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Dynamic Asymmetric Volatility Spillover and Connectedness Network Analysis among Sectoral Renewable Energy Stocks

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Abstract: A wide range of statistical and econometric models have been applied in the extant literature to compute and assess the volatility spillovers among renewable stock prices. This research adds to the body of knowledge by analyzing the dynamic asymmetric volatility spillover between major NASDAQ OMX Green Economy Indices, including solar, wind, geothermal, fuel cell, and developer/operator. The novelty of the research is that it distinguishes between positive and negative volatility spillovers in a time-varying fashion and conducts a connectedness network analysis. To do so, the study implements the Time-Varying Parameter Vector Autoregression (TVP-VAR) approach, as well as the connectedness network. The empirical investigation is based on high-frequency data between 18 October 2010, and 2 April 2022. The main findings may be summarized as follows. First, the analysis reveals a shift in the dominance of positive and negative volatility transmission during the study period, which represents compelling evidence of dynamic asymmetric spillover in the volatility transmission between renewable energy stocks. Second, the connectedness analysis indicates that the operator/developer and solar sectors are the net transmitters of both positive and negative volatility to the system. In contrast, the wind, geothermal and fuel cell sectors receive shocks from other renewable energy stocks. The asymmetric spillovers between the renewable energy stocks are confirmed using the block bootstrapping technique. Finally, the dynamic analysis reveals a substantial impact of the COVID-19 outbreak on the interdependence between renewable energy stocks. The findings above are robust to different lag orders and prediction ranges.

Keywords: connectedness; TVP-VAR; volatility spillover; asymmetry; renewable energy

MSC: 62P12; 91G45; 91G70



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1. Introduction

There has been an increasing focus on reducing pollution in recent decades. Governments and international organizations have set specific short- and long-term objectives to decrease the amount of greenhouse gas (GHG) emissions released into the atmosphere. At the same time, energy transition has been recognized as an important option that might lower the reliance on polluting traditional energy sources. The main objective of the energy transition process adopted by many countries was to promote the substitution of fossil fuels with carbon-free and renewable energy (RE). Based on data from [1], the proportion of primary RE sources (mainly solar, wind, hydropower, and geothermal) in total primary energy consumption increased from 6.45% in 1965 to 8.80% in 2010. It has since expanded rapidly to reach 14.21% in 2022. Furthermore, investments in RE projects experienced a compound annual growth rate of 8.5% from 2013 to 2022, culminating in a historic milestone of USD 495 billion in 2022 [2]. The growing demand for RE has led to a substantial rise in financial investments in this sector and a growth in the value of RE stocks [3].

The current situation in the RE stock markets has spurred increased discussion among academics about the relevance of RE stocks as financial investments and hedging opportunities [4–8]. The sensitivity of RE stocks to internal and external shocks has important implications for the decision making of stock market operators and has been, therefore, thoroughly examined. Previous studies have identified many factors that could influence the performance of RE stocks that should be considered when designing portfolios, managing risks, and implementing hedging strategies. It is important to note that while shock transmission has been extensively explored in various domains, including global stock markets, commodities markets, uncertainty, and inflation, there is a lack of studies on spillovers between RE stocks. Abundant research has examined the association between RE stocks and conventional energy markets, particularly the oil market [9–14]. The outcomes of prior works are inconclusive. Indeed, ref. [15] found no significant linkages between the oil and RE markets. The connections between oil prices, technology stocks and RE stocks have been studied by [9]. The research concludes that the return and volatility spillovers of RE stocks are only influenced by technology stocks. In addition, technology and renewable stocks are net emitters of shocks, whilst the oil market is the recipient of shocks. Another study by [11] examined the interactions between oil prices and different RE sub-sectors using the connectedness approach. The analysis indicates that the degree of connectedness with oil prices depends on the RE sub-sector. Specifically, the wind, geothermal, and fuel cell stocks have a significant spillover with the oil market and are primarily receivers of shocks. In addition, refs. [16,17] concluded a significant association between the oil and RE stock markets. Ref. [18] employed the quantile-on-quantile regression and causality-in-quantile test to study the relationship between oil prices and RE stocks. The findings suggest that (i) the effect of oil prices on RE stocks is higher at the upper quantile than the lower quantile, and (ii) There is evidence of asymmetry, as the impact of a rise in oil prices is more significant than that of a decline. Other studies, including [13], concluded that the connections between RE stocks and oil prices are contingent upon market conditions. Further works have concentrated on the relationship between RE and other factors, including investor sentiment [19–21], geopolitical risk [22–24], environmental indicators [25–28] and green bonds [29–31].

Furthermore, there has been an emphasis on the recoupling hypothesis in stock markets, particularly the RE market. This hypothesis suggests the presence of significant interconnections between stock markets in different countries. For example, [32] analyzed the spillover dynamics between the global, US, Europe and Asia RE stock markets. The investigation reveals that the global and US green economy markets are net contributors of shocks to the system, while the Europe and Asia markets are net receivers. Using the time-varying parameters Vector Autoregressive (TVP-VAR) connectedness, [14] also analyzed the symmetric and asymmetric connectedness between regional RE markets (US, Europe and Asia). The results indicate that the RE markets in the US and Europe act as sources of volatility, while the Asian market is a net receiver of shocks. According to the asymmetric analysis, the US stock market is the primary transmitter of both good and bad volatilities, whereas the Asian market is the main receiver. These findings are in line with [33], who concluded that the US RE market significantly affects the Chinese market.

The recent and limited literature suggested that the rapid expansion of the RE sector has increased interconnection among RE sub-sector stocks. Indeed, market operators are keen to expand their comprehension of the volatility dynamics and spillovers among sectoral RE stocks to diversify portfolios and minimize risks. For instance, ref. [34] explored the interactions between different RE sub-sector stocks in the aftermath of the Russian–Ukraine war, employing the event study and connectedness approach. The network analysis reveals that the fuel cell, wind, and geothermal sectors are transmitters of spillovers, while solar and bio-clean fuels are net receivers of shocks from the system. Additionally, it has been determined that volatility transmission from the fuel cell to the wind market is the most significant. Ref. [35] also investigated the volatility transmission between different RE sub-markets using the BEKK model. The authors considered different RE sub-sector stocks.

The findings confirm significant volatility spillover between the different RE sub-markets. Furthermore, solar energy has a crucial role in volatility spillover in the system, while fuel cell energy has a vital position in transmitting volatility. On the contrary, the wind energy market receives shocks from the system. This indicates that the wind market is vulnerable to external shocks and is influenced by other RE markets.

The previous discussion highlights that the debate surrounding the factors influencing the RE stock market dynamics has primarily centered around the spillover between conventional energy markets, specifically the oil market and RE stock markets. On the other hand, there is a dearth of studies on the interactions between different RE sub-sectoral stocks, specifically those categorized by technology, such as solar, wind, geothermal, and fuel cell. Although studies by [34,35] provide some empirical insights into the dynamics of volatility spillovers across RE sectoral stocks, they fail to consider the potential asymmetry in the transmission mechanisms of volatility between sub-sectors. However, asymmetry holds significance when studying the interconnections between RE stocks, given that the recent fluctuations of these stocks have been characterized by upward and downward movements. Furthermore, comprehending the dynamic interdependence of volatilities between RE stock sub-sectors can lead to improved diversification strategies and a better decision making process. In addition, when examining the volatility transmission between financial assets, it is important to consider two issues. First, it is crucial to employ an appropriate approach for estimating volatility. Regarding this issue, different methodologies have been proposed in the literature, including range-based volatility estimators [36], market-traded option-implied volatility [37], implied volatility [38], realized volatility [39], and conditional volatility [40]. In this context, ref. [41] employed conditional volatility to analyze spillover effects, highlighting its straightforwardness and substantial, informative nature. Second, prior research has established that identifying volatility spillover depends on the statistical method employed, including multivariate GARCH-based models [42,43], copulas [44,45], and causality analysis [46,47], among others.

