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Research article

Asymmetric volatility spillover between oil prices and regional renewable energy stock markets: A time-varying parameter vector autoregressive-based connectedness approach

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Abstract: The rapid expansion of renewable energy sources and their integration into the energy mix has generated scholarly interest in comprehending the interplay between renewable and conventional energy markets. This research aims to examine the (a)symmetric volatility spillover between the oil market and various regional renewable energy stock markets, namely the US, Europe and Asia. To achieve this objective, we employ the time-varying parameter vector autoregressive-based connectedness (TVP-VAR) approach, which allows analysing the interconnection and transmission of shocks between the different markets. Based on an analysis of daily data relative to the different regional renewable energy stock markets and international oil prices, the findings suggest the presence of a dynamic volatility connectedness between the green and brown energy stock markets. The extent of connectedness is contingent upon the specific regional renewable energy market under consideration. Moreover, the decomposition of the volatility series into *good* and *bad* volatility emphasizes an asymmetric pattern, which becomes more pronounced during periods of major events. On average, the oil market and the Asian renewable energy stock market are net receivers of volatility shocks. In contrast, the US and European renewable energy stock markets are net transmitters of shocks. Our findings provide investors with valuable insights for portfolio design and risk management decisions.

Keywords: oil price; renewable energy; stock markets; volatility spillover; connectedness; asymmetry; TVP-VAR
Mathematics Subject Classification: 62P05, 91G15, 91G45

1. Introduction

The latest decades have been marked by increased environmental degradation and the rise of climate change as a severe threat to humanity. At the same time, the energy transition has often been considered a potential solution to prevent further environmental degradation and comply with the objectives of the Paris Agreement on climate change [1]. However, the energy transition process has been relatively slow due to various challenges to its implementation [2]. Indeed, despite the increase in renewable energy (hereafter RE) adoption during the recent decades, most countries still rely on fossil fuels as a primary energy source [3]. The substitution hypothesis has been widely discussed in scholarly circles. It suggests that increasing fossil fuel prices could lead to a faster adoption of RE sources in countries that heavily rely on energy consumption [4–6]. However, the occurrence of some major events suggests that the interconnection between fossil fuel prices and RE sources is still open to debate. For instance, the latest sharp rise in natural gas prices following the Russian-Ukrainian conflict has not increased the demand for RE sources. On the contrary, there has been a significant surge in the demand for coal as an alternative to oil and natural gas.

Scholars have been recently interested in examining the relationship between fossil fuels and RE sources [7–12]. An emerging trend in the literature has mainly concentrated on the potential interdependence between the crude oil market and the RE stock market [13]. The linkage between oil prices and stocks of companies in the RE sector can be primarily attributed to the substitution effect. According to [5], the substitution effect is observed when an increase in the cost of crude oil prompts an upswing in demand for RE sources. This heightened demand leads to enhanced profitability of RE companies and the appreciation of their stock prices. Empirical studies have employed a wide range of econometric methodologies to investigate the interrelationships between fossil fuel prices, particularly crude oil, and RE stocks. The existing studies have used copulas [14,15], quantile-based approaches [13,16], wavelets [17,18,19,20] and connectedness [21,22]. In addition, most studies analyseysed the relationship between the WilderHill Clean Energy Index and oil prices, which tracks the stock market for RE companies around the globe. Scarce research concentrated on the potential geographic heterogeneity in the relationship between oil prices and RE stocks [23,24]. Finally, most studies analysed the symmetric relationship between oil prices and RE stocks [25,26].

This study contributes to the existing literature by examining the dynamic connectedness between the second moment of conventional energy prices and RE stock prices. More specifically, it explores the connectedness between West Texas Intermediate (WTI) oil price volatility and NASDAQ OMX Green Economy indices volatility across different regions, namely Asia, Europe and the United States. The empirical analysis uses the time-varying parameter vector autoregressive (hereafter TVP-VAR) model developed by [27,28] based on daily data ranging from November 10, 2010, to November 15, 2022. The study adds to the literature in several ways. First, despite the expanding interest in the association between oil prices and RE stocks, most works have concentrated on a single RE market. The US market has been the subject of ongoing analysis by academics, such as [13,21,29,30]. In contrast, the European renewable stock market received little attention, as highlighted by [31]. For instance, [26] conducted a study examining the association between the CBOE Crude Oil ETF Volatility Index and the S&P Global Clean Energy Index (SPGCE), which assesses the financial performance of companies involved in clean energy production across various countries. Although the RE stock index considers companies in many countries, it does not allow analyzing their interrelationship. The current understanding of the interplay between the international crude oil market and RE stock markets across different geographical regions is still limited. Research into the connectedness between oil prices and RE stocks of various regional markets is developing but is still in its early stages. To fill this gap, this research focuses on the volatility of the NASDAQ OMX Green Economy index associated with three geographic regions: the US, Europe and Asia. The analysis enables the identification of whether the crude oil market volatility dominates the different RE stock markets. Additionally, it determines which RE stock market (American, European or Asian) has a dominant role and thus explains the volatility associated with the other markets. The importance of conducting such a regional investigation lies in its ability to assess the potential of RE markets to serve as hedging instruments.

Second, the approach implemented in this study involves a combination of the TVP-VAR methodology proposed by [32] with the connectedness approach developed by [27,28]. The dynamic connectedness allows us to comprehend the evolution of volatility transmission over time. Indeed, the nature of volatility spillover may change over time, making the TVP-VAR model more appropriate than decomposing the full period into different sub-periods. Additionally, the time-varying analysis has many advantages, the most significant being the ability to establish linkages between the observed connectedness and potential shocks that may arise. Indeed, oil prices and RE stocks may be characterized by low and high volatility spillover episodes, which can be influenced by various factors, including economic events and policy changes. For instance, [20] showed that the volatility spillover between renewable and oil prices depends on major events, such as the COVID-19 pandemic, the Global Financial Crisis and Brexit. In addition, [33] examined the connectedness between oil price uncertainty, financial stress and economic policy uncertainty using the TVP-VAR. The findings suggest that connectedness increased during the COVID-19 pandemic. Therefore, a time-varying volatility transmission analysis is required to identify these changing patterns and dynamics. In the same vein, [34] suggested utilizing connectedness measures based on the TVP-VAR instead of employing the rolling-window estimation of the VAR model. Additionally, the connectedness approach is favored over Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models because it can ascertain the spillover direction by computing pairwise net spillovers [30].

Third, the present research conducts an asymmetric volatility spillover analysis. Although the symmetric volatility spillover between oil prices and the regional RE stock markets may provide some insights into the interrelationships between the different markets, it may not be adequate in identifying any potential asymmetry. According to the literature on financial markets, asymmetry is commonly used in the literature on financial markets to describe the idea that positive and negative news have different effects on the price and volatility of an asset. For instance, [35] investigated the volatility transmission among crude oil markets and concluded a strong asymmetry in response to shocks during some economic stress periods. To account for asymmetry, we adopt the methodology of [15], which involves inferring the good and bad volatility of RE stock indices using the GJR-GARCH model developed by [36]. In other words, the methodology consists of dividing the volatility caused by positive and negative returns into good and bad volatility. The adopted methodology has been shown to exhibit a robust performance in volatility modelling for financial time series [15]. It is worth noting that the study conducted by [24] is the closest to our research. The authors analysed the connectedness between WTI crude oil prices, US, European and Asian green energy stocks. However, our study outperforms that of [24], which only considers the symmetric volatility spillover between the traditional and green energy stocks. As mentioned, our study fills this gap by providing new insights into the positive and negative volatility spillover between traditional and renewable energy stocks.

The remainder of this paper is organized as follows: Section 2 is devoted to a summary of the existing literature, while a presentation of methods and materials is provided in Sections 3 and 4, respectively. The results of the empirical investigation are addressed in Section 5. Section 6 is reserved for policy implications, and finally, Section 7 concludes the research.

2. Literature review

The association between oil prices and stocks of RE companies has received growing attention in recent times. According to [4], the linkage between the oil and RE markets is unclear and remains in question. Indeed, the relationship between the oil and RE markets is predominantly upheld through pricing mechanisms. [37] state that crude oil price plays a crucial role in determining when RE projects become profitable, the pace at which conventional energy sources are substituted by renewable ones, and the financial viability of companies operating within the RE industry. A positive correlation exists between oil prices and RE, whereby an increase in oil prices fosters the substitution of conventional fossil fuel sources with alternative RE sources [4,25]. Indeed, the substitution effect is observed when oil prices increase, which induces a rise in the demand for RE sources, yielding more profitability for RE companies and an appreciation of their stock prices [5]. Stocks of RE companies may also be linked to oil prices via the production cost channel, as suggested by [13]. The increase in oil prices for companies relying on oil as input leads to increased production costs and decreased demand for oil. This, in turn, could accelerate the shift towards RE sources and lead to an increased market value of RE companies' stocks. The discussion above suggests that prevailing explanations regarding the connection between crude oil prices and RE stock prices have focused on unidirectional impacts from oil prices towards renewables. Little attention has been paid to how RE stocks may affect oil prices. For instance, [37] states that the growth of RE projects may influence oil prices. However, it is essential to note that the impact of renewables on oil prices has received less research attention than the impact of oil prices on renewable energy stocks.

On the empirical side, a growing number of studies with different time frames and methodologies yielded mixed findings on the interconnections between RE stocks and crude oil prices. An investigation was carried out by [25] to examine the relationship between oil prices and the WilderHill Clean Energy Index as a proxy of RE stocks. The authors employed the Lag Augmented Vector AutoRegressive (LA-VAR) Wald test developed by [38] to assess the existence of Granger causality. The findings confirm that oil prices Granger-cause stock prices of RE companies. [4] also investigated the impact of oil prices on RE stocks. The VAR model indicates that variations in oil prices contribute to the performance of RE stock indices. Based on copulas, [14] analysed the systemic risk and dependence between RE stock and crude oil prices. The empirical analysis suggests the presence of significant connections between the two markets. Moreover, about 30% of the potential downside and upside risks associated with RE stocks are attributed to oil price variations. [17] also analysed the association between oil and RE stock prices using wavelet and the Granger non-causality test from 2006 to 2015. The empirical investigation suggests a two-way non-linear causal relationship between oil prices and RE stocks. However, the causal relationship from RE stocks to oil prices is more significant. The wavelet analysis has also been used by [18], who investigated the connections between the Renewable Energy Industrial Index and the NYSE Arca Oil Index using daily data from July 2019 to June 2020. The findings indicate the presence of co-movements between oil prices and RE stocks. Furthermore, the relationship between the two variables exhibited a co-movement pattern only during the initial stages of the COVID-19 pandemic. [20] analysed the volatility spillover between five green indices and oil shocks (supply shock, demand shock and risk shock) between 2007 and 2021 based on the wavelet coherence model and frequency connectedness. The findings confirm the presence of a strong correlation between the oil and green markets in the mid- and long-term. In addition, the green stock market exhibits more significant volatility spillovers from the oil market. The volatility spillover between the two markets is found to be intensified during specific events, such as COVID-19 and the Global Financial Crisis. Finally, [37] analysed the correlation between oil prices and RE stocks using the detrended cross-correlation analysis. The findings confirm the existence of a high correlation between oil and indices of the renewable sector between mid-2008 and mid-2012, which coincides with the Global Financial Crisis.

