The impact of economic uncertainty caused by COVID-19 on renewable energy stocks

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Abstract

By employing time–frequency-domain frameworks, this study analyzes the spillover effects of news-based economic uncertainty caused by the pandemic on three renewable energy stock indices in the USA, Europe, and the world. The empirical results reveal that the total spillover from economic uncertainty to the three renewable energy stock returns was concentrated at a high frequency, whereas those to volatilities appeared at low frequencies. Utilizing a rolling-window method, we observed that the impact of uncertainty caused by COVID-19 on three renewable energy stock returns and volatilities is more significant than that resulting from the global financial crisis (GFC). During COVID-19, the majority of the spillover effects from economic uncertainty to returns and volatilities of the three indices focused on the long term.

Keywords Uncertainty · Renewable energy stock · Spillover effects · COVID-19

1 Introduction

Coronavirus 2019 (COVID-19) is an infectious disease that is highly contagious and spreads rapidly worldwide in the short term. (Linton et al. 2020; Qian et al. 2020; Wilder-Smith and Freedman 2020). On March 11, 2020, the World Health Organization (WHO) declared this infectious disease a global pandemic. With the increase

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in the number of confirmed cases and the mortality rate worldwide, COVID-19 has a crucial impact on the global economy.[1]

With increasingly prominent environmental issues, sustainable development has received huge attention in recent years. In 2015, the Paris Climate Agreement proposed that the energy system based on fossil fuels should be gradually transformed into an efficient system based on renewable energy. Additionally, many countries' governments introduced policies and targets to encourage the development of the renewable energy industry, such as production tax credits (PTCs), feed-in tariffs (FITs), and the renewable portfolio standard (RPS). Investment in the renewable energy industry has received huge global attention from policymakers and investors. Renewable energy stock indices will reflect the development of the industry in the capital market, as renewable energy companies can obtain a steady flow of financial support through stock markets, thereby expanding their businesses and promoting the growth of the industry.

During periods of financial turmoil or crisis, the rise in uncertainty affects investor behavior in financial markets. For investors and policymakers, considering how economic uncertainty caused by COVID-19 influences renewable energy markets is of great practical importance as it can help them make wiser decisions or draft better policies. Thus, this study investigates the influence of economic uncertainty resulting from COVID-19 on renewable energy stock returns and volatilities. Moreover, unlike the economic uncertainty indices used in previous research, we employ a news-based economic uncertainty index that contains infectious disease information.

In addition, due to the different choices of policies on renewable energy and reactions to COVID-19 in different regions of the world, we investigate whether economic uncertainty due to COVID-19 has the same impact on renewable energy stock markets in the USA, Europe, and other regions of the world.

Spillover effects were used to describe the impact of economic uncertainty on renewable energy stocks. Multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) models have been widely used in the literature on spillover effects between different assets (Ewing and Malik 2005; Mensi et al. 2015). However, M-GARCH models are limited in their ability to measure and interpret the results of spillover effects. Such models provide spillover effect information only by measuring the strength of correlations between two variables; these models cannot capture the direction and intensity of spillover effects between different assets. Therefore, based on the forecast error variance decomposition of vector autoregressive models, Diebold and Yilmaz (2009, 2012, 2014)[2] proposed the Diebold–Yilmaz approach to assess spillover effects more effectively. This approach can quantify the intensity and direction of spillovers across different asset markets. Considering that investors have diverse investment horizons, and connectedness across assets also varies according to different frequencies, Baruník and Křehlík (2018) extended the

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[1] According to the WHO (2020), as of October 2020, COVID-19 has caused more than 1 million deaths, and the number of confirmed global infections is over 39 million and continues to increase.

[2] Klößner and Wagner (2014) developed a new algorithm that is faster at calculating the maximum and minimum overall remunerations of the Diebold–Yilmaz spillover index.

Diebold–Yilmaz approach to frequency domains to obtain spillover effects across markets at different frequencies.

The main empirical findings are summarized as follows. First, in the full-sample spillover analysis, the total spillover effects from economic uncertainty to the three renewable energy stock returns were concentrated at high frequencies, while those to volatilities appeared at low frequencies. Second, in the time-varying spillover analysis, economic uncertainty had a similar impact on the returns and volatilities of the three renewable energy stock indices in the USA, Europe, and the world. Third, the impact of uncertainty caused by COVID-19 on renewable energy stock returns and volatilities is more significant than that resulting from the global financial crisis (GFC). Fourth, most time-varying spillover effects of the returns and volatilities focus on the long term during the COVID-19.

