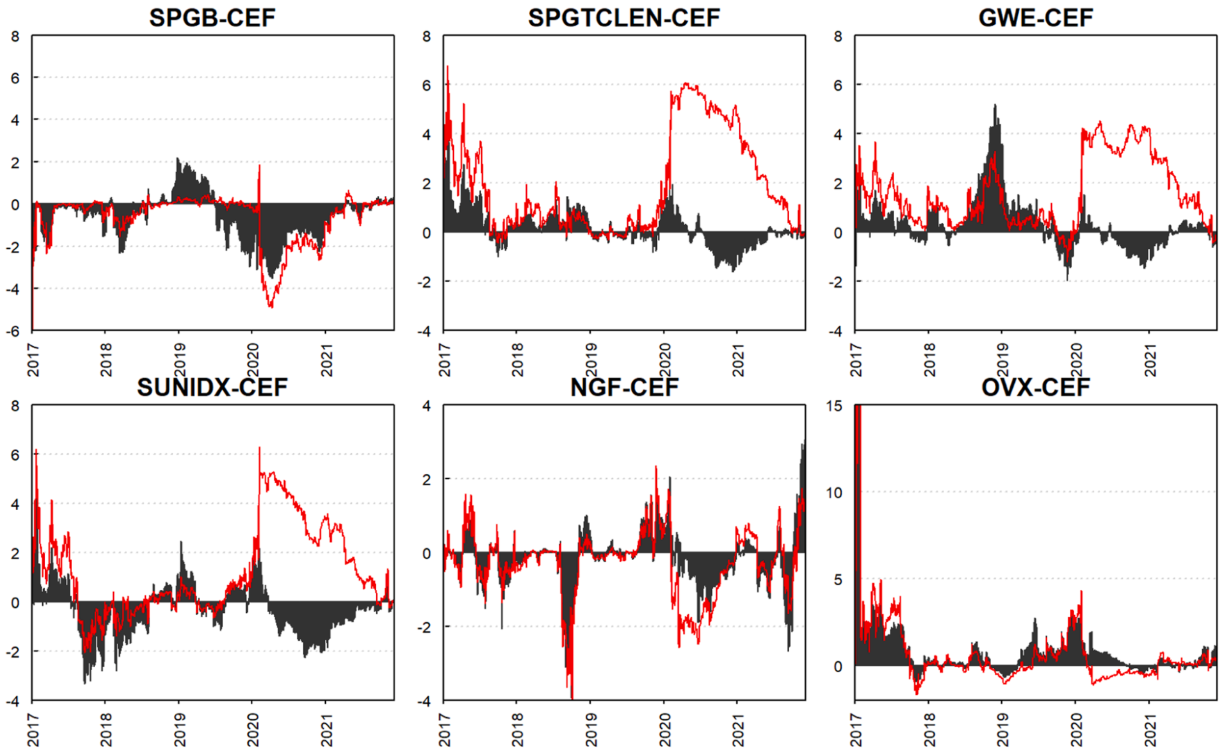

Fig. 4. Dynamic net pairwise directional connectedness: Other indicators to carbon emissions futures.