Other studies employed quantile-based approaches. For example, [13] examined the relationship between oil prices and different sectoral RE stocks. The study employed the nonparametric causality-in-quantiles test introduced by [39] from October 2010 to September 2020. The findings suggest that oil returns cause the renewable stock index returns under normal market conditions, while no significant causal relationships are observed from renewable stock index returns to oil returns. In a similar work, [16] investigated the impact of oil prices on clean energy stock indices using the quantile regression developed by [40]. The results show that a rise in oil prices is associated with an appreciation of different clean energy indices only for low quantiles. The two studies above conclude the importance of accounting for the nonnormal distribution of the variables. [41] accounted for another potential irregularity in the data generation process, namely asymmetry. The asymmetric association between oil prices and RE stocks has been examined using the non-linear ARDL model proposed by [42]. The empirical investigation confirms the presence of asymmetry, as only increases in oil prices affect the WilderHill New Energy Global Innovation Index. [5] examined the impact of oil shocks on RE stock returns between January 2001 and December 2018 by disentangling oil prices into supply, aggregated demand and oil-specific demand shocks. The results provide empirical evidence in favour of the substitution effect, which claims that a decrease in oil prices is associated with a rise in the value of RE stocks. This relationship explains approximately 14.54% of the observed fluctuations in the long-term returns of RE stocks.

Some recent studies have implemented the connectedness analysis to assess the interconnections between crude oil and RE stock markets. For instance, [30] examined the connectedness between the return and volatility of the WilderHill Clean Energy Index and the WTI crude oil price. The author concluded that crude oil prices are affected by the return and volatility of the clean energy index. [21] analysed the association between oil prices and RE stocks. The study employed many indicators related to RE sources and implemented the connectedness analysis and different GARCH-type models. The results generally confirm the presence of connections between oil prices and renewable stocks. However, the author highlighted the existence of heterogeneous interactions between oil prices and RE stocks, which depend on the RE source. [43] implemented the connectedness proposed by [44] to check the relationship between WTI crude oil price and the return and volatility of the Wilder Hill Clean Energy Index. The authors concluded the absence of significant short- and long-run interactions between the two variables. Moreover, [22] employed the connectedness approach proposed by [27,28] to examine the correlation between various fossil fuel energy sources, such as oil, coal and natural gas, and the return and volatility of RE stocks. Two important conclusions have been drawn from the empirical investigation. First, the impacts of oil prices dominate those of RE stocks. Second, volatility transmission between the oil and RE markets is more pronounced than the transmission of returns. A study by [45] investigated the linkages between crude oil prices, gold prices and five sector stock indexes related to new energy vehicles in China using the TVP-VAR of [27,28]. The results confirm that the different stock markets are net transmitters of shocks, while oil and gold markets are net receivers. Finally, [46] investigated the relationship between fossil fuel markets and the RE stock market and concluded a significant linkage between them. Moreover, the policy measures implemented during the Conference of the Parties (COP) meetings have been found to enhance the linkages between the two markets.

It is worth mentioning that an inspection of the existing literature suggests that scarce studies concentrated on the volatility spillover between the oil market and regional renewable stock markets. [23] analysed the connectedness between WTI crude oil prices, on the one hand, and the US Wilder Hill Clean Energy Index (ECO) and the European Renewable Energy Index (ERIX), on the other hand. The analysis suggests that the return and volatility spillovers from the fossil energy markets to US renewable stocks are more pronounced than their European counterparts. Furthermore, [24] investigated the connectedness between traditional energy prices (crude oil and natural gas) and regional renewable energy stock markets (US, Europe and Asia) using the TVP-VAR model. The findings demonstrate a significant spillover between green energy stocks and conventional energy prices. More specifically, it has been observed that there is a spillover effect from green energy stocks to traditional energy stocks, which implies that the renewable energy stock market is a net transmitter of volatility, while the oil and gas markets are net receivers.

3. Methods

The present research follows a two-stage procedure. The first stage involves estimating volatility series using a GARCH-type process, deemed the most suitable approach given the data at hand. The constructed volatility series are then decomposed into good and bad to conduct the asymmetric spillover analysis. The next stage entails using the TVP-VAR model to estimate the symmetric and asymmetric volatility spillover indices based on [27,28].

3.1. Computing good and bad volatility series

According to the literature on financial markets, the concept of asymmetry refers to the idea that the impacts of good and bad news on the price and volatility of a given asset are different. Many approaches have been used to account for the asymmetry in the volatility, including copulas theory, smooth transition GARCH models and high-frequency data, among others. However, the high-frequency data approach, among others, may suffer from some drawbacks, such as microstructure noise in high-frequency data, the jump component contained in stock returns, and the problem of availability of high-frequency data for most financial markets. To overcome these drawbacks, we follow [15] by inferring the good and bad volatilities of the RE stock indices based on the GJR-GARCH model developed by [36]. This model exhibited a robust performance in financial time series volatility modelling. This is attributed, among others, to its ability to incorporate different volatility features, including volatility clustering and the leverage effect.

Let R_t be the return of oil price or a regional RE index at time t. We define the ARMA(p, q)-GJR-GARCH(1,1) model by the following set of equations:

$$R_t = \mu_t + \varepsilon_t, \quad \varepsilon_t = \sqrt{h_t} z_t, \tag{1}$$

$$h_t = w + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{2}$$

$$\varepsilon_t \backslash \Omega_{t-1} \sim Skt(\varepsilon_t, \eta, v), \tag{3}$$

$$\text{where } I_t = \begin{cases} 1\, if \;\; \varepsilon_t < 0 \\ 0\, if \;\; \varepsilon_t \geq 0 \end{cases}. \tag{4}$$

ARMA stands for the AutoRegressive Moving Average process and GJR-GARCH is the Glosten Jagannatan Runkle-Generalized AutoRegressive Conditional Heteroscedasticity model. The term μ_t follows an ARMA(p,q) process with orders p and q, which will be determined based on the AIC information criterion, while ε_t is the error term. Equation (1) allows for a filtered series $z_t = \varepsilon_t/h_t$ from the return series R_t. Equation (2) describes the dynamics of conditional volatility following a GJR-GARCH process, which accounts for the volatility asymmetry. Furthermore, according to Eq (2), it is possible to distinguish the volatility series into two components: good volatility and bad volatility, following the sign of shock indicated by the error term. To account for the skewed and fat-tailed properties observed in the return series, we assume that the error term follows a Skewed Student-t distribution Skt(ε_t, η, v), where ξ represents the asymmetry parameter (skewness), and v represents the tail parameter (degree of freedom or Kurtosis).

Based on Eq (2), one can infer the good and bad volatility series corresponding to the positive and negative shocks, denoted by h_t^+ and h_t^-, respectively, as follows:

$$\begin{cases} h_t^+ = h_t \mathbb{I}_{[\,\varepsilon_t \geq 0]} \\ h_t^- = h_t \mathbb{I}_{[\,\varepsilon_t < 0]} \end{cases}, \tag{5}$$

where $h_t = h_t^+ + h_t^-$.

3.2. The TVP-VAR approach

[34] suggested that connectedness measures derived from the TVP-VAR model are preferred over the rolling-window approach, owing to the benefits of analyzing VAR modelling from a time-varying standpoint. This methodology employs the TVP-VAR model proposed by [32] in conjunction with the connectedness approach developed by [27,28]. This study employs the abovementioned approach to examine the spillovers between the different prices. Let Y_t^+ be $(N \times 1)$ a vector (N=4) of good oil price volatility, and the three regional RE indices measuring good volatilities. The TVP-VAR(p) model is mathematically represented in the following manner:

$$Y_t^+ = c_t^+ + \sum_{i=1}^{p} \Phi_{i,t}^+ Y_{t-i}^+ + u_t^+ ; u_t^+ \setminus \Omega_{t-1}^+ \backsim N(0, S_t^+), \tag{6}$$

$$\Phi_t^+ = \Phi_{t-1}^+ + v_t^+ ; v_t^+ \setminus \Omega_{t-1}^+ \backsim N(0, R_t^+). \tag{7}$$

Similarly, for the bad volatilities vector, denoted by Y_t^-, the TVP-VAR(p) model is defined by:

$$Y_t^- = c_t^- + \sum_{i=1}^{p} \Phi_{i,t}^- Y_{t-i}^- + u_t^- ; u_t^- \setminus \Omega_{t-1}^- \backsim N(0, S_t^-), \tag{8}$$

$$\Phi_t^- = \Phi_{t-1}^- + v_t^- ; v_t^- \setminus \Omega_{t-1}^- \backsim N(0, R_t^-), \tag{9}$$

where Y_{t-i}^+ and Y_{t-i}^- are a $(N \times 1)$ lagged vector at order i of Y_t^+ and Y_t^-, respectively. u_t^+ and u_t^- denote the error terms, which are supposed to be normally distributed with time-varying variance-covariance matrices S_t^+ and S_t^-, respectively. Ω_{t-1}^+ and Ω_{t-1}^- are the information set available at $t-1$ provided by good and bad volatility, respectively. Φ_t^+ and Φ_t^- are $(N \times Np)$ time-varying parameter matrices. The time-varying feature of these two matrices is described by Eqs (7) and (9) as a random walk. The vector with the error terms denoted v_t^+ and v_t^-, respectively, are also supposed to be normally distributed.

