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Risk connectedness between energy and stock markets: Evidence from oil importing and exporting countries

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ABSTRACT

The surmounted environmental and energy challenges have motivated this study to explore the connectedness nexus between oil/renewable energy and stock markets for oil-exporting (importing) countries. We utilize the dynamic conditional correlation (DCC-GARCH) connectedness framework to compare the connectedness of oil/renewable energy with stock markets. Our results showcase higher total connectedness between renewable energy and stock markets. We find increased connectedness during three major pandemics (Swine Flu, EBOLA, and COVID-19). We performed a regression analysis that highlighted the impact of economic and financial uncertainties on connectedness as an additional analysis. The addition of dummy variables for three major pandemics indicates that COVID-19 significantly impacted the connectedness between oil/renewable energy and stock markets. For the robustness of our results, we employed time-varying vector autoregressions (TVP-VAR) connectedness framework to showcase that our results remain qualitatively similar and robust to different specifications. We draw useful implications for oil exporting and oil importing countries in particular, and we draft ramifications for investors, portfolio managers, policymakers, and macroprudential bodies in general.

1. Introduction

The spillover dynamics among crude oil, renewable energy, and stock markets have received substantial attention from policymakers, regulatory authorities, investors, financial market participants, and governments following the upsurge in renewable energy markets and avoiding conventional energy sources. As climate change has attracted immense consideration due to its widespread influence on economic agents and its greater disruption across economic activities, it is imperative to investigate the underlying mechanisms of connectedness between energy markets and international stocks. Guo et al. (2021) claim that the economic value determined by climate change will decline by 10% if the temperature keeps on rising following the current trajectory. The United Nations World Meteorological Organization data of 2018 (UNWMO, 2018) revealed that the past two decades tracked 18 out of 20 warmest years after the global temperature measurements in 1850. The succeeding year recorded a meltdown of 197 billion tons of Greenland ice sheets during July (Danish Meteorological Institute, 2019).

The 2019 summer also experienced unexpected lightning sparks, wildfires, and 648 and 140 thousand hectors of wind blazes across Alaska and Siberia (NASA, 2019), showing burning upheavals even in high latitudes. These environmental concerns utter the attention of humanity to save the planet and offer sustainable green transitions. The Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC, 2018) is the real-time implementation call to

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reduce greenhouse gas (GHGs) emissions and to direct the signatories to financing low-carbon developments and keeping the global temperature escalation within 2^{o} Celsius (C). Underlying Paris Agreement is Nationally Determined Contributions (NDCs) to instigate renewable and energy-efficient technologies to preserve the natural ecosystem, improve land-use practices, and adopt sustainable infrastructures. Several states are reforming their energy policies related to renewable sources, clean energy, and energy efficiency by adopting and implementing energy transitions laws. For instance, wind energy in Germany is fetching the attention of policymakers in achieving energy transitions where it covers >24% of total gross electricity production, as stated by the Federal Statistical Office (KIT, 2021).[1]

Apart from these huge developments, crude oil (conventional energy market) tends to remain the biggest source of primary energy, accounting for 75% of global energy consumption (Ferrer et al., 2018). Along with these facts, the connectedness and integration of energy markets with other financial markets cannot be ignored. There is an intuitive substitution effect between conventional and renewable energy markets as they promote economic energy consumption and are applied to fetch energy sources for households, firms, and companies' energy usage (Jiang et al., 2021). The current study aspires to examine the connectedness between energy markets and international stock markets, particularly key oil-importing and oil-exporting countries, to evaluate their net and dynamic connectedness over a period spanning August 4, 2008 to September 24, 2021. Furthermore, given the underlying uncertainties coming in the way of connectedness between energy markets and stock markets, the current study investigates whether economic, financial, and pandemic uncertainties determine the connectedness and linkages between energy-stock relationships.

While previous empirical studies focused only on the investigation of the fluctuations of the patterns of the connectedness between crude oil/renewable energy markets and stock markets (Tiwari et al., 2022; Benlagha and El Omari, 2022; Dahl et al., 2020; Ferrer et al., 2018; and Reboredo et al., 2017) referring to a specific period of turmoil in financial markets. This paper aims to provide an in-depth analysis by examining the impact of several uncertainty measures on the dynamic connectedness between crude oil/renewable energy markets, specifically for oil-importing (exporting) countries. Methodologically, prior studies employed several techniques; for instance, Jiang et al. (2021) employed the quantile-on-quantile (QQ) and causality-in-quantiles (QC) approach, Hung (2021) applied the traditional connectedness measure of Diebold and Yilmaz (2012); Corbet et al. (2020) utilized Diebold and Yilmaz (2012) approach along with DCC-FIGARCH model; and Chiou-Wei et al. (2019) used DCC-MGARCH technique for the relationships and dependence structures between energy markets. However, the current study differs from many studies by employing the dynamic conditional correlation (DCC-GARCH) volatility connectedness approach. The most distinguished benefit offered by the DCC-GARCH method is that the number of parameters is independent of the time series under consideration to be estimated, which in turn delivers greater computational gains when there are larger variance-covariance matrices (Engle, 2002).

Empirically, after analyzing the patterns of connectedness between oil/renewable energy and the leading oil exporting (importing) stock market indexes, we estimated several economic, financial, and pandemic uncertainties models for a comprehensive assessment of dynamic connectedness between energy markets and stock markets by identifying their potential determinants in the form of economic policy uncertainties, financial volatilities, and pandemic uncertainties namely, Swine Flu, Ebola outbreak, and COVID-19. To the best of our knowledge, this is the first study that examines the connectedness between oil/renewable energy markets and oil-importing (exporting) stocks using the unique methodology of DCC-GARCH. Further, the current study is novel in assessing the impacts of three major sources of uncertainties (economic policy, financial volatilities, and world pandemics, including COVID-19) on the connectedness between energy markets and stock markets from a global perspective. As additional evidence, we utilized the time-varying parameters vector autoregression (TVP-VAR) connectedness approach to verify whether our results remain robust. The main reason to use the TVP-VAR approach for verifying our results is that the TVP-VAR approach allows for predicting a time-varying variance-covariance structure to capture possible changes in the structure of the data and generates several robust results connectedness measures. In addition, the TVP-VAR connectedness approach does not randomly select the rolling-window size required in the standard connectedness technique (Diebold and Yilmaz, 2012), which escapes the loss of observations. Thus, we utilized the TVP-VAR model to examine the appropriateness of model specifications measured by the DCC-GARCH technique. Our analysis revealed that models are correctly specified and bear no problem of misspecifications.

Hence, we contribute to the existing literature in several ways. First, we examined the linkages between crude oil/renewable energy and stock indices of leading oil-importing (exporting) countries to unveil their spillovers during the sample period. Second, we employed the dynamic conditional correlation volatility (DCC-GARCH) connectedness technique to obtain connectedness between energy and stock markets. Third, we employed regression analysis for investigating the determinants of connectedness between oil/renewable energy and oil-importing (exporting) countries, implying that various economic and financial factors play an important role in determining the connectedness among markets. Fourth, we collectively employed economic policy uncertainties, financial volatilities, and the world pandemic uncertainties index to evaluate the determinants of dynamic connectedness between markets. Fifth, we applied the time-varying parameters vector autoregression (TVP-VAR) approach to examine the robustness and appropriateness of specifications applied in DCC-GARCH analysis. Finally, we proposed useful implications for policymakers, governments, individual and institutional investors, and portfolio managers to encourage green and renewable energy investments to conserve energy and protect the ecosystem.