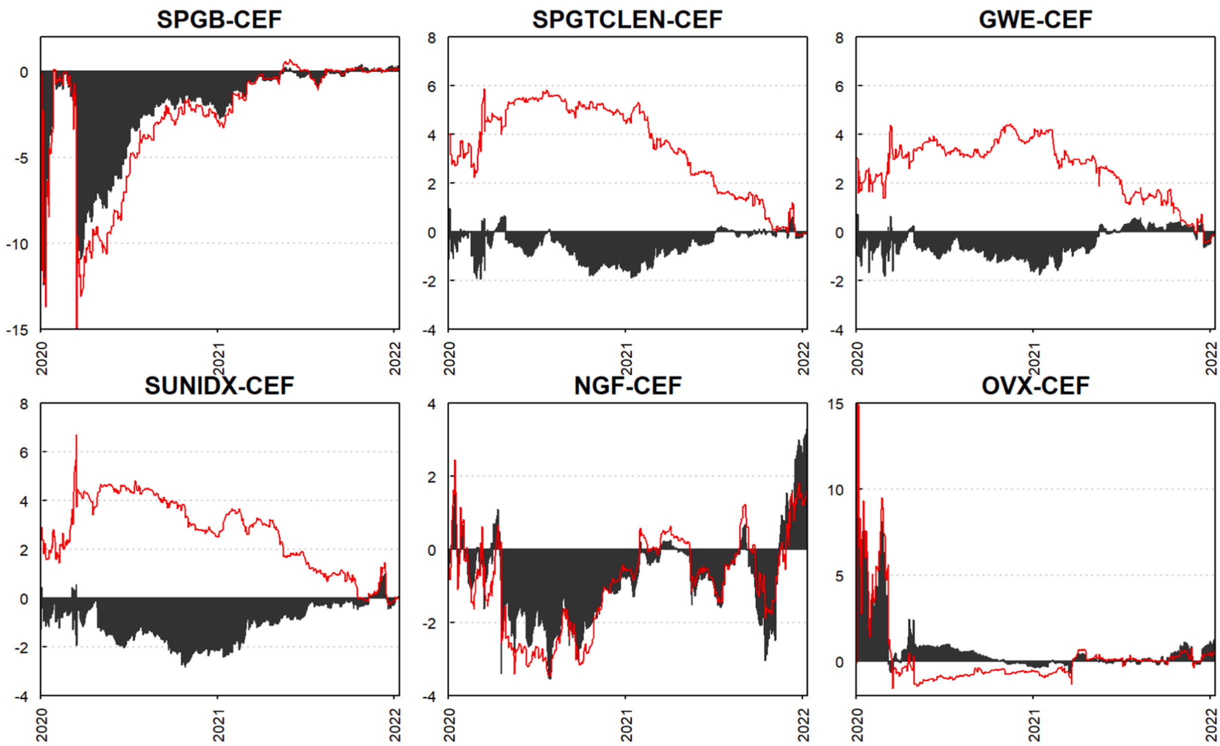

Fig. 5. Dynamic net pairwise directional connectedness: Other indicators to carbon emissions futures during the health crisis of COVID-19.

objectives are to determine the key role of CEF within our system of varied indicators and to illustrate the fluctuation of the renewable energy sector. Our research first investigates spillover impacts connected with carbon prices. Before 2019, CEF transmits shocks to solar energy, green bonds, and natural gas. In other words, the renewable energy sector, except solar energy, is not affected by carbon risk before 2019. On the other hand, investments in solar energy, green bonds, and natural gas are affected by the level of government interest in reducing carbon emissions. Likewise, CEF play a role in identifying the volatility of SPGB, SPGTCLEN, GWE, SUNIDX, and NGF, specifically in theCOVID-19 period. During the pandemic COVID-19, carbon price converts the primary source of shocks to the sector of renewable energy, but the influence of carbon risk fades at the end of our time series. In 2020, worldwide CO_2 emissions dropped by 5.8%. This is the largest drop on record and five times greater than the drop following the GFC in 2009. Because the lockdown measures to combat the pandemic reduced the consumption of oil and coal more strongly than the demand for other energy supplies, CO_2 emissions decreased at a faster rate than energy consumption in 2020. In contrast, interest in electric vehicles, renewable energy, and smart grids has risen. Moreover, from the United Kingdom to California, authorities have declared plans to phase out new gasoline-powered vehicles over the next 10–15 years. Therefore, when demand for energy fell because of the health crisis COVID-19, the volatility of the carbon price accelerated the transition from non-renewable energy consumption to renewable energy. Renewable energy stocks become an attractive investment channel when crises like COVID-19 appear. In terms of scale, CEF play a key role in determining the volatility of the green bond market. This shows that green bonds cannot limit the influence of carbon risk on the renewable energy sector, especially during crises. However, considering the correlations in the energy market, green bonds were seen as a measure to deal with the volatility of this market when COVID-19 emerged. Notably, crude oil may play the role as a transmitter of shocks to CEF throughout time. In net terms, crude oil spillover activity has been rather strong since 2020 (in terms of size), but it was declining by the ending of 2020 to the ending of study data. The crude oil market is often volatile, especially during crises. This result shows that crude oil became the principal net transmitter of shocks under the network. Fig. 5 can show us the results more clearly, and Fig. 6 depicts the importance of CEF to the energy market. Fig. 7.