This research aims to explore how good and bad volatilities are transmitted among various sectoral RE stocks, including solar, wind, geothermal, fuel cell, and developer/operator. This research is, therefore, motivated by the lack of empirical studies considering the potential asymmetries when analyzing the interconnections between different RE stocks. The study employs the GJR-GARCH model introduced by [48] to compute the volatility series. The choice of the GJR-GARCH model is motivated by its ability to capture the asymmetric feature of volatility, which is particularly relevant in the context of financial markets and, more specifically, the RE market. The traditional GARCH model assumes that positive and negative shocks of the same magnitude have identical impacts on volatility. However, this assumption is frequently invalid in financial markets, as negative news typically impacts volatility more significantly than positive news. This is commonly referred to as the leverage effect. The GJR-GARCH model overcomes this limitation by incorporating the GJR-GARCH specification, which enables distinct reactions to positive and negative shocks. Accounting for asymmetry is crucial for accurately modeling RE market dynamics, which are sensitive to policy changes, technological advancements, and investor sentiments. Therefore, the choice of the GJR-GARCH model in this study is justified by its methodological advantages and relevance to the specific characteristics of the RE market. At the same time, the TVP-VAR-based spillover indices in the spirit of [49,50] are used to investigate the asymmetric spillover between sectoral RE stocks. The originality of this paper lies in its novel approach to examining the asymmetric volatility spillover and connectedness within the RE sector, which has not been studied in the existing literature. While previous studies have primarily focused on symmetric volatility spillovers across RE markets, this paper decomposes volatility into good (positive returns) and bad (negative returns) components employing the GJR-GARCH(1,1) model. This decomposition allows for a better understanding of how positive and negative RE market volatilities interact. Using a time-varying VAR model to capture the fluctuating nature of spillovers, the paper provides a dynamic perspective crucial for understanding the behavior of sectoral RE markets.

The contribution of this paper is threefold. First, this study diverges from most previous research by focusing on the spillovers between different RE sub-sectors rather than the spillover between conventional energy markets, particularly the oil market, and an aggregate measure of RE stocks. Indeed, a review of the literature suggests that only [34,35] focused on the interactions between RE stocks. Second, the study examines the dynamic interactions between RE sub-sectoral stocks. Indeed, the TVP-VAR employed in this study improves the connectedness modeling, given its multiple advantages. On the one hand, the time-varying analysis provides a more flexible way to capture potential changes in the underlying structure of the data [51,52]. On the other hand, the TVP-VAR analysis outperforms other techniques that account for structural changes, including the rolling window. Indeed, the TVP-VAR allows for overcoming the problems associated with determining the optimal rolling window size and data loss during the computation of connectedness indices. Third, this study contributes to the literature by considering good and bad volatilities when analyzing the spillover between the different sectoral RE stocks. This is important since the sectoral RE stocks may behave differently during good and bad volatility episodes. Failure to consider asymmetry while investigating volatility spillover may result in an inadequate understanding of the dynamic connections between RE stocks, leading to inaccurate inferences and inappropriate decisions for market participants. Furthermore, this research implements the block bootstrapping technique proposed by [53] to assess the statistical significance of asymmetry. By doing so, the study assesses the robustness of the findings and enhances the reliability of the conclusions drawn. To summarize, this paper fills a gap in the existing literature, provides practical implications for market participants, and contributes to the methodological toolkit for future research in financial econometrics.

The rest of this research is structured as follows: Section 2 outlines the materials and methods, while Section 3 describes the data. Section 4 discusses the findings. Finally, Section 5 concludes the paper and provides policy recommendations.

2. Materials and Methods

To investigate the time-varying transmission of good and bad volatilities among RE stocks, we utilize a three-step approach consisting of estimating volatility, disentangling volatility into good and bad, and measuring volatility spillovers in an asymmetric way.

2.1. Volatility Estimation

The GJR-GARCH model proposed by [48] is used to capture volatility asymmetries, assuming that the ARMA process is followed by the mean of the various RE stock returns. The ARMA(p,q)-GJR-GARCH model is then defined using the subsequent set of equations:

$$R_t = \mu_t + \varepsilon_t, \quad \varepsilon_t = \sqrt{h_t} z_t; \quad (1)$$

$$h_t = w + \alpha \varepsilon_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 + \beta h_{t-1} \quad (2)$$

where $I_t = \begin{cases} 1 & \text{if } \varepsilon_t < 0 \\ 0 & \text{if } \varepsilon_t \geq 0 \end{cases}$.

R_t represents the return series of a given RE stock index at time t . Additionally, μ_t denotes an ARMA(p,q) process having p and q as orders. The error term ε_t in Equation (1) enables obtaining a filtered series by dividing the return series R_t by the conditional volatility $z_t = \varepsilon_t/h_t$. It is assumed here that ε_t has a skewed Student t distribution $\varepsilon_t | \Omega_{t-1} \sim Skt(\varepsilon_t, \eta, \nu)$ to take into consideration the nature of financial series, including RE stocks. This specification then enables us to estimate the volatility of each stock index based on Equation (2).

2.2. Volatility Decomposition

The volatility dynamics h_t given by Equation (2) is decomposed into good and bad volatility series based on the sign of the shock returns of the error term. Next, one could

deduce the good volatility (h_t^+) and bad volatility (h_t^-) associated with positive and negative shocks in the following manner:

$$\begin{cases} h_t^+ = h_t \mathbb{I}_{[\varepsilon_t \geq 0]} \\ h_t^- = h_t \mathbb{I}_{[\varepsilon_t < 0]} \end{cases} \tag{3}$$

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

2.3. TVP-VAR-Based Spillover Measures

2.3.1. TVP-VAR Model

There are multiple approaches to measuring volatility spillover. VAR-based models are considered a powerful tool that can lead to the evaluation of volatility transmission. In this context, the time-varying VAR model introduced by [52] provides an alternate tool to the conventional VAR model estimated using the rolling-window technique. In this paper, the connectedness methodology proposed by [49,50] is used in conjunction with the TVP-VAR methodology developed by [54].

Let Y_t^+ be $(N \times 1)$ vector ($N = 5$) of five measured good volatilities of the sectoral RE indices. For the good volatilities vector, the time-varying vector autoregressive model with p lags is represented by the following equation:

$$\begin{cases} Y_t^+ = c_t^+ + \sum_{i=1}^p \Phi_{i,t}^+ Y_{t-i}^+ + u_t^+; u_t^+ \setminus \Omega_{t-1}^+ \sim N(0, S_t^+) \\ \Phi_t^+ = \Phi_{t-1}^+ + v_t^+; v_t^+ \setminus \Omega_{t-1}^+ \sim N(0, R_t^+) \end{cases} \tag{4}$$

$$\tag{5}$$

Regarding the bad volatilities vector (Y_t^-), the TVP-VAR(p) model may be expressed as:

$$\begin{cases} Y_t^- = c_t^- + \sum_{i=1}^p \Phi_{i,t}^- Y_{t-i}^- + u_t^-; u_t^- \setminus \Omega_{t-1}^- \sim N(0, S_t^-) \\ \Phi_t^- = \Phi_{t-1}^- + v_t^-; v_t^- \setminus \Omega_{t-1}^- \sim N(0, R_t^-) \end{cases} \tag{6}$$

$$\tag{7}$$

where Y_{t-i}^+ and Y_{t-i}^- refer to lagged vectors of Y_t^+ and Y_t^- at order i , respectively. The terms u_t^+ and u_t^- are the error terms, which are assumed to follow a normal distribution with time-varying variance–covariance matrices S_t^+ and S_t^- , respectively. Both Ω_{t-1}^+ and Ω_{t-1}^- represent the information provided by positive and negative volatility at time $t - 1$, respectively.