3.3. Good and *Bad* volatility spillover measures

In order to define spillover measures based on TVP-VAR following the methodology developed by [27,28], it is important to transform the VAR model into a moving average representation, as recommended by [47,48]. Let Y_t be the good or bad volatility vector. This representation is expressed by:

$$Y_t = A_t u_t, \tag{10}$$

where the matrix $A_t = (A_{1,t} \quad A_{2,t}, \quad \cdots \quad A_{p,t})'$ is a $(N \times Np)$ matrix of parameters, which verifies $A_{0,t} = I_N$ if $i = 0$ and $A_{i,t} = \sum_{k=1}^{p} \Phi_{1,t} A_{i-k,t}$ if $i \neq 0$.

Based on Eq (10), one can decompose the forecast error variance as recommended by [27,28]. We use the generalized impulse response functions (GIRF) and the generalized forecast error variance decompositions (GFEVD) to compute the spillover index. The GIRF, denoted by $\Psi_{j,t}^{g}(J)$, can be obtained via the following equations:

$$GIRF\big(J, \delta_{j,t}, \Omega_{t-1}\big) = E\big(Y_{t+J}\{u\big|j, t = \delta_{j,t}, \Omega_{t-1}\big) - E\big(Y_{t+J}\{\Omega\big|t-1\big), \tag{11}$$

$$\Psi_{j,t}^{g}(J) = S_{jj,t}^{\frac{-1}{2}} A_{J,t} S_t u_{j,t}, \tag{12}$$

where J represents the forecast horizon and $\delta_{j,t}$ is the selection vector, which is equal to 1 on the j^{th}position, and 0 otherwise. The GFEVD, denoted by $\Pi_{j,t}^{g}(J)$, can be written as:

$$\Pi_{j,t}^{g}(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}. \tag{13}$$

The expression $\Pi_{j,t}^{g}(J)$ can be understood as the proportion of variance that one variable contributes to the others. The GFEVD verifies $\sum_{j=1}^{N} \Pi_{j,t}^{N}(J) = 1$ and $\sum_{i,j=1}^{N} \Pi_{j,t}^{N}(J) = N$. Therefore, the GFEVD allows the construction of different connectedness indices.

4. Materials

The present research investigates the (a)symmetric volatility spillover between oil prices and renewable energy stocks. Unlike most works on the subject, the empirical analysis intends to check the regional interdependence between various renewable energy stock markets. To do so, it employs daily data on the WTI oil prices and the NASDAQ OMX Green Economy indices across different regions: the United States, Asia and Europe. The empirical research focuses on these three indexes as stand-ins for the renewable energy markets in each geographic region. The data were collected on a daily basis, spanning from November 10, 2010, to November 15, 2022. The WTI oil price series is obtained from the US Energy Information Administration, and the RE data is extracted from *investing.com*. By omitting data points during which at least one market was closed, a total of 3010 observations were obtained. The evolution of the return and volatility of oil prices and the RE index of each region are presented in Figure 1.

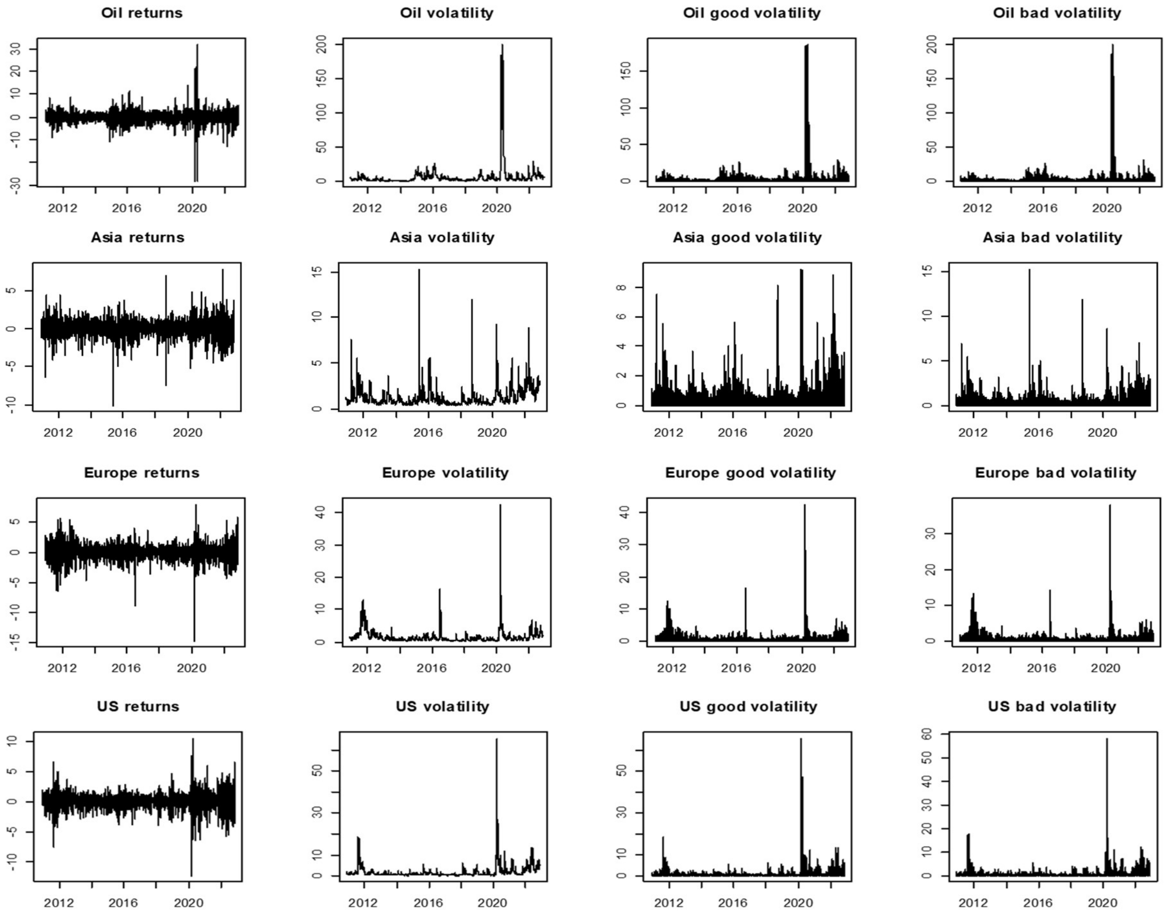

Figure 1. Return and volatility of oil prices and regional RE stock indices.

A close look at both returns and volatility series shows that the oil prices and RE stock markets exhibit high variability periods followed by stable phases supporting the effects of some political and economic events on the oil and RE stock markets. The volatility of oil prices was notably pronounced during the 2015 oil price collapse and the COVID-19 pandemic. Concerning the regional stock indices of RE, it can be observed that the Asian stock index displays a higher degree of volatility than the European and US stock indices. It can be observed that the COVID-19 outbreak has significantly affected both returns and volatility series across all regions. To obtain the good and bad volatility series, we estimate the AR(1)-GJR-GARCH (1,1) model and extract the total conditional volatility series based on Eq (2). Then, the good and bad volatility series are obtained based on Eq (5). The descriptive statistics of the return, full, good and bad volatility series are provided in Table 1. The US RE stock market has the highest return (0.048%), while the Asian RE stock market exhibits a negative return (−0.001%). The oil market displays the highest level of risk, as evidenced by its variance value of 7.334%. All returns series have non-null skewness and kurtosis significantly different from 3, indicating that series deviates from the normal distribution.

Table 1. Descriptive statistics and preliminary tests for returns and volatilities.

	Oil	Asia	Europe	US
Panel A: Returns				
Mean	0.0210	−0.0010	0.0160	0.0480
Variance	7.3340	1.2530	1.5950	1.8480
Skewness	0.113**	−0.439***	−0.791***	−0.565***
Ex.Kurtosis	25.281***	5.663***	9.809***	8.568***
JB	0.0000***	0.0000***	0.0000***	0.0000***
ERS	−11.976***	−9.823***	−13.770***	−19.304***
Q(10)	25.532***	25.165***	22.418***	72.870***
Q2(10)	1033.970***	207.183***	415.863***	2022.191***
Panel B: Volatility				
Mean	7.2260	1.2890	1.6810	1.9920
Variance	251.2910	1.4400	6.7010	14.9560
Skewness	7.709***	3.968***	7.906***	8.762***
Ex.Kurtosis	67.802***	24.449***	89.321***	104.471***
JB	0.0000***	0.0000***	0.0000***	0.0000***
ERS	−6.037***	−9.838***	−9.402***	−8.464***
Q(10)	13575.094***	9802.638***	11594.670***	12505.740***
Q2(10)	10182.280***	5542.408***	7588.899***	8966.033***
Panel C: Good volatility				
Mean	3.8930	0.6550	0.8930	1.1060
Variance	157.6900	1.0180	4.7700	9.6070
Skewness	10.126***	3.220***	9.589***	10.833***
Ex.Kurtosis	120.372***	15.970***	134.818***	167.842***
JB	0.0000***	0.0000***	0.0000***	0.0000***
ERS	−12.047***	−12.229***	−9.421***	−9.839***
Q(10)	3018.774***	801.169***	2118.537***	2261.264***
Q2(10)	3039.616***	1887.965***	2409.057***	2062.904***
Panel D: Bad volatility				
Mean	3.3330	0.6330	0.7880	0.8860
Variance	119.5590	1.2520	3.3400	7.3090
Skewness	10.212***	4.525***	8.835***	11.544***
Ex.Kurtosis	127.079***	34.618***	130.662***	190.531***
JB	0.0000***	0.0000***	0.0000***	0.0000***
ERS	−11.512***	−11.761***	−8.966***	−10.142***
Q(10)	2174.138***	1777.100***	1464.114***	2002.040***
Q2(10)	1594.155***	2628.583***	996.457***	1796.430***

JB is the p-value of the Jarque-Bera normality test, while ERS is the Elliot-Rothenberg-Stock unit root test. Q(10) and Q2(10) are the Ljung-Box tests for 10th-order serial correlations for levels and squared volatilities series, respectively. *** and ** indicate the statistical significance at the 1 and 5% levels, respectively.

Moreover, the Jarque-Bera p-values are null for all returns series, allowing the rejection of the normality hypothesis. The ERS unit root test rejects the null hypothesis of a unit root for all considered series. Furthermore, the Ljung-Box test statistics results suggest the presence of serial correlations in both the oil and RE stock markets. This suggests that a GARCH model is suitable for accurately modelling the data. Regarding the full and decomposed conditional volatility series, results show that oil prices exhibit the highest mean conditional volatility. These findings remain valid when the volatility is decomposed into good and bad volatilities. Additionally, the average values of good volatility tend to be higher than those of bad volatility. We also observe that total, good and bad volatility series have skewness and kurtosis excess different from the normal distribution. This result is confirmed by the Jarque-Bera test, rejecting the normality hypothesis for oil and RE stock indices.