After analysis, we found that connectedness between energy markets and international stocks is substantial where crude oil/renewable energy are major transmitters of spillovers while stocks of Russia, China, and Japan moderately transmit spillovers to stock markets of Canada, KSA, South Korea, and India. Net connectedness of energy markets and stock market indices exhibit similar results where crude oil and renewable energy market are net transmitters of spillovers among various stock markets. Meanwhile, the stock indices of Russia and China show less connectedness from the network, which symbolizes their diversification features when markets are undergoing fragile episodes of economic, financial, and pandemic uncertainties. In addition, dynamic connectedness patterns revealed time-varying patterns between energy markets and stock indices where three significant pandemics are highlighted and extreme risk spillovers are reported in COVID-19 pandemic, while moderate risk spillovers are exhibited during the Swine Flu and Ebola pandemics. Moreover, the influence of economic, financial, and pandemics uncertainties reveal that UK economic policy uncertainty substantially increased the connectedness of energy and stock markets, whereas US economic policy uncertainty indicated insignificant results. Out of financial uncertainties, stock (VIX) and currency (EVZ) showed a substantial impact on the connectedness, whereas bond market volatility (MOVE) highlighted an insignificant effect on crude oil-stock market nexus and significant negative influence on renewable energy-stock market nexus. Out of pandemics, significant findings are reported in oil-stock relationships, but for renewable energy-stock market connection, only negative influence is reported by the Ebola pandemic. With these key results, we formulated useful implications for policymakers, governments of selected countries, regulatory bodies,

[1] Please see: https://www.sciencedaily.com/releases/2021/07/210720114441.htm

environmentalists, green investors, institutional investors, and portfolio managers to relish the study's findings, particularly considering the uneven economic, financial, and pandemic uncertainties.

The rest of the paper unfolds in the following manner: Section 2 describes data and summary statistics; Section 3 elaborates on methodology; Section 4 presents empirical results along with discussion; finally, Section 5 concludes the study with the policy recommendations.

2. Data and summary statistics

2.1. Data

To examine the dependence patterns between energy markets and international stock markets, we use data from Refinitiv on oil prices, renewable energy and stock market indexes of the eight leading oil exporting and importing countries, namely, US, Saudi Arabia, Russia, Canada, China, India, Japan and South Korea for the period spanning August 4, 2008 and September 24, 2021. The returns of these series are calculated as $r_{it} = 100 \times ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)$, where $p_{i,\,t}$ is the stock market index of the country i at time t. These returns are presented in Fig. 1, revealing substantial time-varying patterns for the whole sample period. The spikes in the plots symbolize a significant economic, financial or pandemic event where markets depict extreme connectedness through their spikes. The time trend of the markets included in the study mainly reflects the events of Global Financial Crisis (2008–2009), Swine Flu (2009–2010), European Debt Crisis (2010−2012), Ebola outbreak (2014–2016), Brexit referendum (2015–2016), Shale oil crisis and Chinese stock market crash (2015–2016), US interest rate hike (2018), and globally widespread of COVID-19 (2019-present). The intense spillovers in the evolution of returns series of energy markets and stock returns reflect each of the economic, financial, and pandemic episodes which lead the market into high connectedness.

Additionally, to investigate the influence of the economic, financial and pandemic uncertainties on the dynamic connectedness between oil, renewable energy and stock markets, we collected data on six measures of uncertainties. Firstly, to account for the pandemic uncertainty as a potential factor influencing the total connectedness between stock market indexes, we extracted data on the world pandemic index series (*WPUI*) from The Federal Reserve Bank of St. Louis database. According to Ahir et al. (2021), the *WPUI* Index is constructed by counting the number of times uncertainty is mentioned in proximity to a word related to pandemics in the Economist Intelligence Unit country reports. Secondly, we claim that economic policy uncertainty could be a conceivable contributing factor in the change of the behavior of the dynamic connectedness between the stock markets under investigation. Hence, we collect data on the UK and US economic policy uncertainty indexes.[2]

Finally, to account for financial uncertainty, we collected data on the CBOE Volatility Index (*VIX*), which represents the market's expectations for the relative strength of near-term price changes of the S&P 500 index. This Index is often used to measure financial uncertainty in the financial literature (see, for instance, Gozgor et al., 2016 and Caggiano et al., 2020). We also collected data on the Euro currency volatility index (*EVZ*) and the Bond market volatility index (*MOVE*) extracted from Refinitiv.

2.2. Descriptive analysis

The descriptive statistics for the energy and stock market indexes are reported in Table 1. The table shows that the returns of both energy markets (Crude oil and renewable energy) are, on average, negative. Among the international stock markets, on average, India has the highest stock market return of 4.5%, followed by US (3.5%) and Russia (3%), while China exhibits the lowest average returns. Among the considered series, crude oil and the renewable energy index exhibit the highest variance of 8.35 and 5.13, respectively. The Russian stock index exhibits the highest variance compared to the rest of the international stock market indexes, whereas the lowest is highlighted for the Canadian Index amounting 1.37.

All the series under investigation exhibit negative skewness, except for the crude oil return series. In addition, the D'Agostino test provides significant evidence of skewness in all the return series. The statistics for kurtosis are consistent for all the energy and international stock market indexes, while each exhibit leptokurtic distribution with fat tails. The Anscombe and Glynn test supports the presence of the excess of kurtosis for all these return series. Notwithstanding, the Jarque-Bera test strongly rejects the normality for all the considered return series. The unit-root test (ERS) confirms that all return series are stationary. Finally, the Ljung–Box tests for the correlation in the standardized error terms $Q(10)$ and the squared standardized error term $Q^2(10)$ show no evidence of autocorrelation for all the series under examination.

3. Methodology

3.1. The DCC-GARCH connectedness

In order to describe the dynamic connectedness patterns between the crude oil, renewable energy and stock market indexes of a set of oil exporting and importing countries, we use the dynamic conditional correlations volatility (DCC-GARCH) connectedness approach developed by Gabauer (2020) as an alternative to the traditional connectedness approach of Diebold and Yılmaz (2014).

While Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) have employed the generalized impulse response function (GIRFs) developed by Koop et al. (1996) and considered the J-step-ahead impact of shock in variable i on variable j, Gabauer (2020) employed the volatility impulse response function (*VIRF*) as an alternative to describing the similar impact (the J-step-ahead impact of shock in variable i on variable j).

The volatility impulse response function (*VIRF*) is expressed as:

$$\Lambda^g = VIRF\left(J, \lambda_{j,t}, F_{t-1}\right) = E\left(H_{t+J} \backslash \varepsilon_{j,t} = \lambda_{j,t}, F_{t-1}\right) - E\left(H_{t+J} \backslash \varepsilon_{j,t} = 0, F_{t-1}\right) \tag{1}$$

where $\lambda_{j,\,t}$ is a vector with a one at the j^{th} position and zero otherwise.

To determine the volatility impulse response function (*VIRF*), the multivariate DCC-GARCH model introduced by Engle (2002) is employed. The model assumes that returns from k assets (e.g. international stock market indexes) are conditionally multivariate normal with zero expected value and covariance matrix H_t.

Accordingly,

$$r_t \backslash F_{t-1} \sim N(0, H_t\ ) \tag{2}$$

and

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

where D_t is a diagonal matrix with dimensions $k \times k$ of time-varying standard deviation extracted from univariate GARCH models with $\sqrt{h_{it}}$ on the i^{th} diagonal, and R_t denotes the time-varying correlation matrix.

Based on this, DCC-GARCH modeling of the volatility impulse response function (*VIRF*) can be issued by iteration in three steps.