2.3.2. Good and Bad Volatility Spillover

Ref. [55] suggested transforming the VAR into a moving average representation to obtain spillover indices based on TVP-VAR using the procedure of [49,50]. The representation of the (good or bad) volatility vector Y_t is as follows:

$$Y_t = A_t u_t \tag{8}$$

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

Using Equation (8), one could split the forecast error variances on the various variables of the system (RE stock markets volatilities) in the spirit of [49,50]. Using the generalized impulse response functions (GIRF) and the generalized forecast error variance decompositions (GFEVD), we construct the spillover index. This index measures the proportion of the error variance in forecasting the i th variable that can be attributed to shocks in the j th variable for a given J -step-ahead forecast. The GIRF, represented by $\Psi_{j,t}^g(J)$, can be derived using the following equation:

$$GIRF(J, \delta_{j,t}, \Omega_{t-1}) = E(Y_{t+J} \{u \mid j, t = \delta_{j,t}, \Omega_{t-1}\}) - E(Y_{t+J} \{ \Omega \mid t - 1 \}) \tag{9}$$

$$\Psi_{j,t}^g(J) = S_{jj,t}^{-1} A_{J,t} S_t u_{j,t} \tag{10}$$

where the forecast horizon is represented by J , while $\delta_{j,t}$ denotes the selection vector taking the value one on the j th position, otherwise zero.

Furthermore, the GFEVD, represented by $\Pi_{j,t}^g(J)$, can be derived using the following equation:

$$\Pi_{j,t}^g(J) = \frac{\sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}}{\sum_{j=1}^N \sum_{t=1}^{J-1} \Psi_{ij,t}^{2,g}} \tag{11}$$

where $\Pi_{j,t}^g(J)$ represents the variance generated by one variable over others. The GFEVD verifies $\sum_{j=1}^N \Pi_{j,t}^g(J) = 1$ and $\sum_{i,j=1}^N \Pi_{j,t}^g(J) = N$.

2.3.3. Connectedness Indices

According to [49,50], the GFEVD enables computing several connectedness indices. The total spillover index quantifies how much a shock in one variable affects the others. It may be computed as follows:

$$H_t^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \Pi_{ij,t}^g(J)}{N} \times 100 \tag{12}$$

In addition, one might calculate the total directional connectedness to others “TO”, which represents the shocks that a specific variable transmits to all other variables, as follows:

$$TO_t(J) = H_{i \rightarrow j,t}^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \Pi_{ji,t}^g(J)}{\sum_{j=1}^N \Pi_{ji,t}^g(J)} \times 100 \tag{13}$$

Additionally, the spillover index “FROM” represents the total directional connectedness from others and is defined as the shocks that a specific variable receives from all other variables. It is given by:

$$FROM_t(J) = H_{i \leftarrow j,t}^g(J) = \frac{\sum_{i,j=1, i \neq j}^N \Pi_{ji,t}^g(J)}{\sum_{j=1}^N \Pi_{ji,t}^g(J)} \times 100 \tag{14}$$

To calculate the net spillover index, we subtract the “FROM” index from the “TO” index, as follows:

$$NET_t(J) = H_{i,t}^g(J) = H_{i \rightarrow j,t}^g(J) - H_{i \leftarrow j,t}^g(J) \tag{15}$$

Finally, the net pairwise directional connectedness index “NPDC”, which represents the shock transmitted from a variable i to a variable j , is defined by:

$$NPDC_{ij}^{gH} = H_{ij,t}^g(J) = \left[\Pi_{ji,t}^g(J) - \Pi_{ij,t}^g(J) \right] \times 100 \tag{16}$$

A value greater than zero indicates that variable i dominates variable j and vice versa.

3. Data and Preliminary Analysis

3.1. Data Description

To assess the volatility spillover among RE sectoral stock markets, we collect data on stock prices from the NASDAQ OMX Green Economy Indices. The stock prices denominated in U.S. dollars correspond to different RE sectors, namely solar (SOL), wind (WIN), geothermal (GEO), fuel cell (FUEL), and developer/operator (DEV). The data covering the period between 18 October 2010 and 2 April 2022 is obtained from the Quandl platform. For each RE sectoral index, we compute returns series expressed as $R_t = 100 \times \ln(P_t/P_{t-1})$, where P_t is the stock index price at day t .

3.2. Preliminary Analysis of the Data

Figure 1 depicts the index prices of the different sectors. A close look at the figure shows an upward trend throughout the study period. The RE stock market has generally shown a remarkable appreciation accompanied by high variability over the last three years. This pattern can be due to significant events influencing the RE market, especially the COVID-19 outbreak [56–58].

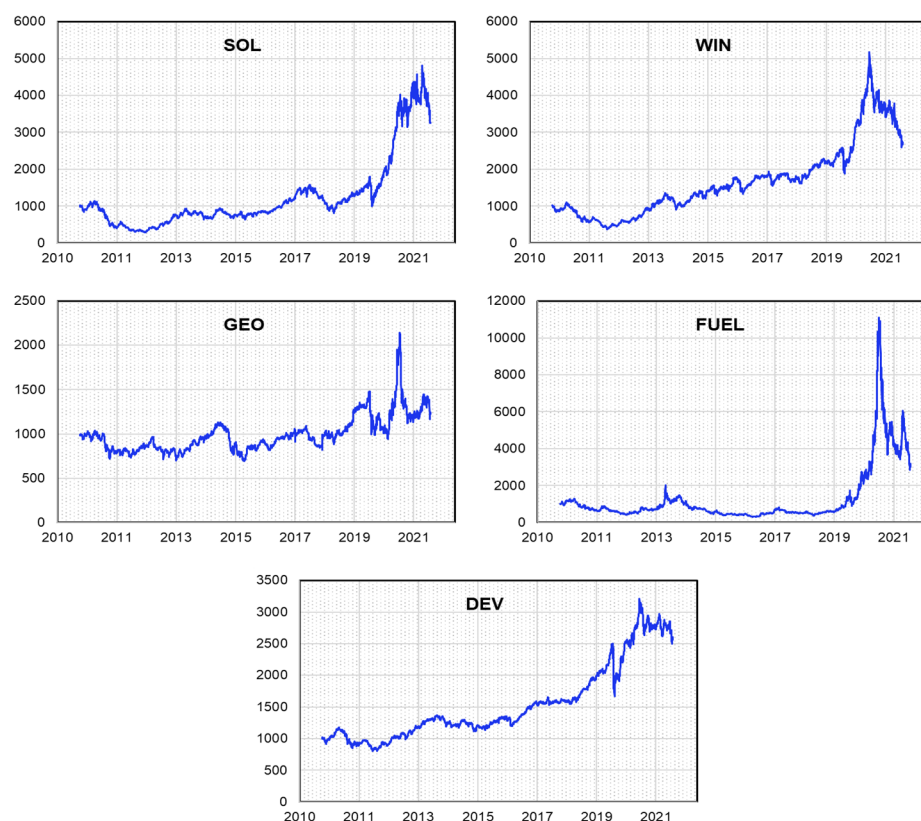


Figure 1. Stock prices of the different RE sectors.