5. Empirical results

5.1. Symmetric volatility spillover results

To explore the volatility spillovers among oil prices and regional RE stocks, we employ the TVP-VAR based on the spillover indices of [27,28]. Before distinguishing positive and negative volatilities, we check the spillover effects within the overall conditional volatility as a benchmark analysis. Table 2 reports the estimation outcomes of the average dynamic spillover measures among oil prices, Asian, European and US RE stock index volatility. The results are derived from a TVP-VAR model that employs a lag length of order one chosen through the AIC and a 10-step-ahead forecast error.

Table 2. Connectedness matrix—full volatility.

	Oil	**Asia**	**Europe**	**US**	**FROM**
Oil	79.12	2.42	6.86	11.6	20.88
Asia	1.67	73.8	13.12	11.42	26.2
Europe	3.28	6.1	65.48	25.13	34.52
US	5.43	4.48	21.19	68.9	31.1
TO	10.39	13.01	41.16	48.15	112.7
INCLUDING OWN	89.51	86.8	106.64	117.04	TCI
NET	-10.49	-13.2	6.64	17.04	28.18

The variance decompositions are based on 10-step-ahead forecasts and a TVP-VAR lag length of order one based on AIC. ‘TO’: directional connectedness transmitted to all other variables; ‘FROM’: directional connectedness received from all other variables; ‘INCLUDING OWN’: Sum of ‘TO’ index and the diagonal element; ‘NET’: difference between the two directional connectedness; ‘TCI’: total connectedness.

The data presented in the table demonstrate that the own-volatility spillover explains the highest share of forecast error variance. This is evident from the higher values of the diagonal elements compared to other elements (from 65.48% for the European index volatility to 79.12% for oil price volatility). On average, the TCI is medium (about 28%). The American RE stock index contributes more to other markets (48.15%), followed by the European index (41.16%). The oil market exhibits a relatively low level of shock transmission to the overall system, accounting for 10.39%. On the other hand, the European RE stock market receives the highest amount of information (about 35%), while the oil market is the lowest receiver of shocks at only 20.88%. The bottom line in Table 2 reports the total net spillovers, defined as the difference between the transmitted and received spillovers by oil prices and each regional RE stock index. A surprising result emphasizes that the oil market is a net receiver of volatility shocks. This suggests that this market is more susceptible to receiving spillovers than transmitting them. These findings support the findings of [24,45], who showed that the oil market is a net receiver of shocks from RE markets. A plausible explanation of such results can be attributed to the expanding RE market, which significantly affects the strategic energy markets like oil. Indeed, the volatility of RE stocks may indirectly impact crude oil price volatility through some channels, such as investor sentiment operating in these markets, the energy market competition[1] and government policies and regulations[2], among others. The findings also suggest that, among the RE stock indices, the Asian RE stock market is found to be a net receiver of shocks, while the European and US markets are, on average, net transmitters of shocks.

The findings discussed above are derived from the averaged analysis conducted over the entire sample period. It is worth noting that such an analysis may hide the dynamic nature of spillover effects and could not identify the underlying mechanism that connects oil prices and RE stock market volatilities. In addition, static spillover analysis assumes that the degree of volatility transmission is constant over time, ignoring the potential changes in the magnitude and direction of spillover effects. In addition, the level of volatility and channels through which it propagates can vary significantly over different periods. Consequently, analyzing time-varying volatility spillover rather than static spillover seems essential, as it allows for a more accurate understanding of how volatility transmits between the different markets over time. Figure 2 plots the evolution of the total connectedness index (TCI) for the full conditional volatility spillovers of oil prices and the different regional RE stocks. Significant fluctuations in the total connectedness index are observed throughout the full period, indicating that the volatility spillover is subject to temporal variations. Therefore, investors actively involved in oil and RE stock markets are recommended to assess their portfolios and make dynamic decisions over time. Following Figure 2, it is evident that the TCI exhibited higher levels during major economic and political events that impacted the oil and RE markets. Indeed, total volatility spillovers decreased from more than 40% to 10% following the 2015 Paris Climate Agreement on climate change, which mandated, among others, the gradual substitution of fossil fuel–based energy systems with RE sources. Such an agreement may indirectly influence the volatility spillovers between the two markets since it aims to reduce greenhouse gas emissions and promote the transition to a low-carbon economy.

[1] The adoption of RE sources has the potential to generate competition for conventional fossil fuel energy sources, including oil. More precisely, the increased deployment of RE technologies, such as solar and wind power, can reduce the overall oil demand, particularly in the power generation sector.

[2] RE stock volatility can be influenced by changes in government policies and regulations, such as subsidies, tax incentives and energy transition targets. These policies can affect the growth and profitability of RE companies, which, in turn, might impact their stock volatility.

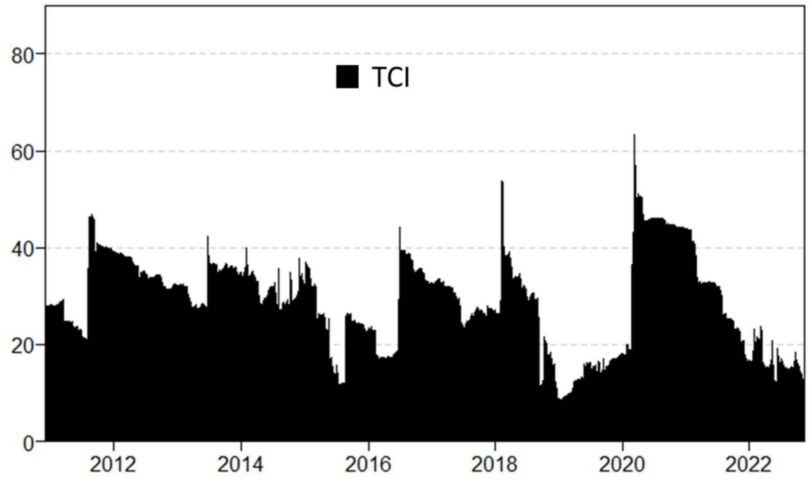

Figure 2. Dynamic total connectedness index (TCI).

The highest volatility spillovers are approximately 65% and were observed during the initial phase of the COVID-19 outbreak, coinciding with the official declaration of the pandemic status of COVID-19. Additionally, there are several other significant peaks in the total spillover index. These peaks correspond with major events, such as the intensification of the European debt crisis in the third quarter of 2011, the global stock market crash in the third quarter of 2015, the vote in favour of Brexit in the second quarter of 2016 and the US stock market crash in the first quarter of 2018. It is worth mentioning that most of the peaks depicted in Figure 2 align with the findings of [24]. This result is unsurprising because oil prices and RE stock markets are interlinked over stress periods, and crisis periods increase the interdependence of global stock markets [49]. The findings can also be attributed to the impact of the COVID-19 outbreak and its rapid global propagation, which led to a decline in economic activity and elicited unfavourable shifts in investor sentiment. These factors can significantly influence investment choices and, in turn, stock market valuations [50]. In addition, during the initial phase of the COVID-19 outbreak, global financial markets experienced significant volatility and disruptions. The results above are consistent with prior research by [24,51], which revealed a significant effect of the COVID-19 outbreak-induced uncertainty on the RE stock market. At the same time, [52,53], among others, have also proven the significant impact of the COVID-19 outbreak on the oil market. Moreover, [54] showed that the degree of connectedness between crude oil markets increased during COVID-19.

We then compute the time-varying spillover indices "TO" and "FROM", defined as the amount of volatility transmitted and received by each RE and oil price volatility to and from the system, respectively. The spillover indices "TO" and "FROM" results in Figures 3 and 4 provide evidence of time-varying fluctuations of the two indices.

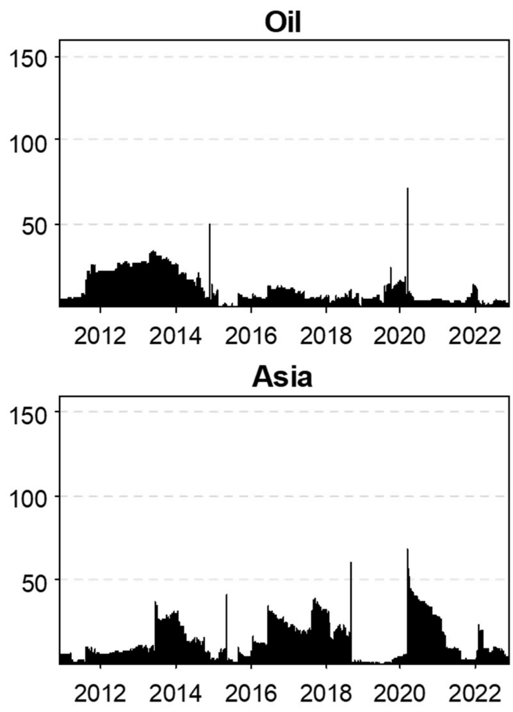

Figure 3. Dynamic directional connectedness indices (TO).

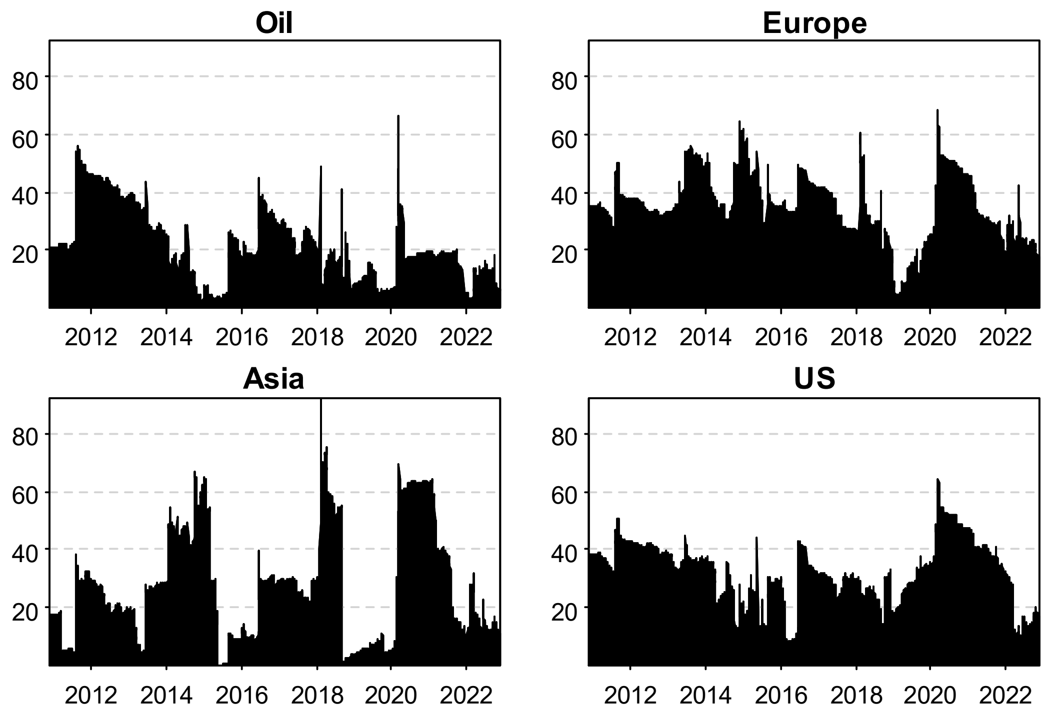

Figure 4. Dynamic directional connectedness indices (FROM).