Our study contributes to the existing literature in five main aspects. First, to the best of our knowledge, this is the first study to examine the spillover effects on renewable energy stock returns and volatilities from economic uncertainty due to COVID-19. Second, we used a recently constructed news-based index as a proxy for economic uncertainty that contains information on pandemic and infectious disease. Third, to investigate whether COVID-19 has the same impact on renewable energy stocks in different regions, we chose three indices to represent the USA, Europe, and the world's renewable energy stock markets. Fourth, based on the Diebold–Yilmaz approach and the Baruník–Křehlík methodology, we obtained the intensity and direction of spillover effects in the time and frequency domains. Fifth, a rolling-window method was applied to depict the time-varying spillovers, allowing us to observe the intensity of such spillovers during the recent financial turmoil (COVID-19).

The remainder of this paper is organized as follows. Section 2 reviews the related studies. Section 3 presents our empirical method. Data analysis is presented in Sect. 4. Section 5 reports and discusses the empirical results. Finally, Sect. 6 concludes the paper.

2 Literature review

The COVID-19 pandemic has had a profound impact worldwide, including the global economy. Several studies have confirmed that the COVID-19 outbreak has seriously affected the financial market (Ali et al. 2020; Baig et al. 2020; Zhang 2020a). Ashraf (2020) indicated that stock markets in 64 countries reacted with negative returns as the confirmed cases of COVID-19 increased. Okorie and Lin (2020) adopted detrended moving cross-correlation analysis (DMCA) and detrended cross-correlation analysis (DCCA) to investigate the fractal contagion effect of COVID-19 on stock markets in 32 countries. The authors confirmed a significant contagion effect on the stock market returns and volatilities. Baker et al. (2020a) confirmed that COVID-19 created an uncertainty shock in the global economy. Moreover, Altig et al. (2020) examined changes in financial uncertainty during the COVID-19 outbreak, and their findings revealed that such uncertainty is substantially increasing. In addition, many countries have sought to control the COVID-19 outbreak by

adopting strict quarantine policies and other measures. Clearly, these reactions have an influence on the economy (Barua 2020; Deb et al. 2020; Ozili and Arun 2020).

Economic uncertainty intensifies considerably during periods of extreme events or market turmoil. In the aftermath of the GFC, economic uncertainty has become the focus of recent research. Since there is no unified measurement standard for economic uncertainty, various proxies were employed in previous studies. For example, the Chicago Board Options Exchange (CBOE) volatility index (VIX) was widely used as a popular proxy for financial market uncertainty (Antonakakis et al. 2013; Bekaert and Hoerova 2014). Economic policy uncertainty (EPU), constructed by Baker et al. (2016), is also commonly used in the financial market (Liu and Zhang 2015; Demir et al. 2018). We employed a news-based economic uncertainty proxy (infectious-disease equity-market-volatility tracker, ID-EMV) that incorporates the uncertainty information of pandemic and infectious diseases, which is different from common proxies for economic uncertainty. Although only recently developed, some empirical research has applied the ID-EMV index. Bai et al. (2020) used the index to analyze the effects of infectious disease pandemics on stock markets in the USA, UK, Japan, and China. Their findings indicated that infectious disease pandemics have a significant positive impact on international stock volatility.

Economic uncertainty has a significant impact on renewable energy markets, as observed in several previous studies (Dutta 2017; Ahmad and Rais 2018; Uddin et al. 2019). Liu and Hamori (2020) analyzed the relationship between financial uncertainty and renewable energy stocks. Ji et al. (2018) illustrated the impact of financial uncertainty on clean energy stocks using time-varying copulas. Their results indicated that renewable energy stocks are influenced by the CBOE-VIX, which is commonly used as a measure of financial market uncertainty.

Using the Diebold–Yilmaz approach and the Baruník–Křehlík methodology, the current study investigated the spillover effects from economic uncertainty due to COVID-19 transmitted to renewable energy stocks. The application of these two methods has been popular in various recent studies for analyzing spillover effects across different markets (He et al. 2020; Zhang et al. 2020a, b). Kang et al. (2017) used the Diebold–Yilmaz approach to examine spillover effects among six commodity futures markets (corn, wheat, gold, silver, rice, and crude oil). Ferrer et al. (2018) investigated the dynamic connectedness among US clean energy stock, crude oil, and other key financial variables by employing the Diebold–Yilmaz approach and the Baruník–Křehlík methodology.