To obtain the positive and negative volatility series for various stocks in the RE sector, we employ the AR(1)-GJR-GARCH(1,1) model. The optimal lag order is selected based on the Akaike Information Criteria (AIC) and Bayesian Information Criterion (BIC). Indeed, the AR(1)-GJR-GARCH(1,1) model is selected after a thorough comparison with alternative models, including the standard GARCH(1,1) and EGARCH(1,1) models, among others. The results indicate that the AR(1)-GJR-GARCH(1,1) model consistently yielded the highest log-likelihood values and the lowest AIC and BIC values. These metrics are crucial for model selection, as they balance model fit and complexity, with lower AIC and BIC values indicating the better model. We then extract the total conditional volatility series using Equation (2) and subsequently generate the positive and negative volatility series, as indicated in Equations (5) and (7). Descriptive statistics for the total, good, and bad conditional volatility series are presented in Table 1. The analysis reveals that the fuel cell sector had the highest mean conditional volatility when considering the total conditional volatility. This statement remains true even if the volatility is decomposed into positive and negative components. Furthermore, it is observed that the mean values of good volatility exceed those of bad volatility across all sectors. The skewness, kurtosis excess, and Jarque–Bera test statistics confirm that total, positive, and negative volatility series do not follow the normal distribution. On the other hand, the ERS strongly rejects the null hypothesis of a unit root for all volatility series, which is a mandatory condition for implementing the VAR model. Finally, the Ljung–Box test confirms the existence of serial correlations, suggesting a nonlinear behavior in all conditional volatility series.

Table 1. Descriptive statistics for conditional, good, and bad volatility series.

	SOL	WIN	GEO	FUEL	DEV
Total volatility					
Mean	4.237	2.720	2.650	10.780	1.046
Variance	28.122	4.131	10.331	94.044	6.075
Skewness	8.679 ***	4.519 ***	5.166 ***	3.208 ***	11.672 ***
Ex. Kurtosis	97.256 ***	29.738 ***	35.233 ***	12.751 ***	156.073 ***
JB <i>p</i> -value	0.000	0.000	0.000	0.000	0.000
ERS	−7.830 ***	−9.894 ***	−7.406 ***	−6.846 ***	−9.391 ***
Q(10)	1.28×10^4 ***	9.76×10^3 ***	1.16×10^4 ***	1.26×10^4 ***	1.16×10^4 ***
Q2(10)	9.89×10^3 ***	7.71×10^3 ***	9.88×10^3 ***	1.05×10^4 ***	8.38×10^3 ***
Good volatility					
Mean	2.270	1.398	1.359	5.484	0.550
Variance	21.476	3.867	5.773	78.999	3.301
Skewness	9.269 ***	3.476 ***	5.073 ***	3.392 ***	14.750 ***
Ex. Kurtosis	124.450 ***	23.203 ***	41.573 ***	16.844 ***	266.004 ***
JB <i>p</i> -value	0.000	0.000	0.000	0.000	0.000
ERS	−9.378 ***	−11.619 ***	−9.823 ***	−11.226 ***	−11.437 ***
Q(10)	2312.672 ***	496.561 ***	872.504 ***	1045.209 ***	2160.477 ***
Q2(10)	3388.061 ***	1586.289 ***	1336.676 ***	1599.442 ***	1480.005 ***
Bad volatility					
Mean	1.968	1.322	1.291	5.297	0.495
Variance	15.581	3.961	8.069	73.157	3.320
Skewness	8.910 ***	3.600 ***	6.217 ***	3.299 ***	15.846 ***
Ex. Kurtosis	128.999 ***	24.172 ***	52.751 ***	15.035 ***	297.924 ***
JB <i>p</i> -value	0.000	0.000	0.000	0.000	0.000
ERS	−10.373 ***	−10.631 ***	−9.638 ***	−10.494 ***	−11.933 ***
Q(10)	1199.504 ***	726.279 ***	2385.239 ***	1043.035 ***	2520.738 ***
Q2(10)	1487.938 ***	1307.231 ***	3434.755 ***	2395.625 ***	2518.039 ***

*** denotes the statistical significance at 1% level.

4. Empirical Results and Discussion

As explained in the methodology section, this study utilizes the TVP-VAR and the spillover indices of [49,50] to assess the volatility transmission between the different RE sectors. We first examine the spillover of overall conditional volatility and then focus on transmitting good and bad volatilities.

4.1. Total Volatility Spillovers

The estimation findings of the average dynamic spillovers for the different RE stock index volatility are summarized in Table 2. The outcomes are generated based on one lag (as suggested by the BIC information criteria) and a 10-step-ahead forecast error. The table illustrates that the volatility spillovers within the same sector contribute the most to the forecast error variance for all RE sectors. This can be observed by comparing the high values of the diagonal elements with those of the non-diagonal elements. The proportion ranges from 59.71% for the developer/operator sector to 79.82% for the fuel cell sector. The total connectedness is 32.9%, suggesting a medium level of spillovers between the different RE stock sectors. The developer/operator sector is the most frequent contributor to other RE sectors (48.3%), followed by solar (39.49%), wind (32.37%), geothermal (26.42%), and finally fuel cell (17.95%). At the same time, the developer/operator and wind sectors are the most frequent receivers of volatility from the system, with 40.29% and 38.42%, respectively.

The total net spillover index for each sector is reported at the bottom of Table 2. The solar and developer/operator sectors are the primary sources of shocks because the transmitted volatility from these sectors exceeds the received volatility (positive net spillover index). However, the remaining RE sectors are net receivers of volatility, i.e., they receive more spillovers from the system than they transmit. The rapid development

of solar energy compared to other clean energy sources may be a plausible rationale for this outcome. The global installed solar energy capacity increased from 141.417 GW in 2013 to 1061.632 GW in 2022 [59]. Furthermore, the developer/operator sector is a net transmitter of volatility to other RE sectors, which may be attributed to the fact that the developer/operator index tracks developers and operators of RE projects, including the wind and geothermal sectors, i.e., it is therefore connected to almost all other sectors within the RE industry.

Table 2. Connectedness table for conditional volatility series.

	SOL	WIN	GEO	FUEL	DEV	From
SOL	64.87	8.7	7.39	4.53	14.53	35.13
WIN	10.85	61.58	4.64	4.28	18.64	38.42
GEO	9.72	5.19	69.5	5.16	10.43	30.50
FUEL	5.03	3.18	7.28	79.82	4.70	20.18
DEV	13.88	15.31	7.12	3.98	59.71	40.29
TO others	39.49	32.37	26.42	17.95	48.30	164.52
Inc. own	104.35	93.96	95.92	97.77	108.01	TCI
NET	4.35	−6.04	−4.08	−2.23	8.01	32.9

4.2. Good and Bad Volatility Spillovers

To comprehensively examine volatility transmission between sectoral RE stocks, we compute the spillover indices using the TVP-VAR model. However, we differentiate in this section between good volatility (positive returns component) and bad volatility (negative returns component). The results shown in Table 3 indicate that the transmission of volatility, whether it is positive or negative, is similar to the overall conditional transmission of volatility. The TCI for both types of volatility is almost similar: 32.69% for good volatility and 31.21% for bad volatility. In addition, shocks received (transmitted) by each sector experienced minor variations, confirming the presence of a symmetric volatility transmission. The solar and developer/operator are still net transmitters of good and bad volatility, whereas the other sectors are net receivers. Notwithstanding the similarity of TCI values of symmetric and asymmetric (positive and negative) volatility spillovers, some disparities are observed in the outcomes presented in Tables 2 and 3. Upon comparing the data in these two tables, one could notice that the asymmetric (good and bad) contributions of the solar, wind, and developer/operator sectors to the system decreased compared to the case of symmetric contribution. On the contrary, the contributions of the geothermal and fuel cell sectors to the system increased when splitting the total volatility into good and bad volatilities. For instance, the contribution of the fuel cell sector increased from 17.95% (for the symmetric spillover) to 22.78% (positive volatility) and 22.49% (negative volatility).

Table 3. Connectedness table for good and bad volatility series.