The US renewable energy stock market is the highest transmitter over almost the entire study period. Moreover, the highest amount of volatility shocks emitted to the system was in 2015, when the

Paris Climate Agreement occurred and in 2018, when solar-plus-storage systems gained wide popularity in the US. In addition, some other factors may explain the fact that the US RE stock market acted as a net transmitter of shocks, including the robust economic expansion and the rising value of the US Dollar experienced in 2018. Oil price volatility appears to be the lowest transmitter of shocks to others in almost all periods, with the highest values between mid-2011 and mid-2014. Finally, the graphs show that the European RE stock index volatility transmitted its maximum amount of shocks over the first stage of the last COVID-19 pandemic in 2020. The above results suggest that the transmission of volatility shocks is done differently among the energy sector (brown or green energy) and regions. Some factors can make this difference in the shock transmission regarding the region, including policy frameworks, regulatory environments, market conditions, technological advancements and regional energy mix. Regarding the time-varying "FROM" volatility spillover index in Figure 4, results show that the volatility spillover among oil prices and RE is time-varying, justified by periods of high connectedness followed by low connectedness periods. By comparing the different regions regarding the received volatility shocks, results from Figure 4 suggest that the European RE market is the best at receiving volatility shocks, followed by the US index. The highest amount of shocks received was around the pandemic (about 50%). During this period, the highest amount of volatility shocks was received by the Asian RE stock market, with values exceeding 60%. The oil market experienced time-varying volatility spillover, with values ranging from less than 10% in 2014–2015 to more than 60% at the onset of the health crisis in March 2020. Moreover, the Asian RE stock market appears to be the best receiver of volatility shocks during the outbreak, justified by the fact that COVID-19 originated in China, which has the most developed RE market. This market faced significant volatility and uncertainty when the pandemic hit in early 2020. The RE sector in China was not immune to these events, and many RE sector stocks experienced sharp declines in value as investors reacted to the economic downturn and uncertain prospects.

To better visualise the volatility spillovers transmitted and received by each RE market and oil market, Figure 5 provides the time-varying "NET" spillover indices. The results suggest that the Asian RE stock index is a net receiver of volatility during most of the study period. A plausible explanation of these results is that volatility in European and US renewable stock markets exerts volatility transmission to the Asian RE stock market to some extent. This is because the RE industry is a global market, and developments in one region can affect others. For instance, if there is positive (negative) news or strong (poor) performance in the European or US RE sector, it could generate investor interest and capital inflows (outflows). This increased demand may lead to higher valuations and potentially increased volatility in the Asian RE stock market as investors reallocate their investments towards RE markets that are performing better.

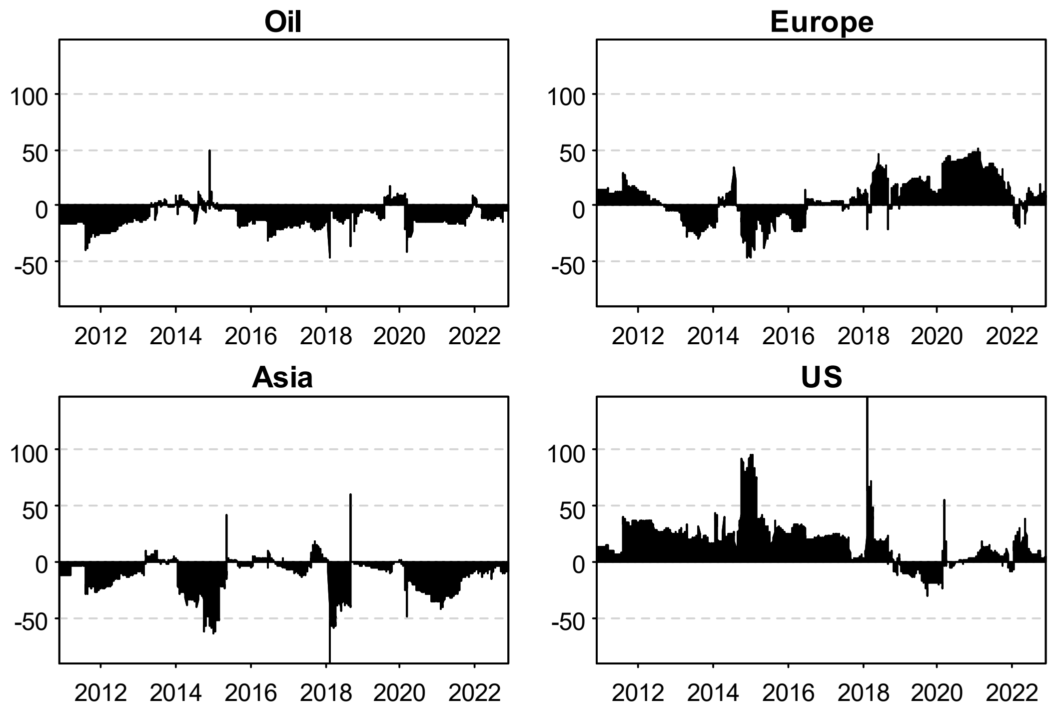

Figure 5. Dynamic NET connectedness.

The oil market is a net receiver of volatility throughout the study period, except for some limited periods during the 2014 and pre-COVID-19 periods. These results corroborate those of [45], who analysed the volatility spillover between WTI crude oil, gold and the Chinese stock markets of new energy vehicles using the TVP-VAR. Moreover, our results are in line with [24], who studied the volatility spillover among WTI crude oil prices, US, European and Asian green energy stocks. These studies confirmed that the oil market is a net receiver of volatility from the renewable energy market. Factors like market dynamics and investor sentiment can explain these findings. Furthermore, government policies may have a substantial contribution to the occurrence of this situation in the oil market. While political pressure, subsidies, ESG initiatives and taxes can enhance the impact of renewable energy dynamics on the oil market, they can also lead to unintended adverse consequences and increased market volatility.

On the other hand, the European and US RE markets switch between being net transmitters and receivers of shocks. The US RE stock market is a net transmitter over most of the period. This result is expected because the US renewable energy stock market is the most developed and mature, making it the most influential among the others. Moreover, the findings show that the European RE stock market is a net transmitter between 2018 and 2022. Possible explanations for this finding include the occurrence of Brexit, trade tensions with the United States, and political events in some European countries. These factors could contribute to increased financial market volatility in Europe. Figure 6 presents the dynamic pairwise spillover from each variable to each other. A positive (negative) value indicates that the variable transmits (receives) more than it receives (transmits).

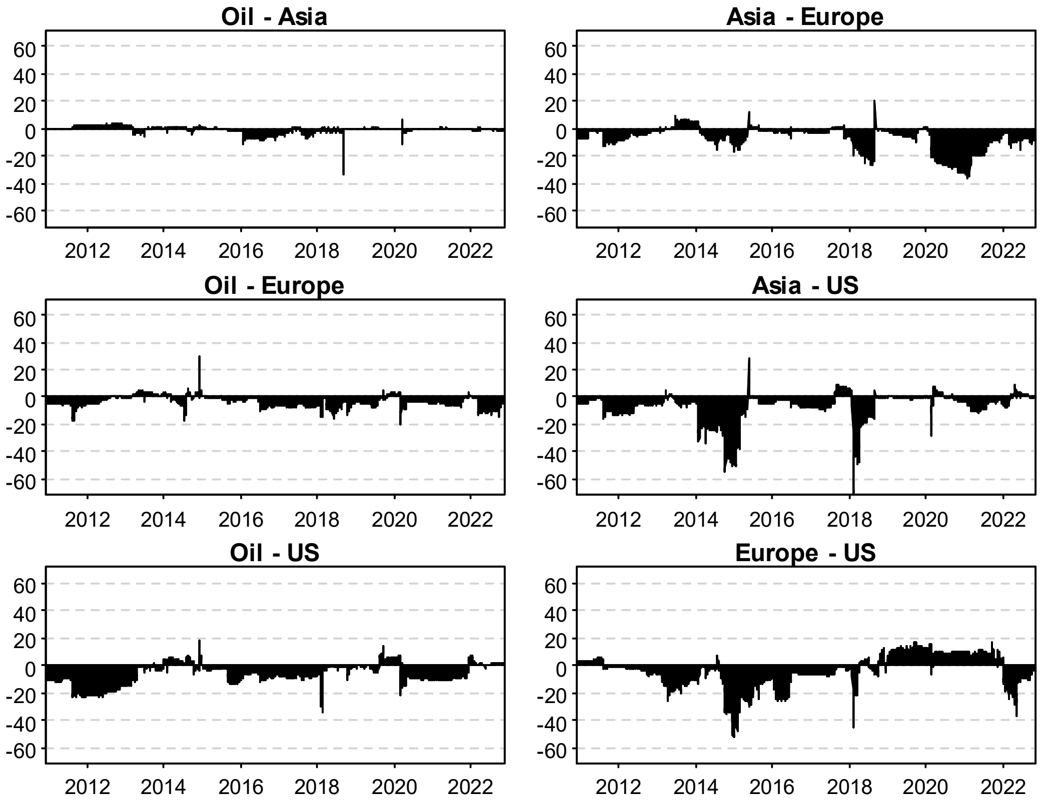

Figure 6. Dynamic pairwise connectedness.