5. Conclusions

Given that the subject matter of this research has been the dynamic connectedness among carbon risk and the energy market, we aimed to investigate interlinkages between carbon emissions futures and the volatility of the renewable energy sector. Accordingly, we employed a system connectedness approach to evaluate the interlinkages of seven indicators: carbon emissions futures (*CEF*), green bond (*SPGB*), clean energy (*SPGTCLEN*), wind energy (*GWE*), solar energy (*SUNIDX*), natural gas (*NGF*) and crude oil (*OVX*), namely in a time-varying fashion. We have collected daily data from February 7, 2017 to January 14, 2022 for the benchmark carbon risk and the renewable energy sector volatility. The empirical results of this research revealed the heterogeneity of dynamic interconnectedness between assets influenced by global scenarios like the outbreak of the COVID-19. Also, all of the seven indicators analysed are

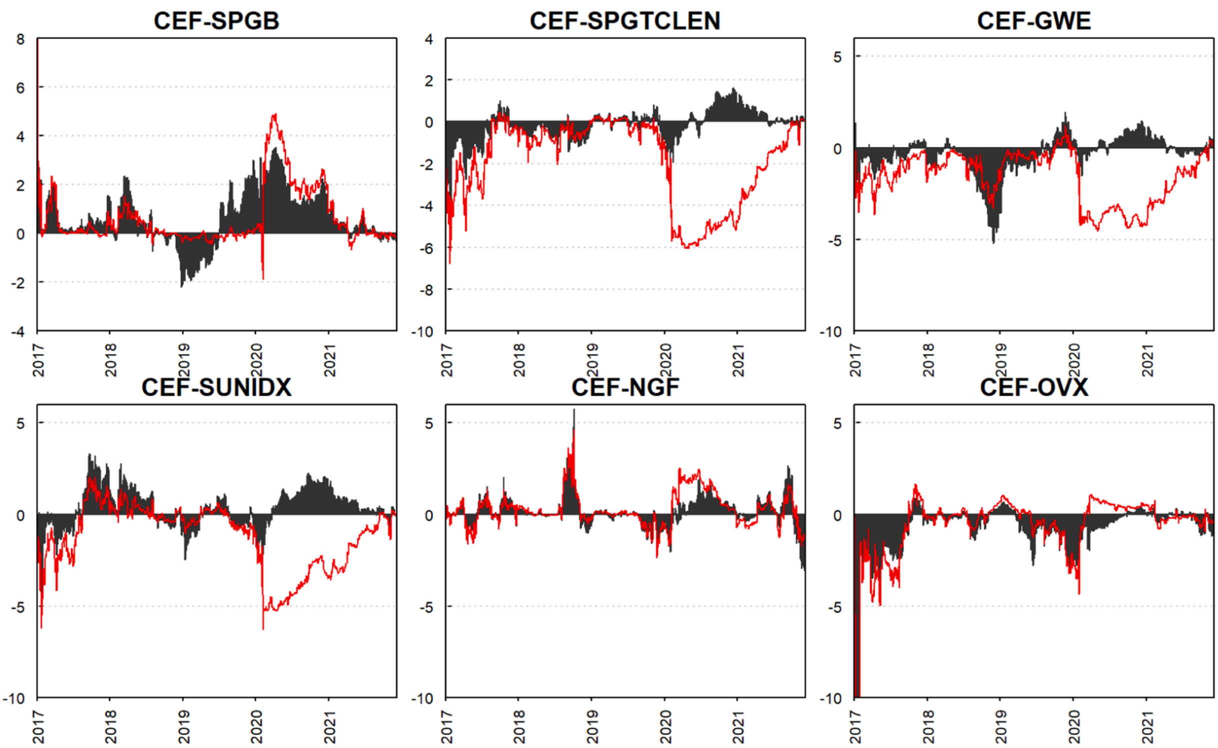

Fig. 6. Dynamic net pairwise directional connectedness: Changes in carbon emissions futures to other indicators.