3 Methods

We utilized the spillover index approach introduced by Diebold and Yilmaz (2014) to measure the spillover effects from the ID-EMV index to renewable energy stocks in the time domain and then decomposed the spillover effects into different frequency domains based on the Baruník–Křehlík methodology. Subsequently, we explored the dynamic spillover effects in the time and frequency domains via the rolling-window approach.

3.1 Diebold–Yilmaz approach

The Diebold–Yilmaz approach is a simple but effective way of measuring connectedness across markets based on the forecast error variance decomposition (FEVD) of a vector autoregression (VAR) model.

Hence, we constructed a VAR model with n variables and p lags:

$$y_t = \sum_{i=1}^{p} \boldsymbol{\Phi}_i y_{t-i} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where y_t represents an $N \times 1$ vector of observed variables at time t, $\boldsymbol{\Phi}$ denotes the $N \times N$ coefficient matrix, and $\boldsymbol{\varepsilon}_t \ i.i.d \sim (\mathbf{0}, \boldsymbol{\Sigma})$ is a white noise error vector with covariance matrix Σ.

Assuming covariance stationarity, the VAR process can be rewritten in the moving-average (MA) form as

$$y_t = \boldsymbol{\Psi}(L)\boldsymbol{\varepsilon}_t \tag{2}$$

where $\Psi(L)$ is an $N \times N$ infinite lag polynomial matrix of coefficients.

The H-step-ahead generalized forecast error variance decomposition in Koop et al. (1996) and Pesaran and Shin (1998) is computed as follows:

$$\theta_{jk}^H = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \left(\left(\boldsymbol{\Psi}_h \boldsymbol{\Sigma} \right)_{jk} \right)^2}{\sum_{h=0}^{H} \left(\boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{\Psi}_h' \right)_{jj}}, \tag{3}$$

where $\boldsymbol{\Psi}_h$ represents an $N \times N$ coefficient matrix of polynomials corresponding to lag h, H denotes the forecast horizon, and σ_{kk} is the kth diagonal element of the Σ matrix. θ_{jk}^H denotes the contribution of the kth variable to the variance of the forecast error of the jth variable at selected forecast horizon H.

According to the definition in the generalized VAR process of FEVD, the sum of the variance contribution of the own and cross-variable shares is not necessarily equal to 1 (within columns). Hence, Diebold and Yilmaz normalized each entry by the row sum as follows:

$$\tilde{\theta}_{jk}^H = \frac{\theta_{jk}^H}{\sum_{k=1}^{N} \theta_{jk}^H}, \ \text{with} \ \Sigma_{k=1}^{N} \tilde{\theta}_{jk}^H = 1, \ \Sigma_{j,k=1}^{N} \tilde{\theta}_{jk}^H = N, \tag{4}$$

where $\tilde{\theta}_{jk}^H$ is defined as a measure of the pairwise spillover effects received by market j from market k at horizon H in the time domain.

Our study focuses on the spillover effects from the ID-EMV index to signal renewable energy stocks and considers the spillover effects on all renewable energy stocks. Hence, the directional spillovers from market k to other markets are defined as "To," which is given by

$$S^H_{\cdot \leftarrow k} = 100 \times \frac{\Sigma^N_{k=1,k\neq j} \tilde{\theta}^H_{jk}}{N}. \tag{5}$$

3.2 Baruník–Křehlík methodology

Following the Baruník–Křehlík methodology, we examined the spillover effects of the ID-EMV index on renewable energy stocks in different frequency domains based on the spectral decomposition of variance.

We considered the Fourier transform on coefficients $\boldsymbol{\Psi}_h$ with $i = \sqrt{-1}$, and the frequency response function is defined as

$$\boldsymbol{\Psi}\left(e^{-i\omega}\right) = \sum_h e^{-i\omega h} \boldsymbol{\Psi}_h. \tag{6}$$