Focusing on the first column of Figure 6, it appears that oil prices received volatility shocks from all regional RE markets during almost the entire study period. These findings are consistent with previous research, including [17], who used wavelet and non-linear Granger causality to conclude that the impact of RE stocks on oil prices is more significant than the opposite effect. This can be attributed to the substantial expansion and attention devoted to the RE sector in recent years as a potential alternative that reduces reliance on fossil fuels. On the other hand, RE sources, such as solar, wind and hydroelectric power, are typical alternatives for fossil fuels, particularly oil. Therefore, the growing demand for renewables leads to a decline in the demand for oil, which may lead to lower oil prices over the long term. To enhance the understanding of spillover and pairwise directions, Figure 7 depicts the network connectedness between the full volatilities of different RE indices and oil prices. Among the three considered regional RE indices, the US RE stock market is a net transmitter to the oil market and the two other RE stock markets (Europe and Asia). Furthermore, the European RE stock market transmits shocks only to the oil market and the Asian RE stock market. Regarding the Asian RE stock market, results show that it is still, on average, a receiver of shocks from the two other RE stock markets. A potential explanation of these findings is that the Asian RE market is underdeveloped compared to the United States and Europe. This is despite China being considered the largest producer of RE globally and the largest consumer of fossil fuels.

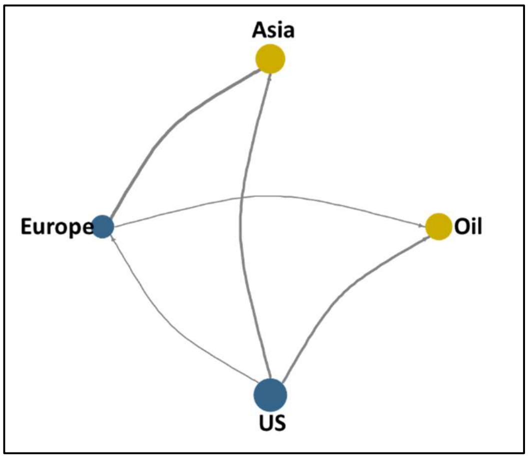

Figure 7. Network connectedness for the full volatility spillover.

5.2. Asymmetric volatility spillover results

To thoroughly analyse the volatility spillover between oil prices and RE stock markets across various regions, we estimate the different spillover indices of [27,28] based on the TVP-VAR (1), but this time by considering the good and bad volatility. The averaged indices are provided in Table 3. The table shows that, on average, the spillovers for good and bad volatilities are not very different from the total conditional volatility spillovers. Indeed, the TCI is 32.52% for good volatility against 32.31% for bad volatility. Furthermore, the contributions received or transmitted by each market to the system exhibit slight variations, supporting the idea that volatility spillovers tend to be symmetric. Oil and Asian RE markets are net receivers of both good and bad volatility, while the other markets are net transmitters. The observed closed values among good and bad volatilities (indicating symmetric spillovers) can be because the spillover effects are considered in averaged values, which could hide asymmetry occurring in different specific periods.

To enhance the understanding of volatility spillover, we consider the time-varying spillover indices and compute the asymmetry as the difference between good and bad volatility indices. The dynamic TCI for both good and bad volatilities are provided in Figure 8. It can be observed that the TCI for good (TCI_g) and bad (TCI_b) volatility exhibits high values, followed by medium levels. Despite the symmetric transmission detected in the case of averaged spillover indices, the figure generally shows different patterns, supporting the asymmetric and time-varying character. Particularly, the TCI values were somewhat high during 2015, 2018 and 2020, reaching more than 60% at the beginning of the COVID-19 crisis over the first quarter of 2020. On the other hand, the asymmetry measure (TCI_As) clearly shows an asymmetric behaviour in total volatility connectedness, which cannot be observed in the static spillover measure, supporting the usefulness of a time-varying analysis instead of a static one. The highest positive values were observed between 2014 and 2016, indicating that good volatility is transmitted more than bad volatility. After that, a negative asymmetry is observed until mid-2018, supporting that bad news transmits more market risk than good news. The same pattern is observed from the beginning of the COVID-19 pandemic until the first quarter of 2021 with the implementation of the vaccination program. The negative asymmetric transmission observed during the COVID-19 crisis is mainly due to the propagation of the pandemic. Indeed, during turmoil periods, bad news dominates the good ones, suggesting that bad volatility is transmitted more than good volatility. On the other hand, the health crises caused a risk, especially for small and medium companies operating in the RE sector. More specifically, the pandemic resulted in the postponement or cancellation of RE projects due to the measures implemented by many countries, leading to heightened uncertainty in economic activity, particularly in implementing RE projects. Moreover, the economic dysfunction that followed the beginning of the health crisis suggested a decreased demand for energy. Therefore, the RE sector is affected because it is still used only for limited domestic uses compared to other economic activities, including industry and transport.

Table 3. Asymmetric connectedness matrix and asymmetry measure.

	Oil	**Asia**	**Europe**	**US**	**FROM**
Good volatility					
Oil	73.97	3.26	8.83	13.94	26.03
Asia	5.14	67.05	10.79	17.03	32.95
Europe	8.03	4.00	62.50	25.47	37.50
US	11.22	3.57	18.80	66.41	33.59
TO	24.39	10.83	38.42	56.43	130.08
INCLUDING OWN	98.36	77.88	100.92	122.85	TCI
NET	−1.64	−22.12	0.92	22.85	32.52
Bad volatility					
Oil	73.49	3.91	9.46	13.14	26.51
Asia	4.86	67.66	11.28	16.20	32.34
Europe	6.89	4.84	63.59	24.67	36.41
US	10.28	4.35	19.35	66.02	33.98
TO	22.04	13.10	40.08	54.01	129.23
INCLUDING OWN	95.53	80.76	103.68	120.03	TCI
NET	−4.47	−19.24	3.68	20.03	32.31
Asymmetry					
Oil	0.48	−0.65	−0.63	0.80	−0.48
Asia	0.28	−0.61	−0.49	0.83	0.61
Europe	1.14	−0.84	−1.09	0.80	1.09
US	0.94	−0.78	−0.55	0.39	−0.39
TO	2.35	−2.27	−1.66	2.42	0.85
INCLUDING OWN	2.83	−2.88	−2.76	2.82	TCI
NET	2.83	−2.88	−2.76	2.82	0.21

The variance decompositions are based on 10-step-ahead forecasts and a TVP-VAR lag length of order one based on AIC. 'TO': directional connectedness transmitted to all other variables; 'FROM': directional connectedness received from all other variables; 'INCLUDING OWN': Sum of 'TO' index and the diagonal element; 'NET': difference between the two directional connectedness; 'TCI': total connectedness.

During the COVID-19 pandemic, it was observed that bad volatility was transmitted more than good volatility between the oil market and RE stock markets. This phenomenon can be attributed to several factors. First, the pandemic has caused economic uncertainty, resulting in a decrease in global oil demand and a sharp decline in oil prices. The renewable energy sector has also experienced decreased profitability and investment and has shown a higher sensitivity to negative news and uncertainties. Therefore, RE market investors exhibited an increased aversion to risk, resulting in a higher propagation of bad volatility. Additionally, the global supply chains were disrupted by the pandemic, which impacted both the oil and renewable energy sectors. This resulted in fluctuations in oil prices and disruptions in the supply chains of the renewable energy sector. These disruptions increased uncertainty and amplified the transmission of negative volatility among markets. In addition, governments and policymakers encountered many challenges throughout the pandemic. These challenges required them to shift their focus and allocate resources to manage the health crisis and stabilize economies effectively. This shift in priorities could have reduced focus on RE policies and incentives, further exacerbating the transmission of bad volatility from the oil market to the RE sector.

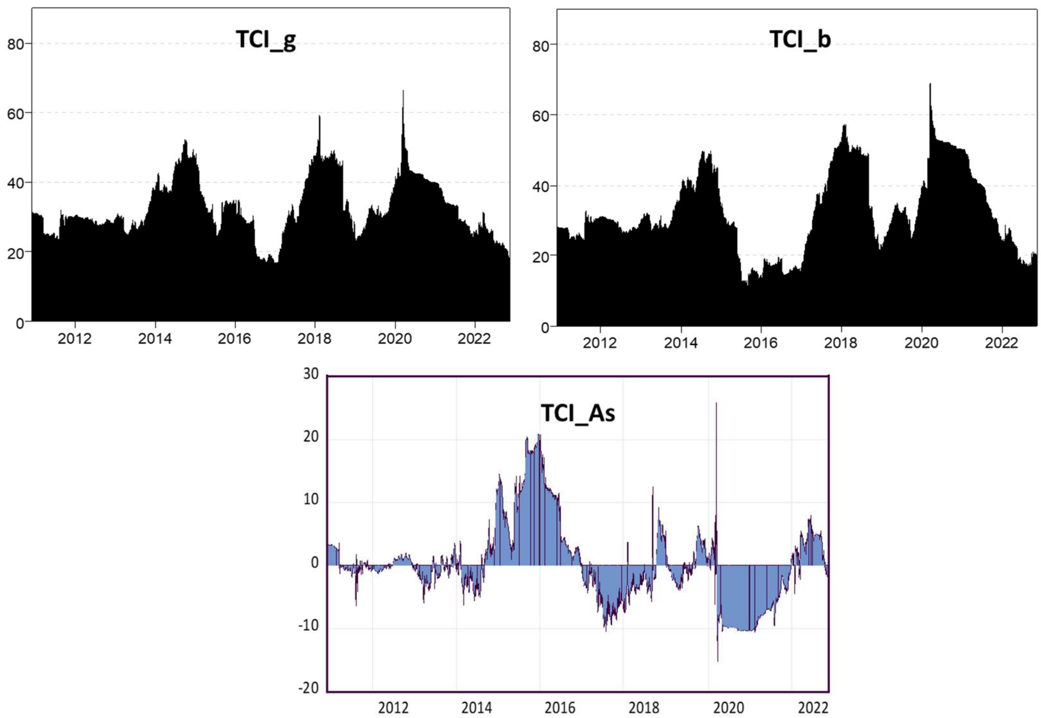

Figure 8. Dynamic asymmetric total connectedness index (TCI).