The first step consists of the prediction of the conditional volatilities ($D_{t+h} \backslash F_t$) by employing a $GARCH(1,1)$ such as;

$$E\left(h_{ii,t+1} \backslash F_t\right) = \omega + \alpha \lambda_{1,t}^2 + \beta h_{ii,t} h = 1, \tag{4}$$

$$E\left(h_{ii,t+h} \backslash F_t\right) = \sum_{i=0}^{h-1} \omega(\alpha+\beta)^i + (\alpha+\beta)^{h-1} E\left(h_{ii,t+h-1} \backslash F_t\right) h > 1, \tag{5}$$

[2] Daily and Monthly Indices of Economic Policy Uncertainty are publicly available at: www.PolicyUncertainty.com

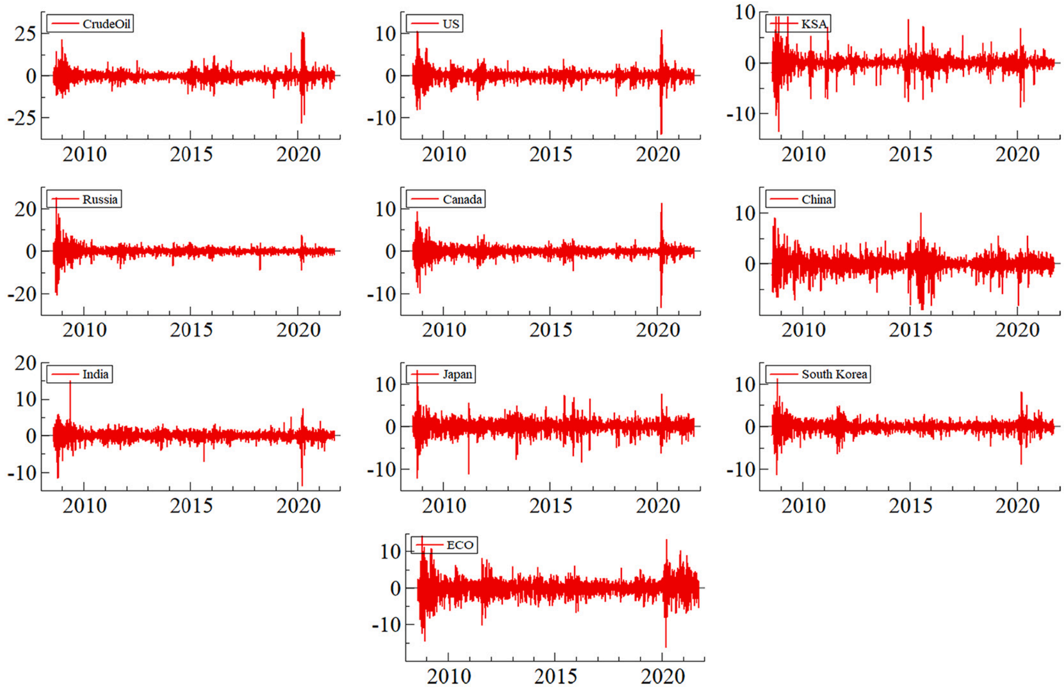

Fig. 1. Time trend of the Energies and stock returns.

Table 1
Descriptive statistics of the return series.

	Crude Oil	ECO	US	KSA	Russia	Canada	China	India	Japan	South Korea
Mean	−0.003	−0.005	0.035	0.009	0.030	0.013	0.008	0.045	0.027	0.021
Variance	8.355	5.134	1.566	1.693	3.429	1.375	2.133	1.591	2.245	1.479
Skewness	0.308***	−0.40***	−0.539***	−0.943***	−0.143***	−0.990***	−0.500***	−0.49***	−0.453***	−0.511***
p − value	0.000	0.000	0.000	0.000	−0.001	0.000	0.000	0.000	0.000	0.000
Kurtosis	17.43***	5.764***	16.836***	14.881***	30.896***	21.09***	6.142***	16.39***	9.037***	11.648***
p − value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
J. B	41318***	4607***	38662***	30563***	129674***	61000***	5260***	36632***	11205***	18572***
p − value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
ERS	−15.78***	−6.93***	−19.45***	−7.44***	−6.78***	−25.25***	−6.78***	−23.0***	−11.30***	−6.69***
p − value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$Q(10)$	38.72***	19.76***	105.15***	36.447***	21.407***	80.42***	11.328**	29.48***	3.062	12.005**
p − value	0.000	0.000	0.000	0.000	0.000	0.000	−0.037	0	−0.811	−0.027
$Q^2(10)$	1326***	1710***	2152***	770.2***	645.57***	2232***	522.9***	443.8***	1582***	1530.51***
p − value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes. *, **and ***indicate significance at the 10%, 5% and 1% level, respectively. Skewness is the D'Agostino test. Kurtosis is the Anscombe and Glynn test, JB is the Jarque-Bera normality test; ERS is the Stock and Watson (1996) unit-root test; The $Q(10)$ and $Q^2(10)$ are the Ljung–Box correlation tests.

In the second step, $E(Q_{t+1}\backslash F_t)$ is forecasted by

$$E(Q_{t+1}\backslash F_t) = (1-a-b)\overline{Q} + au_tu_t' + bQ_t h = 1 \tag{6}$$

and

$$E(Q_{t+1}\backslash F_t) = (1-a-b)\overline{Q} + aE\left(u_{t+h-1}u'_{t+h-1}\backslash F_t\right) + bE(Q_{t+h-1}\backslash F_t)h > 1 \tag{7}$$

According to Engle III and Sheppard (2001), the term $\boldsymbol{E}(\boldsymbol{u}_{t+h-1}\boldsymbol{u}_{t+h-1}{}'\boldsymbol{F}_t) = \boldsymbol{E}(\boldsymbol{Q}_{t+h-1}\backslash\boldsymbol{F}_t)$ of the Eq. (7) is employed to predict the dynamic conditional correlations.

Finally, the third step consists of the prediction of the dynamic conditional variance-covariance as follows:

$$\boldsymbol{E}(\boldsymbol{R}_{t+h}\backslash\boldsymbol{F}_t) \approx$$

$$diag\left[\boldsymbol{E}\left(\boldsymbol{q}_{iit+h}^{-\frac{1}{2}}\right)\Big\backslash\boldsymbol{F}_t\Big), \ldots, \left(\boldsymbol{q}_{NNt+h}^{-\frac{1}{2}}\right)\Big\backslash\boldsymbol{F}_t\Big)\right]\boldsymbol{E}(\boldsymbol{Q}_{t+h}\backslash\boldsymbol{F}_t)diag\left[\boldsymbol{E}\left(\boldsymbol{q}_{iit+h}^{-\frac{1}{2}}\right)\Big\backslash\boldsymbol{F}_t\Big), \ldots, \left(\boldsymbol{q}_{NNt+h}^{-\frac{1}{2}}\right)\Big\backslash\boldsymbol{F}_t\Big)\right], \tag{8}$$

Table 2
Measures of the DCC-GARCH connectedness.

Measure	Index	Description
Total directional connectedness (TCI)	$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^N \tilde{\gamma}_{ij,t}^g(J)}{N} \times 100$	This measure evaluates the spillovers that the energy commodity or stock index of the country "*i*" transmits to the stock indexes of the other countries "*j*".
Total directional connectedness *To others* $(i \longrightarrow j)$	$C_{i\rightarrow j,t}^g(J) = \frac{\sum_{i,j=1,i\neq j}^N \tilde{\gamma}_{ji,t}^g(J)}{\sum_{j=1}^N \tilde{\gamma}_{ji,t}^g(J)}$	This Index measures the spillovers the energy commodity or stock index of the country *i* transmits to all other stock index of the countries *j*.
Total directional connectedness *from others* $i \leftarrow j$	$C_{i\leftarrow j,t}^g(J) = \frac{\sum_{i,j=1,i\neq j}^N \tilde{\gamma}_{ji,t}^g(J)}{\sum_{j=1}^N \tilde{\gamma}_{ij,t}^g(J)}$	This Index measures the spillovers the energy commodity or stock index of the country *i* receives from all other stock index of the countries *j*.
Net total connectedness	$C_{i,\ t}^g = C_{i\rightarrow j,\ t}^g(J) - C_{i\leftarrow j,\ t}^g(J)$	Is the difference between the total directional connectedness *To others* and the total directional connectedness *from others* it describes the influence of the variable "*i*" on the studied network
Net pairwise directional connectedness (NPDC)	$NPDC_{IJ} = \tilde{\gamma}_{ji,t}^g(J) - \tilde{\gamma}_{IJ,t}^g(J)$	A negative value of $NPDC_{IJ}$ indicates that variable "*i*" is dominated by "j", whereas a positive value indicates the opposite.

$$E(H_{t+h}\backslash F_t) \approx E(D_{t+h}\backslash F_t)E(R_{t+h}\backslash F_t)E(D_{t+h}\backslash F_t) \tag{9}$$

Using the volatility impulse response function (VIRF), the generalized forecast error variance decomposition (***GFEVD***) is deduced and interpreted as the variance share of one variable explains others.