The generalized causation spectrum over frequency $\omega \in (-\pi, \pi)$ can be expressed as

$$(\boldsymbol{f}(\omega))_{jk} \equiv \frac{\sigma^{-1}_{kk} \left| \left(\boldsymbol{\Psi}\left(e^{-i\omega}\right)\boldsymbol{\Sigma}\right)_{jk} \right|^2}{\left(\boldsymbol{\Psi}\left(e^{-i\omega}\right)\boldsymbol{\Sigma}\boldsymbol{\Psi}'\left(e^{+i\omega}\right)\right)_{jj}}, \tag{7}$$

where $(\boldsymbol{f}(\omega))_{jk}$ denotes the portion of the spectrum of the jth variable under a given frequency ω due to the kth variable. Subsequently, by weighting the frequency share of the variance of the jth variable, we obtained a generalized decomposition of the variance under different frequencies. The weighting function is defined as

$$\boldsymbol{\Gamma}_j(\omega) = \frac{\left(\boldsymbol{\Psi}\left(e^{-i\omega}\right)\boldsymbol{\Sigma}\boldsymbol{\Psi}'\left(e^{+i\omega}\right)\right)_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\boldsymbol{\Psi}\left(e^{-i\omega}\right)\boldsymbol{\Sigma}\boldsymbol{\Psi}'\left(e^{+i\omega}\right)\right)_{jj}\mathrm{d}\lambda}, \tag{8}$$

where $\boldsymbol{\Gamma}_j(\omega)$ represents the power of the jth variable under a particular frequency and sums through frequencies to a constant value of 2π. Generally, analysis of assessing these shares on frequency bands has received more attention than that on specific single frequencies. Therefore, we set a frequency band $d = (a, b)$: $a, b \in (-\pi, \pi)$; for $a < b$, the GFEVD on frequency band d can be defined as follows:

$$\theta_{jk}(d) = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)(\boldsymbol{f}(\omega))_{jk}\mathrm{d}\omega, \tag{9}$$

GFEVD under frequency band $d = (a, b)$: $a, b \in (-\pi, \pi)$, for $a < b$, is standardized as

$$\tilde{\theta}_{jk}(d) = \frac{\theta_{jk}(d)}{\sum_k \theta_{jk}(\infty)}, \tag{10}$$

where $\tilde{\theta}_{jk}(d)$ measures the pairwise spillover effects from the kth variable to the jth variable at an arbitrary frequency band d.

Table 1 Model variables

Variable	Data
ID-EMV	Infectious-disease equity-market-volatility tracker
ECO	Wilder Hill clean energy index
ERIX	European renewable energy price index
S&P GCE	Standard & poor global clean energy index

Analogously, the spillover effects transmitted from the ID-EMV index to all renewable energy stocks on a given frequency band d are defined as

$$S^F_{\cdot \leftarrow k} = 100 \times \frac{\Sigma^N_{k=1, k \neq j} \tilde{\theta}_{jk}(d)}{N}. \tag{11}$$

4 Data

To analyze the spillover effects of economic uncertainty resulting from COVID-19 on renewable energy stocks, we collected a news-based economic uncertainty index and three renewable energy stock indices: Wilder Hill Clean Energy Index (ECO), European Renewable Energy Price Index (ERIX), and Standard & Poor Global Clean Energy Index (S&P GCE). The daily data spanned from January 2, 2004, to September 2, 2020, consisting of 4168 observations. The data on economic uncertainty were obtained from the website of Economic Policy Uncertainty,[3] and renewable energy stock indices were gathered from Bloomberg. All variables are listed in Table 1.

Previous studies employed many distinct uncertainty proxies, such as the VIX and EPU indices. However, these common uncertainty proxies cannot directly and effectively reflect the economic uncertainty caused by infectious diseases, as they ignore the economic impact of the pandemic and infectious diseases. Constructed by Baker et al. (2020a; b), the ID-EMV is a newspaper-based index that reflects uncertainty in the stock market caused by infectious diseases.

The specific steps of the construction of the ID-EMV index are as follows: First, Baker et al. (2020b) specified four sets of terms, namely, ID: {epidemic, pandemic, virus, flu, disease, coronavirus, MERS, SARS, ebola, H5N1, H1N1}, E: {economic, economy, financial}, M: {"stock market," equity, equities, "Standard and Poors"}, and V: {volatility, volatile, uncertain, uncertainty, risk, risky}. Second, by tracking across approximately 3000 US newspapers, they computed daily counts of newspaper articles that contained at least one term in each of ID, E, M, and V. Third, they scaled raw EMV-ID counts by the number of all articles on the same day. Lastly, by utilizing the overall EMV index, they multiplicatively rescaled the resulting series