	SOL	WIN	GEO	FUEL	DEV	From
Good volatility						
SOL	63.66	6.78	8.23	6.1	15.23	36.34
WIN	9.09	66.29	4.61	4.34	15.66	33.71
GEO	9.71	4.24	69.24	7.00	9.81	30.76
FUEL	7.47	4.06	6.88	74.25	7.33	25.75
DEV	12.7	12.08	6.78	5.34	63.09	36.91
TO others	38.98	27.16	26.5	22.78	48.03	163.46
Inc. own	102.64	93.46	95.75	97.04	111.12	TCI
NET	2.64	−6.54	−4.25	−2.96	11.12	32.69

Table 3. Cont.

	SOL	WIN	GEO	FUEL	DEV	From
Bad volatility						
SOL	65.8	6.38	8.48	5.8	13.54	34.2
WIN	8.13	68.23	4.74	4.77	14.14	31.77
GEO	9.32	4.42	69.49	6.7	10.06	30.51
FUEL	6.71	3.98	5.97	76.65	6.69	23.35
DEV	12.23	11.17	7.59	5.22	63.79	36.21
TO others	36.39	25.95	26.78	22.49	44.44	156.04
Inc. own	102.19	94.18	96.27	99.14	108.23	TCI
NET	2.19	−5.82	−3.73	−0.86	8.23	31.21

4.3. Dynamic Good and Bad Volatility Spillovers

The conclusions drawn in the previous sections were obtained from an averaged analysis spanning the full period. However, this could hide the dynamism of volatility spillover and fail to identify the accurate mechanism related to RE sectoral stocks. Therefore, conducting a spillover analysis in a time-varying fashion is mandatory, which is one of the strengths of the TVP-VAR model. Figure 2 depicts the total connectedness index over time. The upper graph represents the TCI for the conditional volatility, while the lower graph shows the TCI for both good and bad volatility series. To start, one could notice the significant variability of the TCI over the study period. When examining the TCI for symmetric spillovers, we note substantial fluctuations in the total volatility spillovers among RE stocks over time. More specifically, the TCI is found to be more pronounced during economic and financial events that may affect RE markets. The total volatility spillovers varied from less than 10% between 2017 and 2019, i.e., after adopting the Paris Climate Agreement in 2015. This agreement may have significant ramifications for the RE markets and their interconnections, as it advocates, among other things, the transition from conventional fossil fuels-based energy systems to RE sources. The peak volatility spillover reached around 70% and coincided with the beginning of the study period and the COVID-19 outbreak. This finding is expected, given that stock markets, particularly RE markets, become extremely interconnected during stress periods, while crisis episodes heighten the interconnections of global stock markets [60]. Another possible explanation for this finding is that the rapid global spread of the coronavirus pandemic may have a dampening effect on the global economy, generating pessimism among investors and influencing stock market prices via investment decisions [61]. This conclusion supports the outcomes of [57], who documented a substantial influence of the uncertainty resulting from the COVID-19 pandemic on RE stocks.

Moving to the asymmetric volatility spillover analysis, there is evidence of a time-varying pattern in volatility transmission, as the TCI for both good and bad volatility series exhibited considerable variations, with high values followed by medium and low values. The TCI values were high at the beginning of the study period, exceeding 55% for good and bad volatility. Then, they decreased considerably until the end of 2013, when the total good and bad volatility spillovers reached their minimum values of about 14% and 19%, respectively. Subsequently, there were ongoing asymmetric total spillovers with moderate values ranging from 20% to 40% between 2015 and mid-2017. However, the TCI experienced a significant decline, reaching approximately 15% by the end of 2017. Moreover, we note some minor divergences between good and bad volatility spillovers during specific periods, especially in 2018. The highest RE stock sector volatility spillovers were observed over the first quarter of 2020. Indeed, total connectedness between good and bad volatility reached 72.87% and 75.93%, respectively, in mid-March 2020.

To provide a clearer picture of the asymmetric spillover in the RE stock sectors, we computed the asymmetric volatility spillover (AVS) as the difference between good and bad volatility spillover. Figure 3 depicts the AVS index over time. It should be noted that

positive (negative) AVS values imply that the volatility spillover caused by positive shocks is higher than that caused by negative shocks and vice versa. One could notice a pattern of changing dominance between the two types of volatility in terms of shock transmission, as indicated by positive values followed by negative ones. From the beginning of the study period until mid-2012, the transmission of volatility caused by positive shocks was higher than that caused by negative shocks. Furthermore, negative shocks became dominant between August 2012 and November 2013. After that, the values of AVS were always positive. One possible rationale for these outcomes is that the market participants altered their risk perceptions and began anticipating greater levels of positive shock transmission, leading to increased expectations for stock returns.

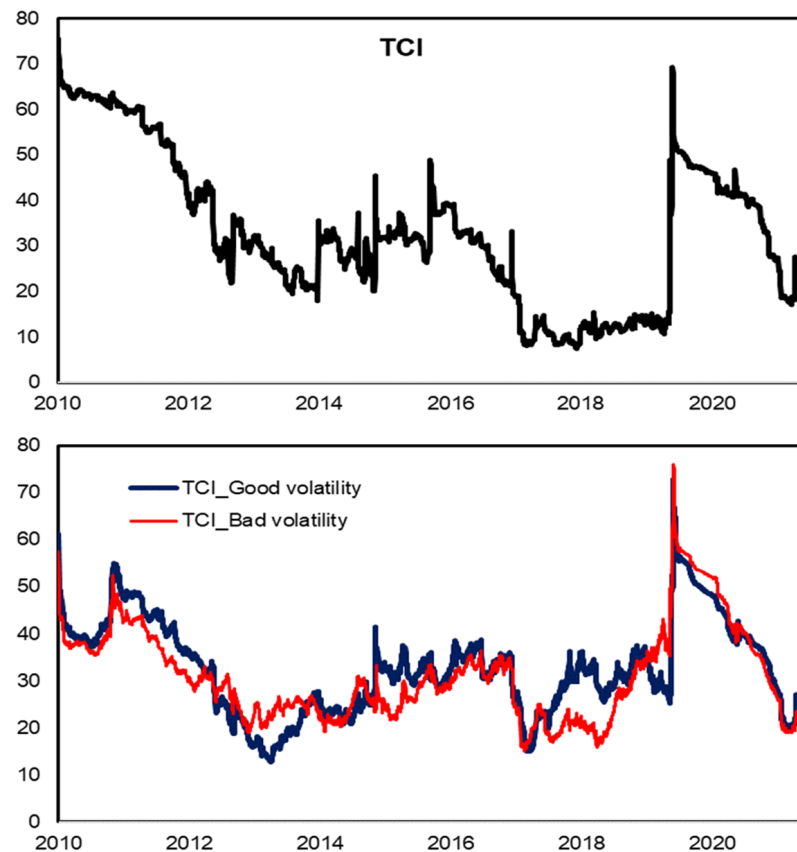


Figure 2. Time-varying TCI for symmetric and asymmetric volatilities.

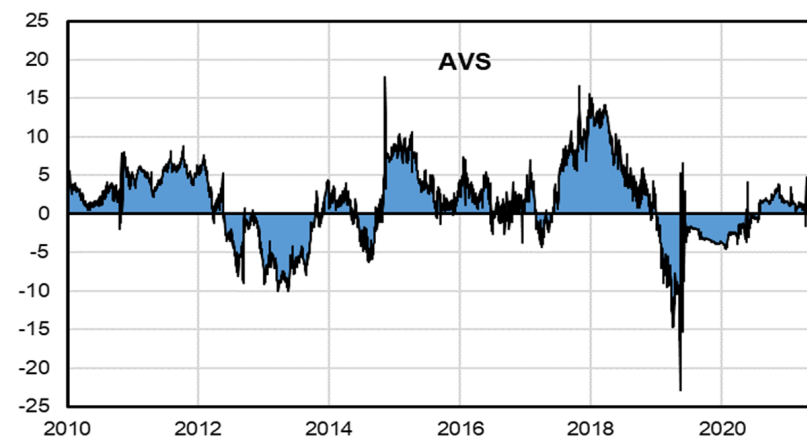


Figure 3. Asymmetry in Volatility Spillover (AVS).