The variance share is normalized as following;

$$\tilde{\gamma}_{ij,t}^g(J) = \frac{\sum_{t=1}^{J-1} \Lambda_{ij,t}^{2,g}}{\sum_{j=1}^{N}\sum_{t=1}^{J-1} \Lambda_{ij,t}^{2,g}} \tag{10}$$

where $\sum_{j=1}^N \tilde{\gamma}_{ij,t}^g(J) = 1$ **and** $\sum_{i,j=1}^N \tilde{\gamma}_{ij,t}^g(J) = N$.

The generalized forecast error variance decomposition (***GFEVD***) allows to compute several measures of connectedness. The measures are reported and explained in Table 2.

3.2. Dynamic connectedness and uncertainties

To investigate the influence of the economic, financial and pandemic uncertainties on connectedness between oil, renewable energy and the international stock indexes, we extract the series of connectedness between the financial assets using DCC-GARCH connectedness approach. Then, we regress the total series on several uncertainty measures.

Three models are proposed and estimated using the robust regression alternative to least squares regression when data is contaminated with outliers or influential observations. This estimation method is appropriate since the total connectedness series and other independent variables contain several outliers.

In Model 1, we consider a linear relationship between the dependent and all the independent variables. This model considers the world pandemic uncertainty index as a continuous variable. Besides, in Model 2, we assume a nonlinear relationship between the world pandemic index and the total connectedness. Finally, in Model 3, we measured the impact of each the three pandemics by constructing dummy variables such as: $D_{it} = \begin{cases} 1 \ \textit{The period of pandemic } i \\ 0 \ \textit{if not}. \end{cases}$

The models are presented as follows:

Model 1.

$$DC_t = \beta_0 + \beta_1 WPUI_t + \beta_2\ EPU\_US_t + \beta_3\ EPU\_UK_t + \beta_4 VIX_t + \beta_5 EVZ_t + \beta_6 MOVE_t + \varepsilon_t$$

Model 2.

$$DC_t = \beta_0 + \beta_1 WPUI_t + \beta_2 WPUI_t^2 + \beta_3\ EPU\_US_t + \beta_4\ EPU\_UK_t + \beta_5 VIX_t + \beta_6 EVZ_t + \beta_6 MOVE_t + \varepsilon_t$$

Model 3.

$$DC_t = \beta_0 + \beta_1\ EPU\_US_t + \beta_2\ EPU\_UK_t + \beta_3 VIX_t + \beta_4 EVZ_t + \beta_5 MOVE_t + \sum_{i=1}^{3} D_{it} + \mu_t$$

Where;

DC_t: The total dynamic connectedness series issued from the DCC-GARCH connectedness estimation.

WPUI: The world pandemic uncertainty index.

$WPUI_t^2$: The world pandemic uncertainty index squared.

EPU_UK_t: The UK economic policy uncertainty index

EPU_US_t: The US economic policy uncertainty index

VIX_t: The CBOE Volatility Index

EVZ_t: Euro Currency Volatility Index

$MOVE_t$: Bond Market Volatility Index

D_{it} is a dummy variable representing the occurrence of the three considered pandemics, namely; *Swine Flu*, *Ebola* and *COVID* − 19, respectively.

The total dynamic connectedness index often contains extreme values (outliers) due to several events, such as financial and economic crisis, geopolitical events and pandemics (for instance, see Fig. 3). These data points are not data entry errors and then should not be excluded from the analysis. Accordingly, using an ordinary least square estimation method (OLS) to explore the determinants of the total connectedness in the presence of extreme observation might lead to biased results. Therefore, in this paper, we use a robust regression as an alternative strategy since it is a compromise between excluding the extremes (outliers) from the analysis, including all the data points, and treating of them equally in OLS regression. The idea of the robust estimation framework is to weigh the observations unequally based on how these observations are well-arranged.

4. Empirical results

4.1. Connectedness tables

Tables 3 and 4 report the averaged dynamic connectedness measures and outline the energy markets and stock markets transmission

Table 3
Dynamic connectedness table for oil and the country stock markets indexes.

	Crude Oil	US	KSA	Russia	Canada	China	India	Japan	South Korea	FROM
Crude Oil	88.98	2.00	0.57	3.33	2.20	0.90	0.73	0.78	0.51	11.02
US	22.24	46.75	1.39	8.15	14.97	1.55	2.21	1.73	1.02	53.25
KSA	7.94	1.71	70.58	4.82	1.30	3.87	2.78	3.94	3.06	29.42
Russia	12.54	2.56	1.29	73.11	2.39	2.27	2.67	1.64	1.53	26.89
Canada	28.95	16.26	1.25	8.91	38.12	1.85	2.16	1.48	1.02	61.88
China	3.72	0.69	1.09	2.40	0.57	79.29	2.49	5.33	4.41	20.71
India	7.52	1.93	1.85	7.11	1.59	6.10	63.98	5.08	4.82	36.02
Japan	4.58	1.04	1.63	2.35	0.64	7.74	3.01	67.79	11.23	32.21
South Korea	5.43	0.07	2.26	4.35	0.85	11.39	5.42	19.80	49.42	50.58
CTO	92.93	27.27	11.34	41.42	24.51	35.67	21.46	39.78	27.61	321.98
NDC	81.91	−25.98	−18.08	14.53	−37.38	14.96	−14.56	7.56	−22.97	TCI
NPDC transmitter	0	6	8	1	7	2	5	3	4	35.78

Notes. CTO: contribution to others, NDC: Net directional connectedness, TCI: Total connectedness Index.

Table 4
Dynamic connectedness table for renewable energy and international stock indexes.

	ECO	US	KSA	Russia	Canada	China	India	Japan	South Korea	FROM
ECO	79.14	7.53	0.78	3.18	5.65	1.18	1.00	0.95	0.58	20.86
US	42.17	34.47	1.13	6.13	11.02	1.24	1.66	1.39	0.78	65.53
KSA	5.64	1.74	72.31	4.93	1.32	3.98	2.88	4.07	3.13	27.69
Russia	7.65	2.71	1.44	76.92	2.57	2.46	2.87	1.77	1.62	23.08
Canada	39.62	13.44	1.14	7.62	32.51	1.65	1.84	1.31	0.87	67.49
China	2.80	0.70	1.15	2.47	0.57	79.86	2.56	5.43	4.45	20.14
India	5.96	1.95	1.96	7.24	1.61	6.23	64.92	5.23	4.90	35.08
Japan	3.16	1.06	1.72	2.44	0.67	7.88	3.09	68.63	11.34	31.37
South Korea	3.92	1.11	2.37	4.50	0.89	11.55	5.55	20.07	50.04	49.96
CTO	110.92	30.24	11.70	38.52	24.31	36.17	21.45	40.21	27.67	341.20
NDC	90.06	−35.29	−16.00	15.45	−43.18	16.03	−13.63	8.84	−22.29	TCI
NPDC transmitter	0	4	8	1	6	2	5	3	7	37.91

Notes. CTO: contribution to others, NDC: Net directional connectedness, TCI: Total connectedness.

mechanism. The results in Table 3 show that on average, 35.78 of a shock in one-market spills over to all others. This indicates, in turn, that on average, 64.22% of the shock affects its own in the coming periods revealing a highly interconnected market. Considering the renewable energy with the countries stock markets (Table 4), the results indicate that on average, 37.91% of renewable energy in one market spills over to all other stock markets, indicating that about 62.09% of the shock is average influences itself. This result reflects that the markets under study are highly interconnected. More interestingly, the results reveal that the international stock markets are more connected with renewable