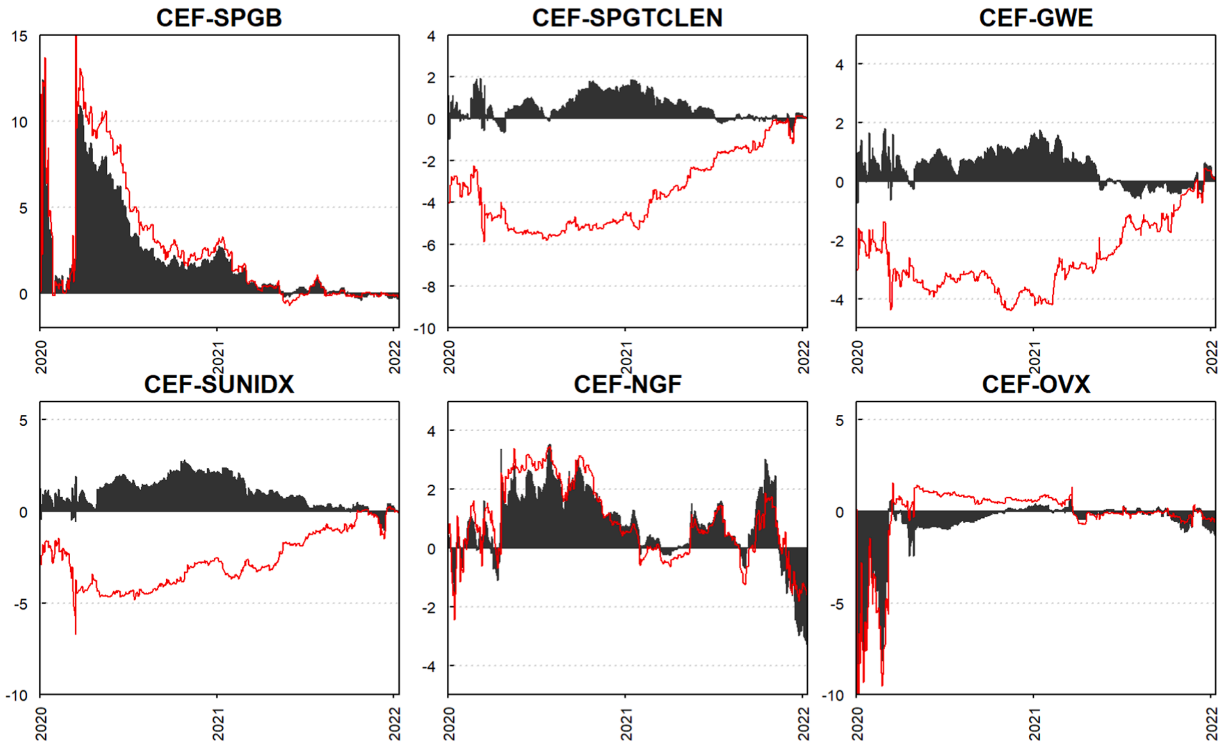

Fig. 7. Dynamic net pairwise directional connectedness: Changes in carbon emissions futures to other indicators during the health crisis of COVID-19.

significantly interrelated when the entire setoff data is taken into consideration. Likewise, when we utilised the entire sample, we obtained the TCI value of 41.06%. Our paper illustrates the change in the function of each indicator inside the intended network overtime. We use the time-variant of net total and pair-wised directional connectedness analyses. Carbon emissions futures play the role of both net transmitters and net receivers of shocks in the periods before and after the crisis of the COVID-19. During the COVID-19, carbon price converts the primary source of shocks to the renewable energy sector, but the influence of carbon risk fades at the end of our time series. Carbon emissions futures have a role in identifying the volatility of green bonds, clean energy, wind energy, solar energy, and natural gas, particularly during the outbreak of the COVID-19. Crude oil transmits shocks to carbon emissions futures (CEF) throughout time. Based on the results, our designed system is prone to a significant degree of indicator risk.

This paper makes some contributions to the extant literature. First, there are very few studies on the effects of carbon risk on global equity prices, green bonds, and nonrenewable and renewable energy stocks, particularly for the light of the COVID-19 crisis, or studies in positioning of carbon pricing in this connection. However, among the meagre amount of studies in this field, Balcılaretal. (2016) investigated the risk spillover among energy futures prices and carbon emission trading in Europe. Until now, especially under light of the pandemic COVID-19, no research has provided a detailed and comprehensive examination of the dynamic connectedness among the carbon price and the renewable energy sector. Our article has filled this void, aiming to assess the volatility spillover among the carbon price and the renewable energy sector. Second, the findings reveal the heterogeneity of dynamic interconnectedness between assets influenced by global crises, e.g., the COVID-19, and make three methodological contributions to the literature: (a) we examined the relationship among green bonds and renewable energy stocks employing the TVP-VAR and LASSO-DY methods; (b) we investigated the impact that carbon pricing has on the sector's volatility; (c) extant literature mostly analyzes the GARCH modeling to assess the spillover impact among carbon and energy sectors (Aristeidis and Elias, 2018; Samitas et al., 2022a). Moreover, this method cannot effectively examine the directional features of the spillover impact. Third, many current literatures address the volatility spillover impact using static models, but there exists a paucity of research on the dynamic spillover impact (Bouteska et al., 2023c). Given this backdrop, our research has focused on the spillover effect of carbon futures and particularly the impact of the pandemic COVID-19 on the volatility of the renewable energy sector and, in this way, delved into an issue that previous studies have failed to notice.