Regarding the directional asymmetric spillovers between the different markets, results emphasize a slight difference between the case of symmetric and asymmetric spillovers. The findings supporting the symmetric feature characterizing the volatility spillovers should not be relied upon and cannot be considered a conclusion. In this case, further analysis in a time-varying context should be considered to provide complete information regarding RE stocks volatility transmission. Figure 9 presents the good and bad volatility transmitted by the system to each RE regional index. In the third column, we also provide the asymmetry measure (in blue). Results show evidence of asymmetric behaviour in the volatility transmission. This pattern is justified by a positive asymmetry followed by a negative one. Moreover, this asymmetry is more pronounced in European and US RE stock markets, which receive and transmit more than the others. Particularly, the asymmetry in the European market reached its maximum positive values in 2015, when the Paris Agreement was signed. Following this event, many countries have made ambitious commitments to reduce emissions and shift to a low-carbon economy. Therefore, RE sources hold a significant position in different economies, resulting in the appreciation of RE stock markets. Indeed, the Paris Agreement has encouraged investment in RE by transmitting a market signal, promoting climate diplomacy, reinforcing the urgency of action, identifying investment opportunities and supporting the accelerated deployment of renewables.

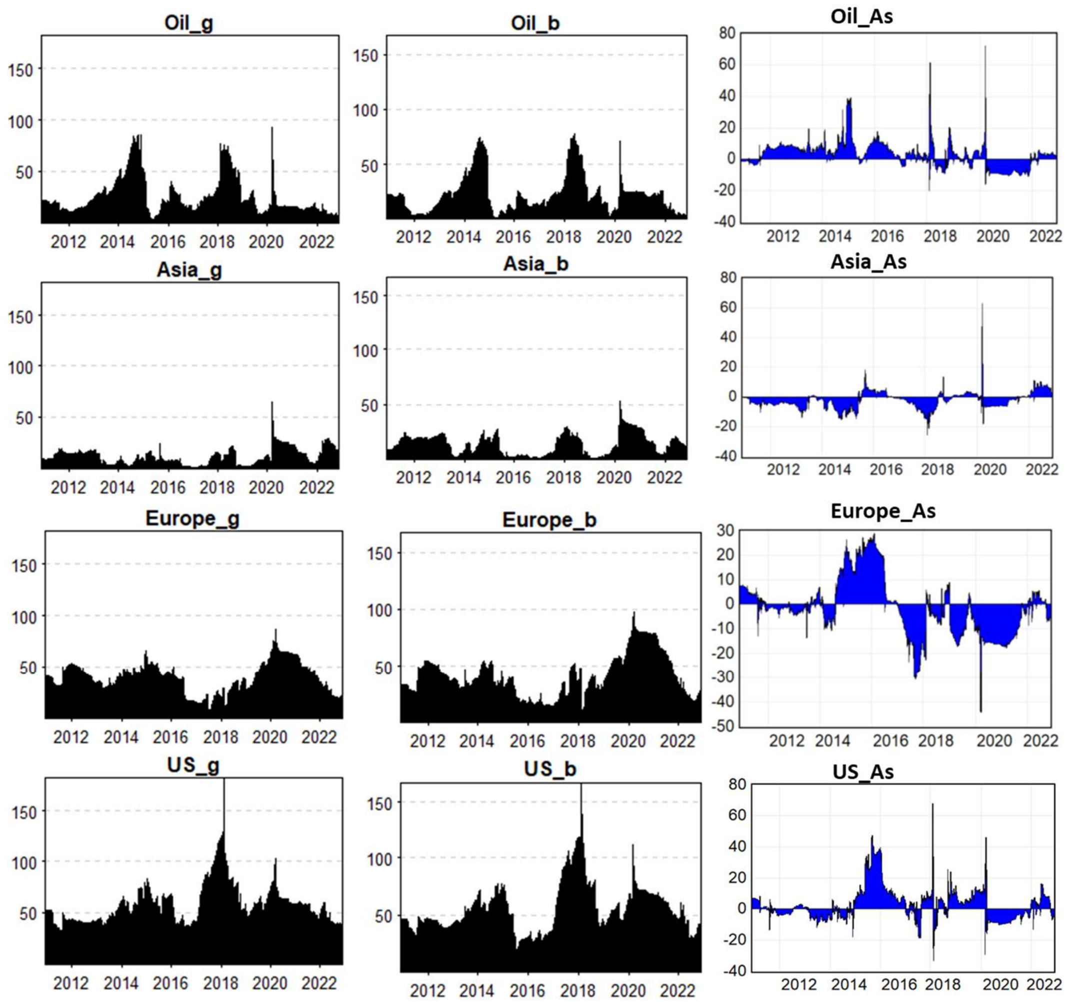

Figure 9. Dynamic asymmetric directional connectedness indices (TO).

Figure 10 plots the index "From" for good and bad volatility and the asymmetry index (in blue). The asymmetry index indicates different periods of positive asymmetry followed by negative ones, showing a dynamic and asymmetric feature in the volatility transmission. This finding implies that the sources of transmission change among the types of news. Therefore, investors and policymakers operating in these markets should pay more attention to this reality. Moreover, the examination of Figure 10 shows that the COVID-19 period generally induced a negative asymmetry in the volatility transmission, implying that the bad news was dominant during this period due to the increased uncertainty. After that, a positive asymmetry is observed over the vaccination phase, indicating that the good news becomes more influential than the bad news. Furthermore, the observed positive asymmetry during the vaccination phase can be attributed to the asymmetry in the impact of news, the shock value of good news during crises, changes in market sentiment and shifts in risk appetite.

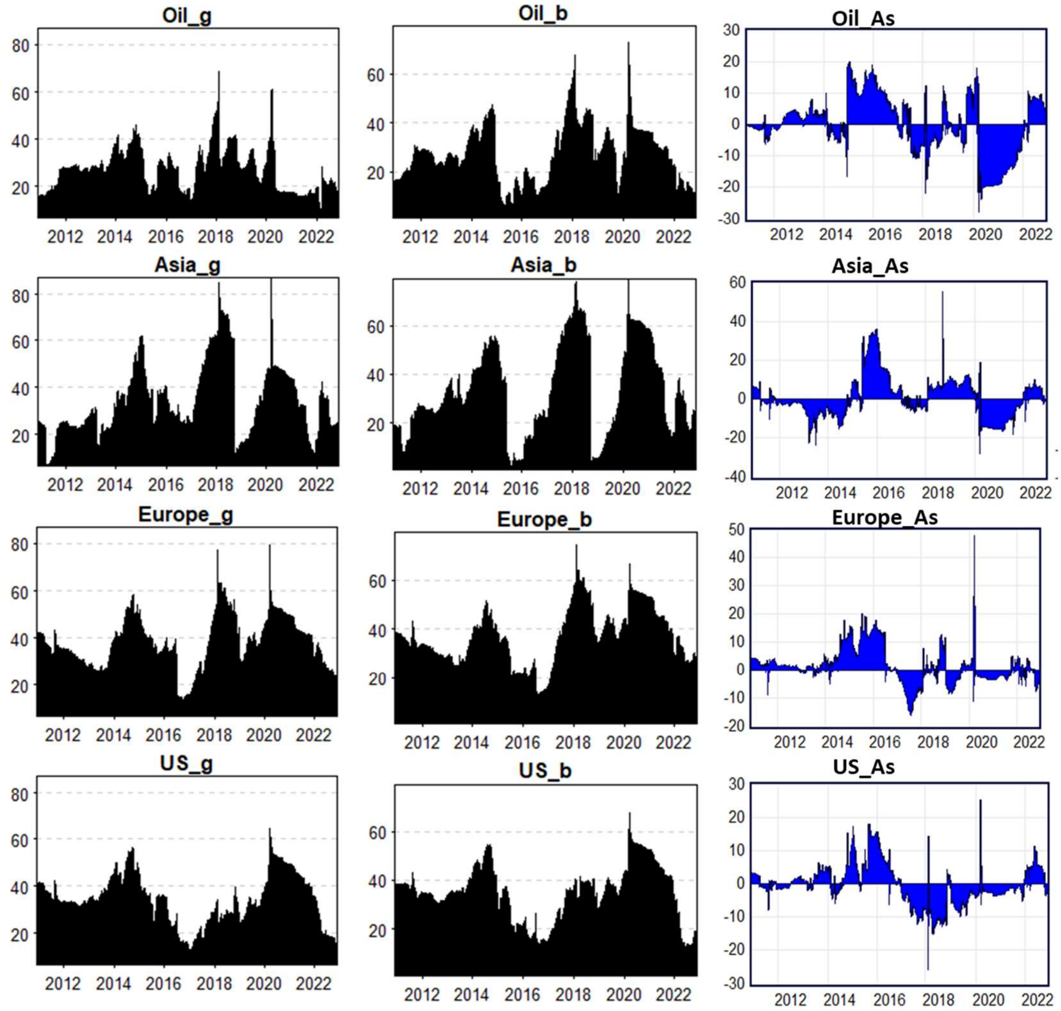

Figure 10. Dynamic asymmetric directional connectedness indices (FROM).

To be more intuitive in visualising the good and bad volatility transmission, we analyse the net transmission index and asses the asymmetry index for oil price and each regional RE stock market volatility. As shown in Figure 11, the US RE market is a net transmitter of good and bad volatilities, and the Asian market is a net receiver during the period. However, the oil and European RE stock market switched between a net transmitter and a net receiver of good and bad volatilities. More specifically, by comparing good and bad volatility transmission in the oil market and the US RE stock market, we find that good volatility is transmitted more than bad volatility in almost the entire sample period, suggesting that good news is more frequent in the risk spillover of the oil market. However, for Asian and European RE stock markets, the results show a different picture in which the bad news dominates the good news most of the time. This result can be explained by the US RE markets being more developed and investors being more experienced. Furthermore, the US has emerged as a leader in renewable energy innovation and technology development. This leadership position has the potential to shape and impact the renewable energy markets, including those in Europe and Asia. In addition, US institutional investors and funds may have holdings in European and Asian RE stock markets as part of their stock market investments. Hence, changes in investment strategies within the US can result in spillover effects on these markets. On the other hand, by focusing on COVID-19, we observe different patterns regarding the asymmetry in the volatility spillovers. Indeed, the US and oil markets exhibit a positive asymmetry, while the other markets transmit with a negative asymmetry (bad volatility transmission is higher than good volatility).