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[3] Details on the ID-EMV index can be found at http://www.policyuncertainty.com/infectious_EMV.html.
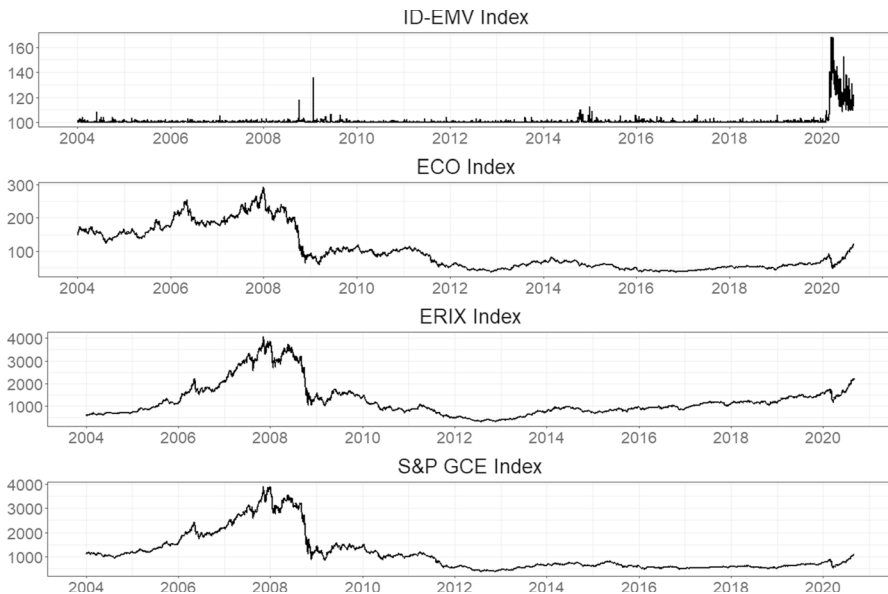
Fig. 1 Time variations of variables. *Note*: *ID-EMV* Infectious-disease equity-market-volatility tracker, *ECO* Wilder Hill clean energy index, *ERIX* European renewable energy price index, *S&P GCE* Standard & poor global clean energy index

to match the VIX level and then scaled the ID-EMV index to reflect the ratio of ID-EMV articles to total articles.

Moreover, to investigate the spillover effects on the overall renewable energy markets, we employed the ECO, ERIX, and S&P GCE indices, representing the renewable energy stock markets in the USA, Europe, and the world, respectively. The ECO is a weighted index that tracks the stock prices of approximately 40 clean energy companies in the USA. These companies focus on the renewable energy business and technologies, most of which have a market capitalization of more than USD 200 million. ERIX consists of the ten largest European renewable energy enterprises in the geothermal, water, marine, wind, solar, and biomass fields. The S&P GCE is composed of a diversified global mix of 30 companies in clean energy equipment and technology and clean energy-related production.

The change values of the ID-EMV index and the daily closing prices of the three renewable energy stocks are depicted in Fig. 1. The ID-EMV had two sharp increases during the GFC in 2008 and COVID-19 in 2020. Furthermore, all renewable energy stock prices exhibited a similar pattern of high sustained growth and continued until 2008. The prices of all renewable energy stocks suddenly declined in 2008 and 2020.

We calculated the logarithmic returns for the three renewable energy stocks and volatilities by fitting the AR-GARCH model. The descriptive statistics for the returns and volatilities of the three renewable energy stocks and the ID-EMV index are reported in Table 2. The mean returns for the ECO and S&P GCE were positive, while the ERIX index had a negative mean return. In terms of skewness, the returns

Table 2 Descriptive variable statistics

Descriptive statistics

	Minimum	Mean	Maximum	Std. Dev	Skewness	Kurtosis	JB	ADF	PP
Descriptive statistics of the return									
ECO	−0.1624	−0.0001	0.1452	0.0206	−0.5385	9.7310	8067.8000***	−43.3543***	−62.7870***
ERIX	−0.1696	0.0003	0.1582	0.0204	−0.4685	10.7932	10,697.0000***	−44.0653***	−60.5480***
S&P GCE	−0.1497	−0.0000	0.1809	0.0183	−0.6356	16.6478	32,621.0000***	−43.2679***	−56.2230***
Descriptive statistics of the volatility									
ECO	0.0001	0.0004	0.0064	0.0006	5.3084	36.8020	217,951.0000***	−4.0144***	−6.1594***
ERIX	0.0001	0.0002	0.0072	0.0005	6.6496	57.2696	542,069.0000***	−3.9054***	−5.3209***
S&P GCE	0.0001	0.0003	0.0080	0.0007	6.3399	49.5227	403,703.0000***	−4.1344***	−5.2607***
Descriptive statistics of infectious-disease equity-market-volatility tracker index									
ID-EMV	100.0000	101.3000	168.4000	5.1939	7.1143	61.5095	629,533.0000***	−10.1981***	−12.5060***