The positive values of the AVS index in 2018 can be attributed to several significant events that profoundly impacted the RE sector. Indeed, there was a sharp increase in market volatility during this period, owing mostly to geopolitical risks, trade conflicts, particularly between the United States and China, and regulatory changes impacting RE markets. These factors resulted in heightened investor uncertainty and risk aversion, which gave rise to disproportionate reactions to positive over negative news within the RE sectors. Good volatility increased in 2018 due to the occurrence of favorable events, such as advancements in renewable technologies and related policy shifts. However, negative events, including policy rollbacks and trade tensions, still exist and have contributed to an increase in bad volatility. However, good volatility remained dominant over bad volatility until the end of 2018. Nevertheless, the most recent period, primarily affected by COVID-19, displayed negative AVS values, indicating that RE stock markets tend to communicate more bad volatility than good volatility on average. Therefore, market participants changed their risk perceptions by expecting higher levels of bad shock transmission through low stock return expectations.

The distinction between good and bad volatility spillover may not provide compelling evidence for the presence of divergent risk transmission between the different RE sub-sectors. Therefore, it is mandatory to assess whether these indices are statistically different from zero. This will be achieved by using the block bootstrapping technique based on the work of [53]. Table 4 displays the outcomes of the block bootstrapping technique used to examine the significance of the AVS index presented in Figure 3. The table presents the mean value and bootstrap *p*-value for different block sizes (50, 100, 150, 200, 250, and 300).

Table 4. Block bootstrapping technique results based on the test of [53].

Block Size	50	100	150	200	250	300
Mean	0.927	0.927	0.927	0.927	0.927	0.927
Bootstrap <i>p</i> -value	0.6	0.8	0.3	0.7	0.4	0.6

The *p*-values ranging from 0.3 to 0.8 are above the common significance threshold of 0.05. According to these findings, there is no evidence to reject the null hypothesis that the asymmetry in volatility spillover index is different from zero at the 5% significance level, regardless of the chosen block size. The relatively high bootstrap *p*-values provide strong evidence that the index is statistically significant, suggesting the presence of significant asymmetric spillover between the RE stock markets.

4.4. Net Volatility Spillovers

This section analyzes the net directional spillover indices for each RE sector to better explore the symmetric and asymmetric spillovers between the different sectoral RE stocks in a time-varying framework. Results are provided in Figure 4. It is worth noting that the net directional spillover index of a specific RE sector is computed as the difference between the amount of shocks transmitted by the sector to the system (To) and the amount of shocks received from the system (From). It is worth noting that positive (negative) net spillovers indicate that the sector is a net transmitter (receiver) of volatility to other RE sectors. As shown, the different RE sectors were both transmitters and receivers of volatility over the study period. The developer/operator sector is a net transmitter throughout the study period. The solar energy sector also transmitted shocks to the system during the whole period, except for 2018–2022, corresponding to the COVID-19 outbreak, during which it became a net receiver of shocks. On the contrary, the wind, geothermal, and fuel cell sectors were mostly net receivers of shocks.

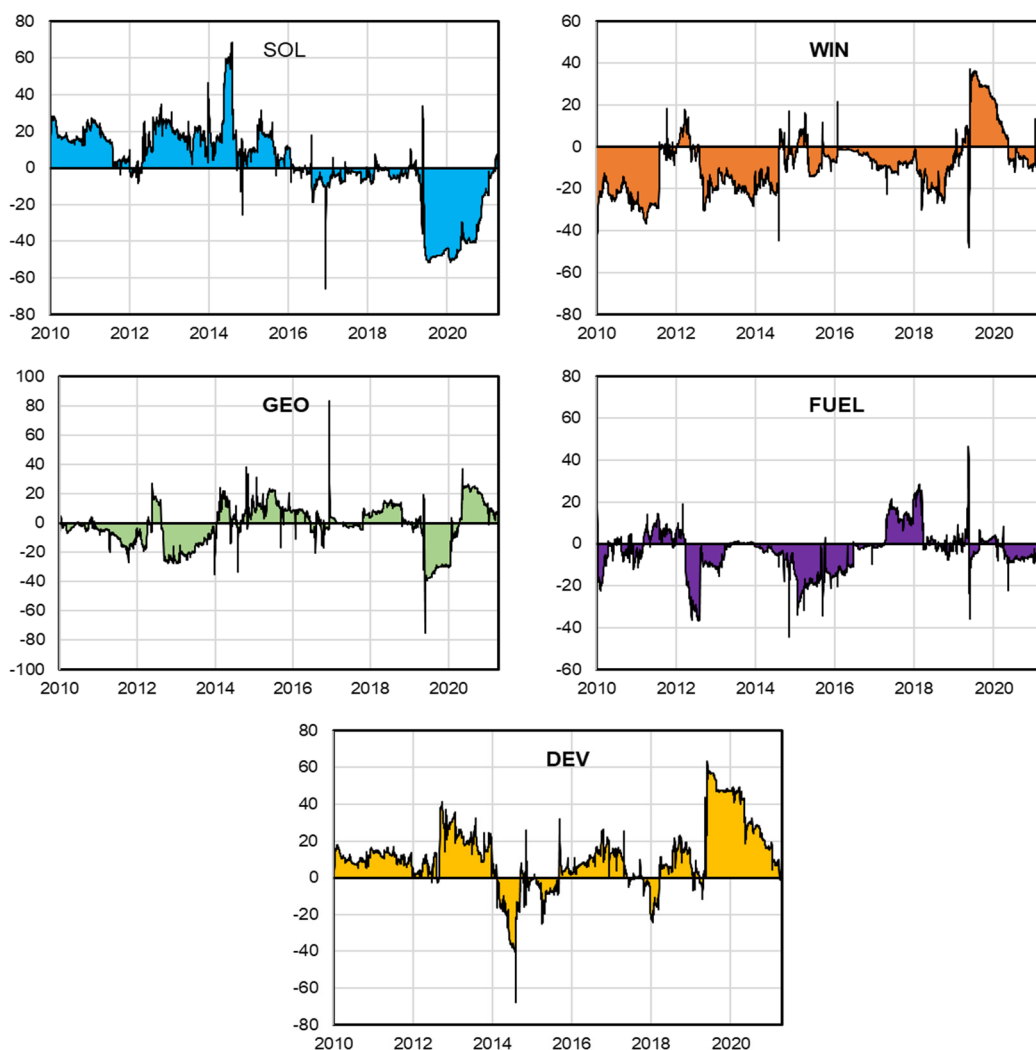


Figure 4. Net Volatility Spillovers.

Figure 5 plots the asymmetric net spillovers for each RE stock sector (first and second columns) and the net spillover AVS (third column). The findings generally indicate quasi-similar trends in the transmission of positive and negative volatilities. Nevertheless, the observed trend differs from the symmetric net volatility spillovers depicted in Figure 4, affirming the necessity of performing the asymmetric analysis.

The solar sector transmitted both positive and negative volatilities between 2010 and 2017. After that, this sector began to receive positive and negative volatility, except during the COVID-19 pandemic, when it began to transmit positive volatility. The wind and fuel cell sectors are generally net receivers of good and bad volatilities over almost all of this period. The same results are observed for the geothermal sector, but with a slight difference as it becomes a net transmitter of good and bad volatility during the pandemic. The AVS for net spillovers is presented in the right column of Figure 5. From this figure, it can be seen that the high variability of the AVS indicates the asymmetric character of good and bad net volatility spillovers. The findings also indicate the presence of swings between positive and negative values of AVS, suggesting that the prevalence of good or bad volatility swings over time. Such results are important for RE market operators, who should revise their decisions frequently depending on the source of volatility spillovers.