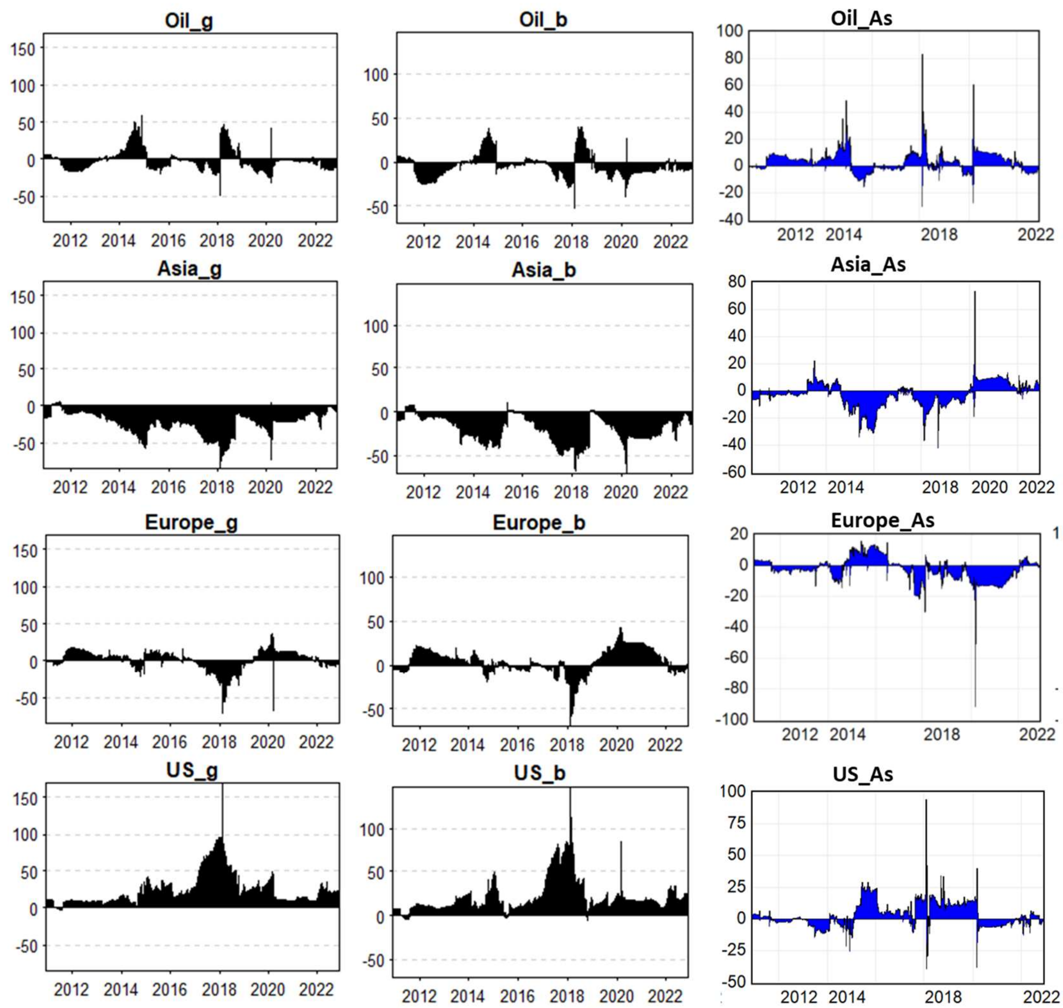

Figure 11. Dynamic asymmetric NET connectedness.

Figure 12 presents the network connectedness for good and bad volatility. Since the two networks provide an averaged picture of the interaction between the considered markets, there are no significant differences regarding the good and bad volatility transmission. The difference between good and bad volatility transmission can be observed in the time-varying spillovers more than in static spillovers.

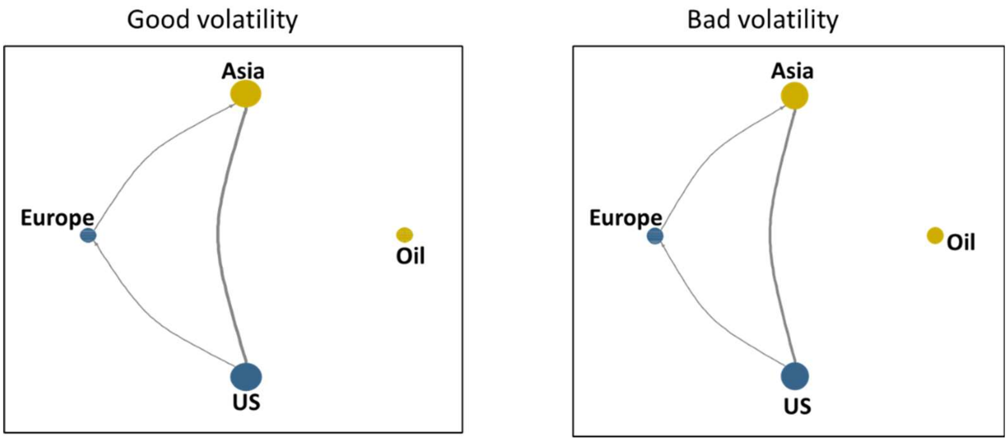

Figure 12. Network connectedness for the good and bad volatility spillovers.

6. Policy implications

Findings regarding the good and bad volatility spillovers between the oil market and regional RE stock markets are important and carry various policy implications for investors and policymakers.

First, regarding the diversification and risk management issues, the low spillover effects of good and bad volatility transmission imply that investors should emphasize the importance of diversifying different energy assets in the same portfolio. Such diversification may lead to a significant share of RE, which can help mitigate the risks associated with fluctuations in oil prices.

Second, the results indicate that policymakers should consider implementing supportive mechanisms to mitigate the bad volatility spillover effects and promote the growth of the RE sector. This can include providing financial incentives, such as tax credits, subsidies and grants, to RE companies. Indeed, the existing policies may mitigate some of the risks and volatility in the RE sector. However, it is important to acknowledge that the RE sector can still experience volatility even with existing policies, especially during market and/or economic uncertainty. Furthermore, the effectiveness of risk mitigation can be influenced by the magnitude and structure of incentives, which may vary from region to region. Policymakers should adjust their policies to ensure they remain effective in promoting the development and stability of the RE sector.

Third, given the spillover effects between oil prices and RE stock volatilities in different regions, policymakers should emphasize international cooperation and collaboration in the RE sector. Collaborative efforts can include knowledge sharing, joint research and development initiatives, and coordinated policy frameworks. Through collaborative efforts, countries may mitigate the adverse effects of fluctuating oil prices on the performance of RE stocks, thereby promoting a more solid and environmentally sustainable energy framework.

Fourth, given the dynamic spillovers of volatility that change from one period to another, energy market operators should conduct dynamic risk assessments and develop contingency plans to mitigate the potential adverse effects of oil price volatility on RE stocks. This involves identifying vulnerabilities and designing strategies to address market fluctuations. Policymakers can effectively mitigate disruptions and foster the growth of the RE sector by proactively anticipating potential adverse volatility spillovers.

Finally, reducing the asymmetry of volatility transmissions between energy markets is a complex challenge that requires a combination of monetary, fiscal and regulatory policies. In this way, policymakers can implement a diversified energy mix and investment strategies, maintain and enhance policies that support the renewable energy sector, and develop and implement climate resilience plans. While mitigating the adverse effects of volatility spillovers from oil to the RE sector is important, policymakers should also consider the potential spillovers in the other direction. It is essential to recognize that a developed renewable energy stock market and a successful transition to cleaner energy sources require careful consideration of the interactions between traditional and renewable energy markets. By adopting proactive measures and fostering a supportive policy environment, policymakers can create a resilient and sustainable energy system that is less reliant on oil and more resilient to market fluctuations.

7. Concluding remarks

In conjunction with the rapid growth of the renewable energy sector and the implementation of policies aimed at facilitating the shift towards environmentally sustainable economies, there has been a surge of interest in examining the interplay between conventional and clean energy sources. The analysis of good and bad volatility spillovers between stock indices of RE and crude oil prices holds significant importance. In this context, the present study aimed to investigate the symmetric and asymmetric volatility transmission between the oil market and RE stock markets across various regions, namely the United States, Europe and Asia. To do so, we employed a TVP-VAR framework based on the forecast error decomposition developed by [27,28].

Many conclusions can be drawn from the analysis. First, the full volatility connectedness between the considered variables exhibits a medium level of volatility spillover on average, amounting to approximately 28%. Moreover, the results show that the US renewable energy stock market is the most significant contributor to other markets, followed by the European market. The oil market has been identified as the least significant transmitter of shocks to the overall system. In addition, the European RE stock market receives the highest amount of shocks, while the oil price receives the least. An analysis of the net spillover index shows that the oil market and the Asian RE stock markets tend to receive volatility shocks. In contrast, the remaining markets (US and Europe) tend to transmit volatility shocks. In order to better understand volatility spillover, we proceeded with a time-varying spillover framework to estimate the amount of volatility shock transmission over time. The findings indicate evidence that the volatility spillover is subject to temporal variations in response to some major events. Specifically, the spillover effects are affected by the Paris Climate Agreement on climate change, the global financial crisis and the COVID-19 health crisis.

To conduct an asymmetric analysis of the volatility spillover between oil prices and regional RE stock markets, we estimate the different spillover indices by separating the volatility series into good and bad volatility series. By analysing the averaged spillover indices, results emphasize similar total connectedness between the different variables. However, by extending the analysis to the time-varying framework, results show different patterns, supporting the asymmetric volatility transmission between oil prices and RE stock markets. The total connectedness was particularly high during 2015, 2018 and 2020. Moreover, the highest positive values of the asymmetry measure were observed between 2014 and 2016, indicating that good volatility is transmitted more than bad volatility. After that, a negative asymmetry is observed until mid-2018, supporting that bad news transmits more market risk than good news. The same pattern is observed from the beginning of the COVID-19 pandemic until the first trimester of 2021 with the propagation of the vaccination program. This study also focused on the pairwise asymmetric spillovers between the volatility of oil prices and regional RE stock markets.

Results show evidence of an asymmetric behaviour in the pairwise volatility transmission. Accordingly, positive asymmetry is found to be followed by a negative one. This asymmetry is more pronounced between oil prices in the European and US RE stock markets, which receive and transmit more than the others. The asymmetry in the European market notably reached its maximum positive values in 2015, when the Paris Agreement was signed.

Although the present study provided some novel insights into the static and dynamic (a)symmetric interconnections between the crude oil market and different renewable stock markets, it has some limitations and could be improved in future research. First, the analysis may be extended by considering alternative fossil fuels, including natural gas and coal. Second, the RE markets considered in the analysis could also be extended to include other markets. Finally, it would also be interesting to investigate the volatility spillover between the oil and renewable energy markets for different time horizons (short-, medium- and long-term).

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflict of interest.

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