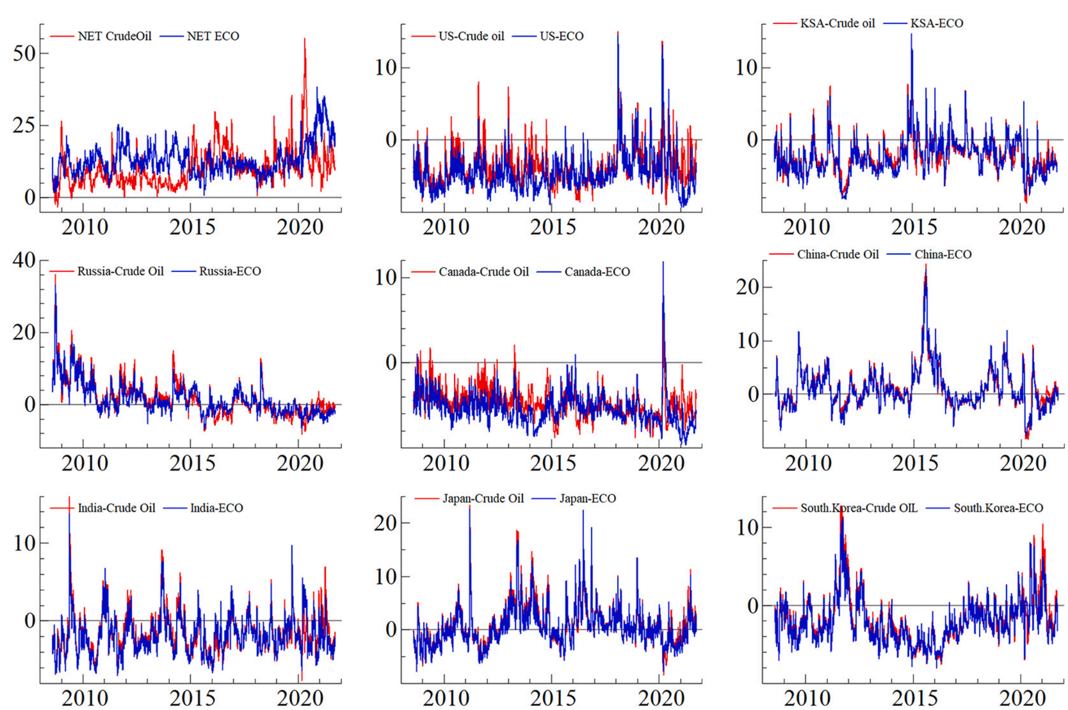

Fig. 2. Net connectedness indexes for crude oil, renewable energy and the stock market indexes.

energy than with oil. Our results are in line with Ferrer et al. (2018), Jiang et al. (2021), Hung (2021) and Corbet et al. (2020), Naeem et al. (2022a, 2022b), Karim et al. (2022a, 2022b), who reported renewable energy market is more connected with other financial and commodity markets.

In addition, the results show that crude oil is the main transmitter of shock, followed by the Chinese and Russian stock market indexes with positive net directional connectedness of 81.91%, 14.96% and 14.53%, respectively, while, the Japan stock market index is shown to be the least transmitting Index with 7.56% of net connectedness directional index. Our results are well-aligned with the findings of Dahl et al. (2020), who reported crude oil as the net transmission market among other financial and commodity markets. In this first system composed of crude oil and the considered stock markets, the Canadian and US stock markets are the largest receivers of chocks with negative net connectedness of −37.38% and − 25.98%, respectively. In addition to these two stock markets, the KSA stock market is also highly receiver of chocks with a net transmitter index of −18.08%. The results indicate that while crude oil is the main transmitter of shocks, the top producing counties of this commodity are the most receiver of chocks. Consequently, the results suggest a presence of a significant pass-through effect of exogenous chocks via oil prices, spilling over to the oil-producing countries' stock markets, echoing the findings of Luo and Ji (2018), Chiou-Wei et al. (2019), Pal and Mitra (2020), Naeem and Karim (2021), Karim and Naeem (2021, 2022).

Similarly, Table 3 indicates that the renewable energy index is the major transmitter of a shock to the other international markets, whereas the least transmitter is the Japan stock market index. In this second system comprising the renewable energy and the stock markets indexes of the leading producer and consumers of crude oil, the Canada, U.S and KSA stock markets are revealed to be the largest receivers of shocks from the other markets with net connectedness index of −43.18, −35.29 and − 16.00. By focusing more on the energy commodities, oil and the renewable energy index are major transmitters of shock. Consequently, these commodities contribute significantly to increasing the interconnectedness among international stock markets and thus can be considered drivers of market risk. In addition, whereas energy commodities are driving the market, the three major producers of crude oil are driven by the market. These findings corroborate the results of Naeem et al. (2022c, 2022d), Karim et al. (2022c, 2022d), Tiwari et al. (2022), Elsayed et al. (2020), and Reboredo et al. (2017), who found the renewable energy market as the net transmitter of shocks to other markets.

4.2. Net connectedness

Fig. 2 depicts the dynamics of the net connectedness indexes between crude oil and the stock markets (red line) and renewable energy and the stock markets (blue line). The figure shows that the net connectedness of the two energy and the stock markets move approximately together in line with Reboredo et al. (2017), who documented strong dependence between crude oil and renewable energy. Both crude oil and the renewable energy index behave as transmitters of shocks to stock markets throughout the entire studied period which corroborates the findings of Tiwari et al. (2022) and Jiang et al. (2021). On average, the renewable energy index has higher levels of net connectedness than crude oil. However, the spikes in the level of connectedness are more important for crude oil than for the renewable energy index revealing a higher sensitivity of the crude oil in periods of turmoil. The figures also show that US, and Canada are the largest receivers of shocks during the studied periods, followed by KSA and India. While Japan stock market mostly behaves as a transmitter of shock with several peaks reaching exceeding the levels of 20% of positive net connectedness, Russia and China are typically neutral to external shocks. The weaker connectedness of Russia and Chinese stocks echoes their diversification avenues against other energy markets and stock indices which necessitates that investing in these stocks shield from external economic, financial, and pandemic effects. Moreover, these stocks can rescue investments from highly volatile periods, offer risk-mitigation properties, and can yield returns for the investors when markets are undergoing intense crisis episodes (Appiah et al., 2022; Alawi et al., 2022; Billah et al., 2022).

4.3. Dynamic total connectedness

Plot 1 in Fig. 3 displays the dynamic connectedness between oil and the stock markets indexes of the countries, while Plot 2 in Fig. 3 shows the dynamic connectedness between the renewable energy index and the selected stock markets. Compared to Diebold and Yilmaz (2012); Diebold and Yılmaz (2014), dynamic connectedness based on the

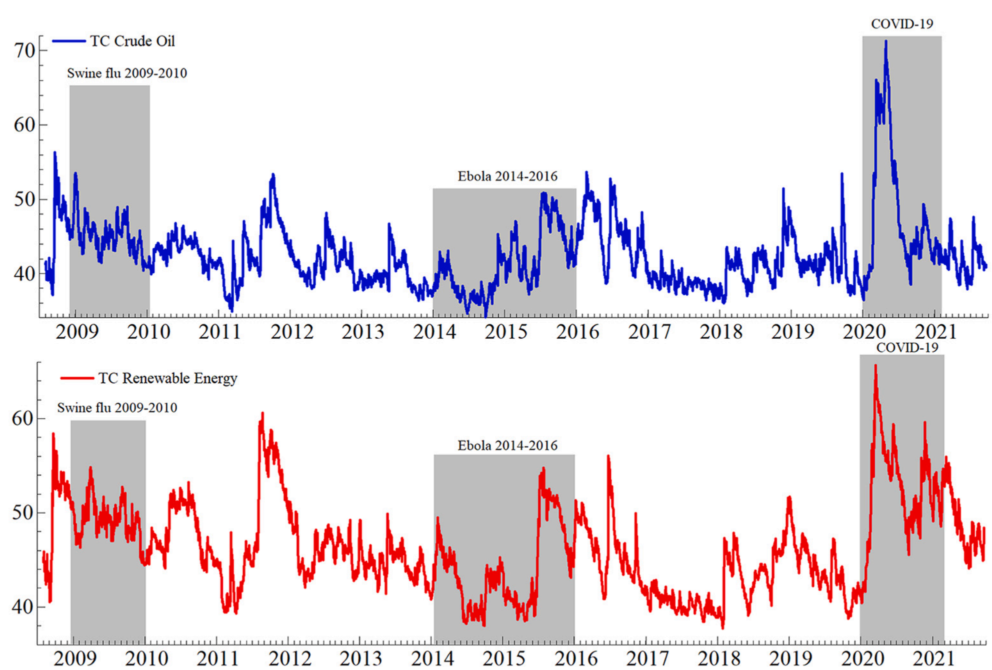

Fig. 3. Total connectedness between energies (crude oil, Renewables) and the country stock markets returns.

rolling-windows technique, the DCC-GARCH connectedness approach estimates the total Index along with all the sample size, which makes it possible to cope with the lack of information caused by the window size. As the aim of the paper is to investigate not only the dynamic connectedness but to focus more on the impact of the pandemic along with other measures of uncertainty, we focus our analysis on the change in the dynamic connectedness trends in pre- and post- eras of the three major world pandemics that happened during the studied period (*Swine Flu*, *Ebola* and *COVID* − 19).