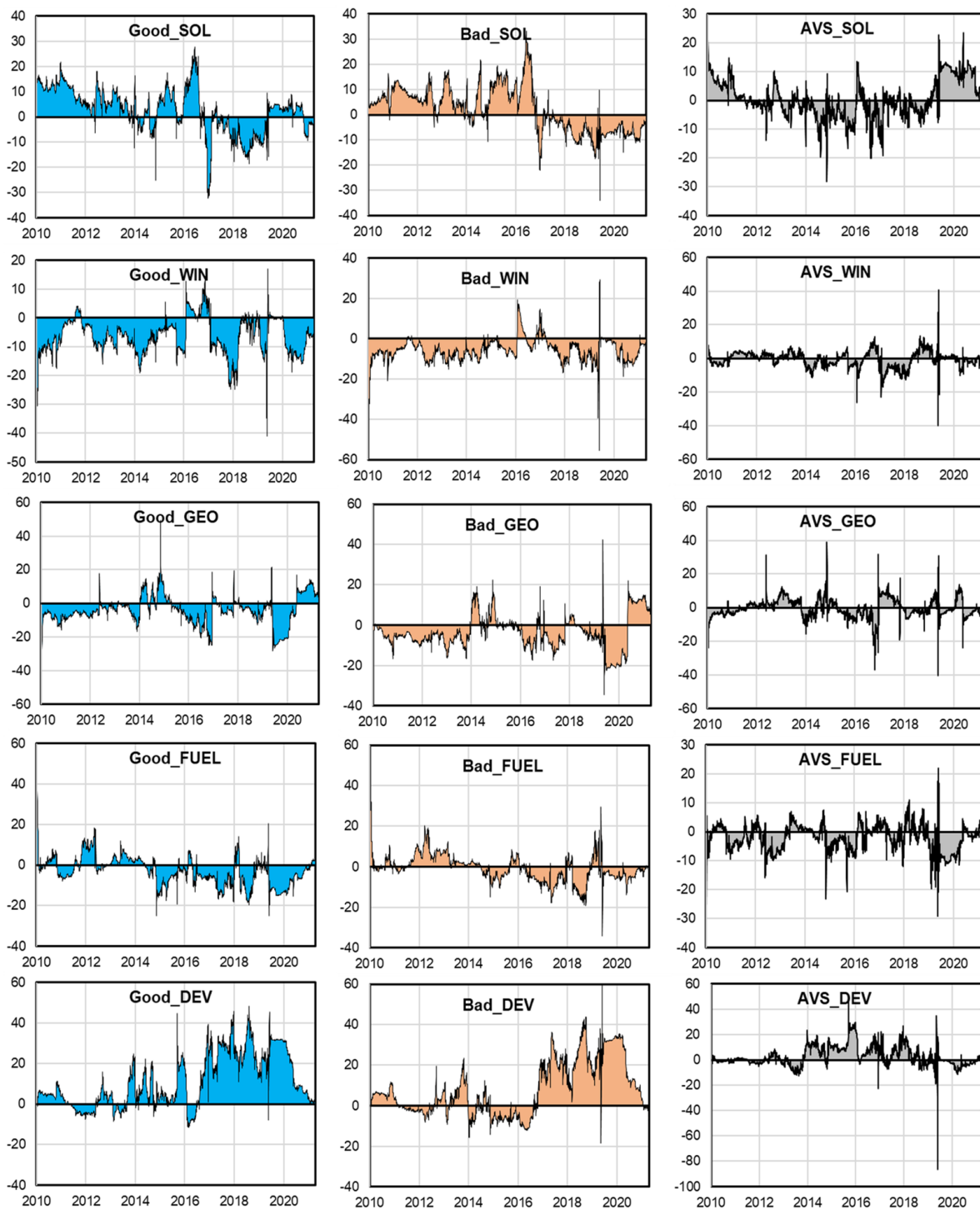


Figure 5. Net good and bad volatility spillovers.

4.5. Connectedness Network Analysis

Figure 6 depicts the connectedness networks among the RE stock sectors, which shows the pairwise transmission measure among different stock indices. The blue nodes represent the net transmitter of volatility, while the yellow nodes represent the net receiver of volatility. The vertices are assigned weights based on the average net pairwise directional connectedness indices. Finally, the node size of each RE sector is determined by the weighted average net total directional connectedness.

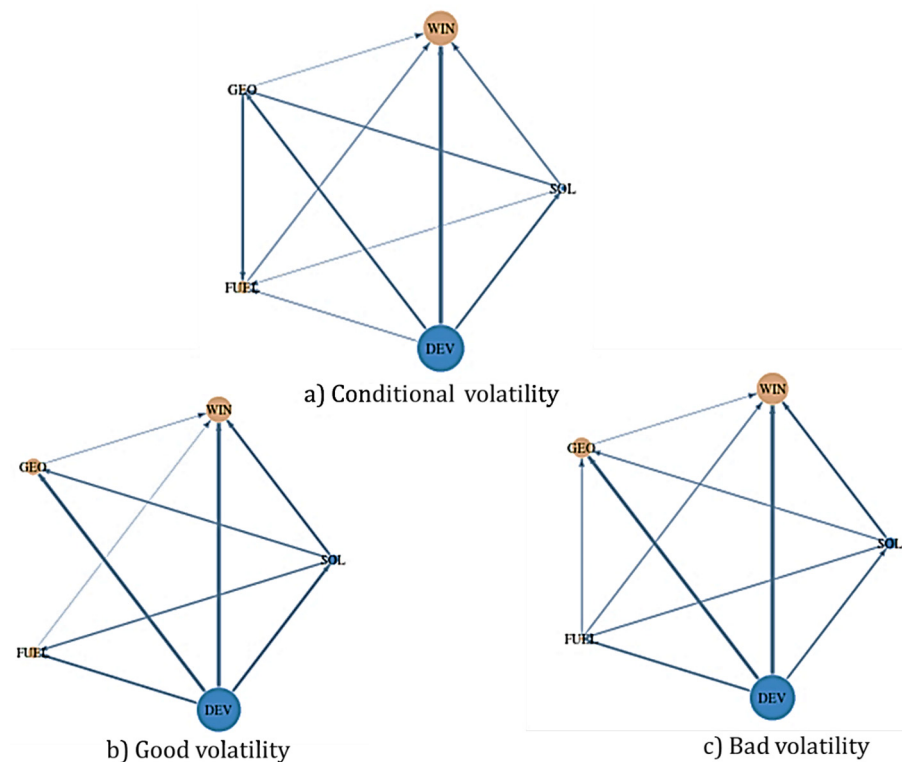


Figure 6. Connectedness networks.

Through a comparison of connectedness networks for symmetric and asymmetric spillovers, significant similarities are observed regarding shock transmitters and receivers. Specifically, the developer/operator sector is the primary source of shocks to other sectors, with the solar sector being the second largest transmitter of shocks. In contrast, the wind sector is the most frequent receiver of shocks compared to other RE sectors. Regarding the pairwise spillovers, the highest spillover is observed from the developer/operator to the wind sector. On the other hand, results suggest a minor divergence between the good and bad volatility spillovers. Indeed, the pairwise bad volatility spillovers are generally more pronounced than the good volatility spillovers. According to a market microstructure perspective presented by [62], in the stock markets, uninformed traders exhibit dominance when there is a significant magnitude of negative transmitted spillovers. Conversely, in situations where positive volatility spillovers occur, informed traders predominantly control the market. Our study shows that uninformed investors dominate the RE stock market. A plausible explanation of this finding is that this market is relatively emergent, and market operators do not have much information regarding RE dynamics.