In this study, we claim to fill the voids in literature and establish the originality of our research by making a number of contributions to literature. Given that extant literature does not offer sufficient insights of the effect of carbon risk on global prices in equity, green bonds, and nonrenewable and stocks of renewable energy in light of the recent pandemic or in the case of the positioning of carbon pricing, we attempted to fill the gap by exploring the volatility spillover among the price of carbon price and the renewable energy sector in the wake of a very recent phenomenon, i.e., the COVID-19. Until now, especially during the COVID-19, no research has provided a detailed and comprehensive examination of the dynamic connectedness between the price of carbon and the sector of renewable energy. As a result, our article aims to investigate the volatility spillover among the carbon price and the renewable energy sector. Our goals are to avoid rapid fluctuations in prices of carbon, make the price of carbon stable, and limit the negative influence of carbon risk on the energy market. Simultaneously, it promotes the protection of systemic financial risks in the renewable energy sector and ensures a green energy supply. However, in connection with the availability of studies on the topic of our research, we recognize the study by Liu et al. (2021) that explored the risks produced by the Russia-Ukraine conflict and recorded a larger impact on the returns and fluctuations of green power equities than the uncertainty caused by the Global Financial Crisis (GFC). Nonetheless, we are able to contribute further to literature by estimating the spillover impact among carbon risk and the sector of renewable energy during the pandemic period, an area that Liu et al. missed to address. We also recognize the study by Balcılaretal. (2016) that investigated the risk spillover between energy futures prices and carbon emission trading in the context of Europe, not specific to the COVID-19 phenomenon. We are therefore able to contribute to literature on this topic by offering useful findings from a deep examination of the dynamic connectedness among the carbon price and the renewable energy sector in connection with the COVID-19 pandemic.

Our findings have significant policy implications to investors and governments, as well as methods from the spillovers across the various indicators and their interconnections. Accurate information on the primary contagions among these indicators aids politicians in designing the most appropriate policies. Their goals are to lessen the threats of these indicators as well as the transmission of risk across the network. Our study reveals significant interconnections between carbon risks and the energy market, highlighting the risk of little or excessive variety or investors in these areas. We highlight the growing interconnections between unanticipated crises. Due to the identification of the relation among carbon risks and energy markets, authorities need to adjust carbon prices reasonably to keep the energy market stable, especially during crises. Our research also provides evidence of conditions that need to be created for developing the sector of renewable energy, as it promotes the replacement of renewable energy for fossil energy. The results show that a shock in a common indicator has an impact on the whole network. Moreover, the conclusions of this research maybe used to inform policy, thereby improving public welfare. Our research supports efforts to limit the effect of carbon risks on the sector renewable energy. It is critical to apply the valuable insight gained from this study that there are uncertainties in the carbon risks to the renewable energy sector and vice versa. This means that authorities should consider them when they formulate policies for a vulnerable group to improve the welfare of society.

The main limitation of our study was the small number of markets included in the network analysis. Therefore, a natural avenue for future research would be to apply high-dimensional network models, such as the recently introduced quantile network autoregressive (QNAR) model, to examine tail-risk spllovers for a large sample of green and renewable energies against a wider range of possible hedging instruments such as bonds, currencies, cryptocurrencies (Bitcoin), commodities (Gold and Oil), and Islamic investments during the COVID-19 and Russia-Ukraine war. Moreover, we acknowledge the fact that the research of volatility spillover and interconnectedness among financial markets or network is still an evolving issue. We therefore emphasise that vital empirical, methodological and theoretical contributions can be made to the extant literature by holding further studies on this topic. A possible way forward for future research in this connection could be to investigate changes in the pattern of contagion based on more than one crisis and assess the responses from different markets to these crises in the recent times.

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CRediT authorship contribution statement

Bouteska Ahmed: Conceptualization, Formal analysis, Writing – original draft. **Ha Le Thanh:** Conceptualization, Data curation, Writing – original draft. **Sharif Taimur:** Methodology, Supervision, Writing – review & editing. **Abedin Mohammad Zoynul:** Formal analysis, Resources, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

There is no competing interest among the authors.

Data Availability

Data will be made available on request.

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Consent for publication

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