Plot 1 shows that prior to 2008, the level of connectedness between crude oil and the considered stock markets ranges between 38% and 56%, with an exceptional peak. From the end of 2008 to 2009, the connectedness levels increased sharply, reaching a peak of approximately 60%. This increased connectedness between oil and the considered stock markets is explained by the impact of the 2008–2009 global financial crisis (GFC). This finding supports the results in the previous empirical studies on the impact of the GFC on the connectedness between markets (Pham et al., 2022; Zhang and Broadstock, 2020). A similar trend is observed for the total connectedness index between the renewable energy index and the stock markets, revealing the effect of the GFC on the connectedness between markets. Regarding the period of *Swine Flu*, the plots do not exhibit any exceptional peak. Thus, the *Swine Flu* pandemic had no significant impact on the connectedness between the energy and stock markets.

The period covering the EBOLA pandemic, Fig. 3 shows a slight increase in the total connectedness, this increase in the connectedness is similar to several spikes in the connectedness levels external to the pandemic period. Then it cannot be considered as a pandemic effect. For a similar period of EBOLA pandemic, the connectedness among the renewable energy and the international stock markets displays an increase of the connectedness level but only for a very limited period, indicating that the dropping dependence could be caused by other linked financial events other than the pandemic.

By comparing the pre and during COVID-19 periods, the two plots in Fig. 3 clearly show an unprecedented upward trend in the connectedness between crude oil and the stock markets, reaching a peak of >70% and a spike in the dependence between renewable energy and stock markets of approximately 68%. These results indicate that COVID-19 has a severe influence on the dependence among energy markets and international stock markets, surpassing the historical effects of the global financial crisis on the relationship between several types of commodities and standard financial markets. Our results are in line with Corbet et al. (2020) and Dahl et al. (2020), who also reported pronounced connectedness during the pandemics and declining spillovers when markets turned to stability.

4.4. Dynamic connectedness and uncertainty

To apprehend the complete behavior of the dynamic connectedness, partially depicted and analyzed in Fig. 3, we regress the total connectedness index on several uncertainty measures. In Models 1 and 3, we consider the Index WPUI to measure a measure for the pandemic uncertainty, whereas the pandemic uncertainty is represented in Models 2 and 4 by considering three dummy variables reflecting *Swine Flu* , *Ebola* and *COVID* − 19 pandemics.

The results from the estimation of Model 1 are reported in Table 5, Column 1 for crude oil and Column 4 for renewable energy. The most relevant finding from the estimation results is the significant positive effects of the pandemic uncertainty on the levels of total connectedness between crude oil and the stock markets indexes. Similarly, results indicate a significant positive influence of the pandemic uncertainty on the connectedness among renewable energy and the stock market indexes. Comparing the parameters related to pandemic uncertainty in Model 1.a and Model 1.b, the results indicate that the pandemic uncertainty has a higher impact on the connectedness between renewable energy and the stock market indexes than crude oil returns with the stock markets indexes. These results have several interpretations: first, as shown in Table 3 and Table 4, the own connectedness of crude oil in the considered system is much higher than the own connectedness of the renewable energy index (88.15% Vs. 75.04%). This indicates that the residual part of the total connectedness explained by the other factors is higher for the system, including renewable energy.

Second, considering a linear relationship between the total connectedness and the pandemic index seems to be nonrealistic. Hence, the pandemic index levels depend on the occurrence of a pandemic. The Index generally increases for a particular period and then decreases due to prevention policies or vaccination complaints, reaching the value of zero for the period spanning from the end of one pandemic and the

Table 5
The estimation results of the contributing factors in the connectedness dynamics.

	TCI/Oil with other indexes			TCI/ECO with other indexes		
	Model 1.a	Model 2.a	Model 3.a	Model 1.b	Model 2.b	Model 3.b
Intercept	33.76***	33.57***	33.09***	37.90***	37.67***	38.68***
	(0.229)	(0.231)	(0.249)	(0.251)	(0.250)	(0.267)
WPUI	0.0440**	0.177***	–	0.160***	0.511***	–
	(0.0142)	(0.0387)	–	(0.0156)	(0.042)	–
WPUI2	–	−0.00699***	–	–	−0.018***	–
	–	(0.00189)	–	–	(0.002)	–
EPU_US	0.0138***	0.0138***	0.0129***	−0.000237	−0.00005	0.0001
	(0.0007)	(0.000783)	(0.0008)	(0.000859)	(0.0008)	(0.0008)
EPU_UK	0.0017	0.0025*	0.0026*	0.00781***	0.0079***	0.009***
	(0.0011)	(0.00113)	(0.0011)	(0.00123)	(0.0012)	(0.0012)
VIX	0.229***	0.226***	0.257***	0.354***	0.336***	0.407***
	(0.0110)	(0.0111)	(0.0107)	(0.0120)	(0.012)	(0.0115)
EVZ	0.109***	0.128***	0.0827**	0.0987***	0.157***	0.0583
	(0.0247)	(0.0253)	(0.0280)	(0.0270)	(0.0274)	(0.0301)
MOVE	0.0021	0.0011	0.0075*	−0.0163***	−0.0184***	−0.0303***
	(0.0033)	(0.0034)	(0.0035)	(0.00372)	(0.0036)	(0.0038)
Swine Flu	–	–	−1.177***	–	–	0.0227
	–	–	(0.308)	–	–	(0.331)
D − Ebola	–	–	0.340**	–	–	−1.402***
	–	–	(0.130)	–	–	(0.139)
D − COVID19	–	–	0.375**	–	–	0.192
	–	–	(0.190)	–	–	(0.210)
N	3136	3136	3136	3136	3136	3136
R^2	0.494	0.501	0.524	0.615	0.622	0.645

Notes: Standard errors in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

beginning of another. Intuitively, the impact of the pandemic uncertainty on the connectedness is also increasing and then decreasing, allowing for an inverted U-shaped relationship between the considered variables. This last claim is modeled in Model 2. The results of the nonlinear specification are reported in Table 5, Column 2 and Column 5. The results show that *WPUI* is significantly positive at the 1% level for the crude oil and stock markets and renewable energy and the stock markets. The squared *WPUI* is significantly negative at the 1% level, indicating an inverse U-shaped pandemic uncertainty-total connectedness relationship.

The result is in line with the intuition that an increase in the pandemic uncertainty could increase the total connectedness between energy (crude oil and renewable energy) and the stock market index of the considered countries only for a certain period. Besides, the relationship between these variables is inverted, implying that our specification combining *WPUI* and the squared *WPUI* along with the other measures of uncertainty is credible. It is worth noticing that the coefficients estimated for pandemic uncertainty in the nonlinear specification is also higher than the one estimated for crude oil. This means that the pandemic uncertainty has a larger influence on the total connectedness between renewable energy and the stock markets indexes than for crude oil with other stock markets.