4.6. Robustness Analysis

To ensure the robustness of previous findings, we conducted a further analysis by changing the lag order from one to two and extending the prediction range to 10, 15, and 20 periods. The results reported in Tables 5 and 6 represent the different connectedness indices (TCI, To, From, and Net) for total and decomposed good and bad volatilities. The consistency of the results across different lag orders and prediction ranges supports the stability and reliability of our previous conclusions. According to Table 5, the connectedness indices for various lag orders and prediction ranges indicate that the developer/operator sector is still the main source of shocks, while the wind, geothermal, and fuel cell sectors are net receivers. In addition, the findings in Table 6 suggest that both developer/operator and solar sectors are the main transmitters of shocks for both good and bad volatilities. This robustness check supports our findings and underscores the heterogeneity in volatility spillover between the different RE sub-sectors. Some RE sectors, particularly

developer/operator and solar, are net transmitters, while the other sectors are net receivers. These results also confirm the suitability of the asymmetric connectedness in analyzing the spillover between sectoral RE stocks.

Table 5. Connectedness measures with different lag orders and prediction ranges for total volatility series.

	Lag = 1					Lag = 2				
	SOL	WIN	GEO	FUEL	DEV	SOL	WIN	GEO	FUEL	DEV
J = 10										
TCI	29.24					29.49				
To	31.58	31.65	22.19	14.87	45.9	30.4	31.64	23.37	13.59	48.47
From	33.89	35.72	23.72	16.12	36.75	35.87	36.62	23.3	15.28	36.4
Net	−2.31	−4.07	−1.53	−1.25	9.15	−5.47	−4.98	0.07	−1.69	12.07
J = 15										
TCI	32.83					32.96				
To	35.15	32.39	26.92	18.89	50.79	33.53	31.85	28.54	17.41	53.5
From	37.91	39.07	28.18	19.27	39.7	36.82	33.34	31.9	26.69	38.28
Net	−2.76	−6.68	−1.26	−0.38	11.09	−3.29	−1.49	−3.36	−9.28	15.22
J = 20										
TCI	35.63					35.64				
To	37.89	32.8	30.44	22.45	54.56	36.03	31.9	32.32	20.82	57.1
From	41.02	41.61	31.61	21.86	42.05	43.01	42.1	30.52	21.27	41.29
Net	−3.13	−8.81	−1.17	0.59	12.51	−6.98	−10.2	1.8	−0.45	15.81

Table 6. Connectedness measures with different lag orders and prediction ranges for good and bad volatility series.

	Lag = 1					Lag = 2				
	SOL	WIN	GEO	FUEL	DEV	SOL	WIN	GEO	FUEL	DEV
Good volatility										
J = 10										
TCI	32.14					31.91				
To	41.06	25.46	28.29	21.91	44	40.78	26.58	27.88	20.96	49.28
From	34.84	31.84	29.59	25.06	39.38	36.44	33.04	31.53	26.42	38.05
Net	6.22	−6.38	−1.3	−3.15	4.62	4.34	−6.46	−3.65	−5.46	11.23
J = 15										
TCI	33.41					32.15				
To	33.53	31.85	28.54	17.41	53.5	41.16	26.71	28.05	21.07	50.04
From	39.97	39.79	27.46	18.5	39.1	36.82	33.34	31.9	26.69	38.28
Net	−6.44	−7.94	1.08	−1.09	14.4	4.34	−6.63	−3.85	−5.62	11.76
J = 20										
TCI	32.15					33.49				
To	41.06	25.46	28.29	21.91	44.01	40.78	26.58	27.88	20.96	49.28
From	36.44	33.04	31.53	26.42	38.05	36.44	33.04	31.53	26.42	38.05
Net	4.62	−7.58	−3.24	−4.51	5.96	4.34	−6.46	−3.65	−5.46	11.23

Table 6. Cont.

	Lag = 1					Lag = 2				
	SOL	WIN	GEO	FUEL	DEV	SOL	WIN	GEO	FUEL	DEV
Bad volatility										
J = 10										
TCI	31.21					31.91				
To	37.83	25.63	29.32	21.52	41.77	37.09	26.07	29.08	21.72	45.6
From	33.45	31.41	28.65	24.5	38.05	35.04	31.4	31.77	24.05	37.3
Net	4.38	−5.78	0.67	−2.98	3.72	2.05	−5.33	−2.69	−2.33	8.3
J = 15										
TCI	31.22					32.23				
To	37.84	25.63	29.33	21.52	41.79	37.43	26.19	29.38	21.86	46.3
From	33.46	31.41	28.66	24.51	38.06	35.4	31.64	32.25	24.32	37.55
Net	4.38	−5.78	0.67	−2.99	3.73	2.03	−5.45	−2.87	−2.46	8.75
J = 20										
TCI	31.22					32.31				
To	37.84	25.63	29.33	21.52	41.79	37.54	26.21	29.46	21.89	46.47
From	33.46	31.41	28.66	24.51	38.06	35.5	31.7	32.37	24.39	37.61
Net	4.38	−5.78	0.67	−2.99	3.73	2.04	−5.49	−2.91	−2.5	8.86

5. Concluding Remarks

The RE sector has experienced substantial expansion in recent decades due to the growing demand for RE sources, which are deemed mandatory for a successful energy transition process. This study adds to the existing body of knowledge by assessing the symmetric and asymmetric volatility spillover among sectoral RE stocks from 2 April 2022 to 18 October 2010. The analysis considers five RE sectors: solar, wind, geothermal, fuel cell, and developer/operator. On the statistical level, the study begins by estimating the conditional, good and bad volatility series using the GJR-GARCH(1,1) model. Then, we employ the connectedness methodology alongside the TVP-VAR approach, as described by [49,50]. This allows us to estimate the symmetric and asymmetric volatility spillover between the different RE sectors. Afterwards, we assess the validity of asymmetry using the block bootstrapping technique suggested by [53]. Finally, we conduct a connectedness network analysis to check the pairwise volatility transmission. The robustness of the statistical outcomes is then checked using different lag orders and prediction ranges. The symmetric analysis suggests that the solar and developer/operators RE sectors are net transmitters of shocks on average. In contrast, the wind, geothermal, and fuel cell sectors are net receivers of shocks from the system. These conclusions hold even when we decomposed total volatility into good and bad volatilities. The time-varying connectedness reveals an increase in the total, good, and bad volatility spillover between the different RE sectors during the COVID-19 pandemic. The asymmetric volatility spillover analysis shows changing dominance between the two types of volatility in terms of shock transmission, suggested by positive values followed by negative ones. However, the transmission of volatility caused by positive shocks was more prevalent during the study period, while negative shocks dominated during the pandemic. Finally, the net volatility spillover analysis confirms the role of developed/operator and solar sectors as transmitters of shocks to the system.

The findings of this study have important policy implications for stakeholders in the RE sector. First, recognizing the solar and developer/operator sectors as net transmitters of shocks implies that these sectors play a critical role in influencing the overall stability and performance of the RE market. Therefore, policymakers should prioritize the development of robust regulatory frameworks and support mechanisms for these two key sectors to enhance their stability and resilience. This could include incentives for innovation, subsi-

dies, or tax benefits. Since these sectors significantly influence other sectors, ensuring their stability could have positive spillover effects across the entire RE industry. Furthermore, the observed dominance of positive shock transmission during the study period, particularly in times of market stability, indicates the potential for positive market sentiment and investor confidence to drive growth in the RE market. However, the prevalence of negative shock transmission during the COVID-19 pandemic underscores the sector's vulnerability to global crises. This calls for policies to improve risk management and crisis readiness within the RE market. Implementing measures, such as creating emergency funds, promoting the diversification of energy sources, and fostering international cooperation, will strengthen the resilience of the sector to potential global shocks. By implementing these measures, governments and regulatory bodies can enhance the resilience of the RE sector to overcome shocks, thereby promoting its expansion and contribution to the transition towards sustainable energy sources.

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