Comparing the R square of Models 1.a and Model 2.a and Models 1.b and Model 2.b in Table 5, we find that the R square of Model 2.a (0.501) is higher than that of Model 1.a (0.494) and R square of Model 2.b (0.622) is higher than that of Model 1.b. (0.615). This indicates that Model 2 (the nonlinear model), is a better model of total connectedness-pandemic uncertainty than Model 1, the linear model. Table 5 also reports the results of Model 3. In this model, we consider three dummy variables specifying the occurrence of a particular pandemic. We considered three pandemics that occurred in the period of study, namely, *Swine Flu*, *Ebola* and $COVID-19$. The results are reported in Table 5, Column 3 and Column 6.

The results of Model 3.a show that the coefficients associated with the pandemics Ebola and COVID-19 are significantly positive at the 5% level, indicating that the occurrences of these pandemics have significantly increased the connectedness between the crude oil and the stock markets under investigation. However, the coefficient associated with the *Swine Flu* is significantly negative at the 1% significance level, indicating that this pandemic negatively influences the connectedness between crude oil and the stock markets. While the findings on the impacts of Ebola and COVID-19 are in line with the results of Model 1 and Model 2, indicating a positive influence of pandemic uncertainty on the total connectedness, the results on the impact of *Swine Flu* seem to be inconclusive.

In addition to the influence of pandemic uncertainty, the results of the estimated models allow apprehending the impact of the economic and financial uncertainties on the dynamics of the total connectedness among the renewable energy and the stock market indexes of the selected countries. Regarding economic uncertainties, the results show that the coefficient associated to the US economic policy uncertainty is positively significant at the 1% level and stable for three specifications modeling the relationship between the crude oil and the stock markets under investigation. This finding supports the results of the emerging literature on the role of US economic policy uncertainty as a driver of a global financial cycle. For instance, Albulescu et al. (2019) suggest the presence of a significant pass-through effect of US economic policy uncertainty via oil prices, spilling over to the currency market. The results also show that the coefficient associated with UK economic policy uncertainty in the first three columns of Table 5 is significantly positive at 10%, except for model 1.a. The results show that the impact of the UK economic policy uncertainty on the dynamic connectedness between crude oil and the considered stock markets is very limited and significantly lower than the effects of the US economic policy uncertainty index.

Concerning the impact of the policy uncertainty index on the dynamic connectedness between clean energy and economic policy uncertainty, the results show no significant influence of the US economic policy uncertainty on the dynamic connectedness. However, the coefficient associated with the UK economic policy uncertainty is significantly positive at 1% for all the estimated models. We can infer from these findings that the US economic policy uncertainty does not influence the connectedness of crude oil, renewable energy and stock markets, but connectedness gets stronger with the increase in UK economic policy uncertainty. When it comes to the financial uncertainties, the results show a significant influence of most financial variables on the dynamic connectedness between energy and the selected stock market indexes. In particular, the VIX Volatility Index (VIX), a measure of investors' risk sentiment, is statistically significant across all the estimated models and shows a stable and expected positive sign. VIX measures the volatility of the stock market and we conclude from the regression results that with the increase in the volatility of stock market, connectedness among markets tends to increase, supporting the prior studies which indicate that market tensions and economic pressures enhance the volatility and connectedness of markets (Naeem et al., 2021a, 2021b; Mensi et al., 2021; Balli et al., 2021).

Similar to VIX, the Euro Currency Volatility Index (EVZ) measures the market's expectation of 30-day volatility of the EUR/USD exchange rate is statistically significant at 1% level for all the estimated models and exhibits a stable and expected positive sign which reveals a direct relationship between variations in the EVZ and connectedness of energy markets and stock indices. We also infer that with the increase in EVZ, connectedness among markets tends to increase. Surprisingly, in the case of MOVE, we observed the least significance across all models while regressing with crude oil. However, a strong significance is reported for regression between renewable energy and MOVE across all sub-models. A strong negative relationship between MOVE and connectedness between renewable energy and stock markets reveals that with the increase in the bond market's volatility, connectedness tends to decrease and vice versa. Our results present strong justification for the impact of global pandemic uncertainties, policy uncertainties and financial uncertainties as most of the relationships are directly related.

Meanwhile, different pandemics occurrences indicate varied results in each instance, such that Swine Flu is negatively related in Model 3.a, whereas the relationship turns insignificant in Model 3.b. While in case of Ebola, the relationship is direct and significant in Model 3.a and shifts to negative significant in Model 3.b. However, COVID-19 shows a positive relationship between crude oil and stock markets in Model 3.a, whereas the relationship is insignificant in Model 3.b showcases no impact of COVID-19 on the connectedness between renewable energy market and stock markets. The significant results with crude oil and pandemics reflect the notion that crude oil remained volatile among other financial markets; therefore, the impact of various pandemics with crude oil is either significantly positive or negative. Moreover, crude oil exhibits strong market integration (Luo and Ji, 2018; Dahl et al., 2020) and its connectedness with other financial and commodity markets is higher than renewable energy. Conversely, the renewable energy market is still emerging and requires sufficient time to expand compared to crude oil. Thus, various pandemics reveal insignificant relationships with the renewable energy market.

4.5. Robustness check

To examine the sensitivity of the total connectedness to the connectedness index construction, we use the time-varying parameters vector autoregression (TVP-VAR) approach as an alternative to the DCC-GARCH connectedness employed in the paper. The time-varying parameters vector autoregression (TVP-VAR) approach is developed by Antonakakis et al. (2020), which predicts a time-varying variance-covariance structure to capture possible changes in the structure of the data and generates several robust connectedness measures. Both TVP-VAR and DCC-GARCH connectedness approaches do not arbitrarily set

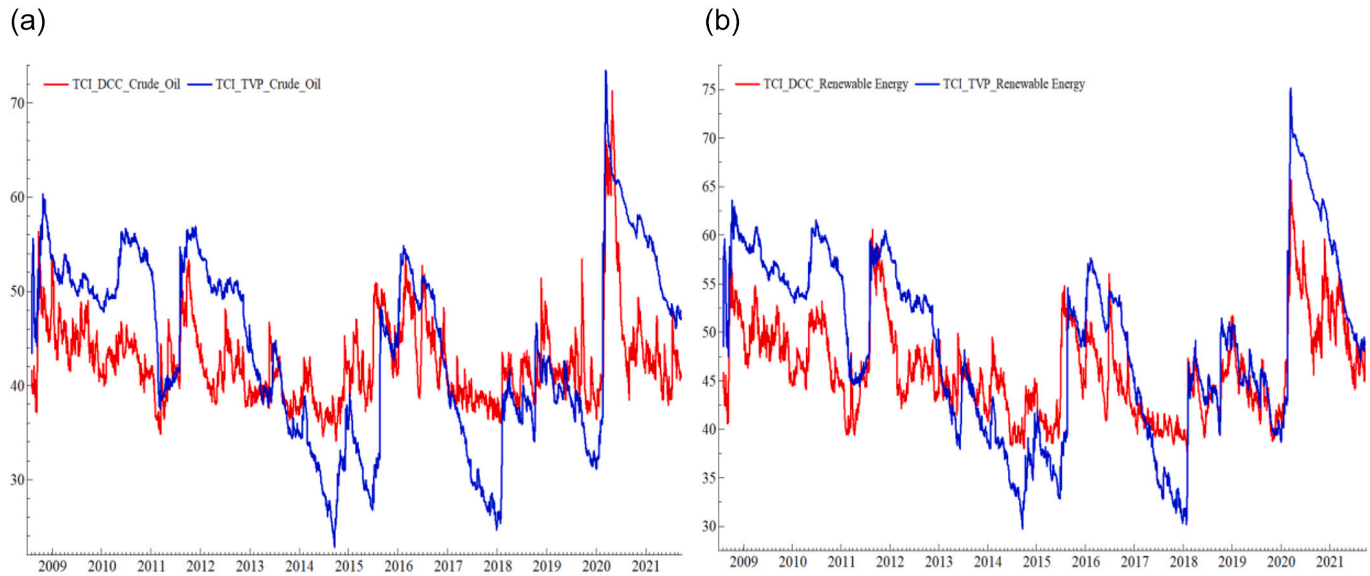

Fig. 4. Total connectedness between energies (crude oil, Renewables) and the country stock markets returns: DCC-GARCH versus TVP-VAR approaches.

Table 6
The estimation results using the TVP-connectedness approach.

	TCI/Oil with other indexes			TCI/ECO with other indexes		
	Model 1.a	Model 2.a	Model 3.a	Model 1.b	Model 2.b	Model 3.b
Intercept	23.51***	23.42***	27.34***	28.48***	28.88***	32.29***
	(0.561)	(0.533)	(0.611)	(0.505)	(0.476)	(0.544)
WPUI	0.699***	0.692***	–	0.603***	0.359***	–
	(0.0348)	(0.0895)	–	(0.0313)	(0.0799)	–
WPUI2	–	−0.0017***	–		0.0117**	–
	–	(0.0003)	–		(0.00389)	–
EPU_US	0.0148***	0.0145***	0.0186***	0.0123***	0.0113***	0.0155***
	(0.00192)	(0.00181)	(0.00199)	(0.00173)	(0.00162)	(0.00177)
EPU_UK	0.0117***	0.0139***	0.0180***	0.0170***	0.0193***	0.0221***
	(0.00276)	(0.00260)	(0.00277)	(0.00248)	(0.00232)	(0.00247)
VIX	0.267***	0.279***	0.412***	0.348***	0.336***	0.445***
	(0.0269)	(0.0255)	(0.0263)	(0.0242)	(0.0228)	(0.0234)
EVZ	0.880***	0.827***	0.793***	0.650***	0.582***	0.644***
	(0.0604)	(0.0584)	(0.0689)	(0.0543)	(0.0522)	(0.0613)
MOVE	0.0132	0.0128	−0.0521***	0.0179*	0.0207**	−0.0481***
	(0.00831)	(0.00786)	(0.00869)	(0.00748)	(0.00702)	(0.00774)
Swine Flu	–	–	0.902	–	–	2.863***
	–	–	(0.758)	–	–	(0.674)
D − Ebola	–	–	−5.888***	–	–	−5.202***
	–	–	(0.319)	–	–	(0.284)
D − COVID19	–	–	2.118***	–	–	2.171***
	–	–	(0.480)	–	–	(0.428)
N	3136	3136	3136	3136	3136	3136
R^2	0.520	0.545	0.530	0.582	0.601	0.591

Notes. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

the rolling-window size as required in standard connectedness techniques. In this way, these two approaches avoid the loss of observations in the computation of the dynamic measures of connectedness.

The dynamic connectedness table from the TVP-VAR approach indicates that the total connectedness measure for crude oil with the international stock markets is approximately similar to that obtained from the DCC-GARCH, with values 42.6% and 44.14%, respectively. Equally, the total connectedness index of the system composed of clean energy and the considered return indexes appears to be close, with values of 48.94 from the TVP-VAR versus 46.21% from the DCC-GARCH. This small difference is also depicted in Fig. 4, in which the dynamics of the total connectedness obtained from the two approaches (DCC-GARCH and TVP-VAR) are presented. Fig. 4 also shows that the dynamic total connectedness is similar when applying both connectedness frameworks.

For robustness check, we also examine the effects of using the alternative connectedness approach (TVP-VAR) on the estimated regressions performed to identify the determinants of the total connectedness. The results are reported in Table 6. In the models reported in Table 6, the dependent variable is the total connectedness index provided by the TVP-VAR approach. The results appear similar to those provided when using the total connectedness from the DCC-GARCH (reported in Table 5). The similarities are mostly depicted in the sign of the coefficients and in the statistical significance. In addition, the inverted U-shape relationship between the pandemic uncertainty index and the total connectedness of the considered assets. Finally, we notice some differences in terms of the values of coefficients. This difference refers to the over-estimation of the total connectedness index, as stated previously.

5. Conclusion

This study investigates the influence of economic, financial, and pandemic uncertainties on the connectedness between crude oil, renewable energy, and stock markets for the period encompassing August 4, 2008 to September 24, 2021. At first, the study employed the DCC-GARCH technique and time-varying parameters vector-autoregression (TVP-VAR) approach to validate our findings' robustness, which remarkably surpassed the traditional connectedness technique proposed by Diebold and Yilmaz (2012); Diebold and Yılmaz (2014). Secondly, we employed OLS regressions to examine the impact of various economic, financial, and pandemic uncertainties on the linkage between crude oil, renewable energy, and stock markets. Our study catered to three pandemics, namely Swine Flu, Ebola outbreak, and COVID-19, to assess whether these pandemics influence connectedness.

Our results pertaining to connectedness between energy markets and international stocks reveal that crude oil, and renewable energy are major transmitters of spillovers. In contrast, Russia, China, and Japan stocks moderately transmit spillovers to stock markets of Canada, KSA, South Korea, and India. Net connectedness of energy markets and stock market indices exhibit similar results where crude oil and renewable energy market are net transmitters of spillovers among various stock markets. Meanwhile, the stock indices of Russia and China show less connectedness from the network, which symbolizes their diversification avenues when markets are experiencing economic, financial, and pandemics turmoil. In addition, dynamic connectedness patterns revealed time-varying patterns between energy markets and stock indices where three significant pandemics are highlighted and intense spillovers are reported in COVID-19 pandemic, while moderate risk spillovers are exhibited during the Swine Flu and Ebola pandemics.

Findings related to the influence of economic, financial, and pandemics uncertainties reveal that UK economic policy substantially increases the connectedness of energy and stock markets, whereas US economic policy indicator indicated insignificant results. Out of financial uncertainties, VIX and EVZ showed substantial impact on the connectedness (either positive or negative), whereas MOVE revealed an insignificant effect on crude oil and stock market nexus and a significant negative influence on the renewable energy-stock market nexus. Out of pandemics, significant findings are reported in oil-stock relationships, but for renewable energy and stock market nexus only negative influence is reported by Ebola pandemic. In this way, we document the substantial impact of economic, financial, and pandemic uncertainties on the relationship between energy markets and stock indices. With these enlightenments, we devise useful implications for policymakers, governments of selected countries, regulatory bodies, environmentalists, green investors, institutional investors, and portfolio managers to relish the study's findings, particularly considering the uneven economic, financial, and pandemic uncertainties.

Policymakers can use these findings by planning and strategizing new renewable energy and crude oil market policies to pick those beneficial avenues for protecting environmental concerns and abiding by the ecosystem parameters. Governments of the selected markets in particular, and the global world in general, can appreciate these findings by inculcating proactive plans and proposing practical strategies to their states to initiate and encourage renewable energy projects to back the sustainability and energy conservation mechanisms globally. Similarly, macroprudential bodies can facilitate a smooth transition from traditional energy to renewable energy sources as they are also beneficial for the investors, whether evaluating them in economic or financial aspects.

Whether individual or institutional, investors can take up these findings as a necessary benchmark when deciding about conventional and renewable energy stocks. While measuring the benefits of renewable markets, green investors can add the renewable energy market to their investment portfolios as their performance over the period, compared with crude oil, is not lagging in any respect. By doing this, both individual and institutional investors can include green avenues of investments in their portfolios for obtaining environmental sustainability and reducing resource depletion. Portfolio managers can also cherish the findings of the study by carefully observing the diversifiers among international stock markets and avoiding potential losses when markets are undergoing episodes of economic and financial fragility. Hence, the study portrays valuable insights for practitioners and research scholars by providing expedient findings and policy implications, particularly in conventional and renewable energy sources.

CRediT authorship contribution statement

Noureddine Benlagha: Conceptualization, Data curation, Methodology, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Sitara Karim:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Muhammad Abubakr Naeem:** Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing, Project administration. **Brian M. Lucey:** Conceptualization, Methodology, Writing – review & editing, Supervision. **Samuel A. Vigne:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106348.

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