ID-EMV Infectious-disease equity-market-volatility tracker, *ECO* Wilder Hill clean energy index, *ERIX* European renewable energy price index, *S&P GCE* Standard & poor global clean energy index, *JB* Jarque–Bera test (1980), *ADF* Augmented Dickey–Fuller unit root test (1979), *PP* Phillips–Perron unit root test (1988)

*, **, and ***=rejection of null hypothesis at the 10%, 5%, and 1% significance levels, respectively

of the three renewable energy stocks were left-skewed, while the ID-EMV index and volatilities were right-skewed. Additionally, the returns and volatilities displayed a leptokurtic distribution. Jarque–Bera (JB) test results indicated that the ID-EMV index, returns, and volatilities of the three renewable energy stocks strongly reject normality at the 1% significance level. The results of the augmented Dickey–Fuller (ADF) unit root test and the Phillips–Perron (PP) unit root test supported the rejection of the null hypothesis of nonstationarity at the 1% level of significance for all cases.

5 Empirical results and discussion

This section presents the empirical results of the spillover effects from the ID-EMV index to clean energy stock returns and volatilities, based on the Diebold–Yilmaz approach and Baruník–Křehlík methodology. Before discussing the empirical results, we briefly describe the details of the methods applied herein. We determined the optimal lag length for the return and volatility sets of the four variable VAR models based on the Schwarz criterion (SC). Based on the generalized variance decomposition of VAR models, the Diebold–Yilmaz approach was applied to assess directional spillover effects in the time domain. Following Baruník–Křehlík (2018), the methodology will not work if the length of the forecasting horizon is less than 100 days. Thus, we applied a 100-day-ahead forecasting horizon (H).[4] Following Baruník and Křehlík (2018) and Toyoshima and Hamori (2018), we decomposed the spillovers into three separate frequency bands. The high-frequency band (short term) included periods from 1 to 5 days, the medium-frequency band (medium-term) corresponded to 5 to 21 days, and the low-frequency band (long term) refers to periods longer than 21 days. Finally, we depicted the dynamic spillover effects via a rolling window with a window length of 400 days. To check the robustness of the results, we repeated the analysis of the window lengths of 300 and 500 days, which showed similar results to that of 400 days. The results of the spillover effects of the full sample in the time and frequency domains are reported in Sect. 5.1, and those of time-varying spillover effects are summarized in Sect. 5.2.

5.1 Full-sample spillover analysis

The spillover effects of ID-EMV on renewable energy stock returns in the time and frequency domains using the Diebold–Yilmaz approach and Baruník–Křehlík methodology are presented in Table 3. The column "Directional Spillover (To)" represents the average value of the total spillover effect from ID-EMV to the ECO, ERIX, and S&P GCE returns. The results obtained using the Diebold–Yilmaz approach revealed that the total spillover effects from ID-EMV to ECO, ERIX, and S&P GCE returns were 0.058%, which indicates an extremely

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[4] The results of Diebold–Yilmaz approach spillover index with different forecasting horizons (H) (H = 200, 300, 400 days) are presented in Tables 5 and 6 in the Appendix and show similar results.

Table 3 Spillovers from ID-EMV to returns: Diebold–Yilmaz and Baruník–Křehlík

	ID-EMV to ECO	ID-EMV to ERIX	ID-EMV to S&P GCE	To
D–Y	0.068	0.108	0.058	0.058
Freq H	0.062	0.101	0.055	0.055
Freq M	0.002	0.001	0.001	0.001
Freq L	0.004	0.006	0.002	0.003

ID-EMV Infectious-disease equity-market-volatility tracker index, *ECO* Returns of Wilder Hill clean energy index, *ERIX* Returns of European renewable energy index, *S&P GCE* Returns of S&P 500 global clean index, *D–Y* Diebold–Yilmaz approach, *Freq H* High-frequency (Baruník–Křehlík) methodology, *Freq M* Medium-frequency band (Baruník–Křehlík), *Freq L* Low-frequency band (Baruník–Křehlík)

Table 4 Spillovers from ID-EMV to volatilities: Diebold–Yilmaz and Baruník–Křehlík

	ID-EMV to ECO	ID-EMV to ERIX	ID-EMV to S&P GCE	To
D–Y	13.719	1.964	5.218	5.225
Freq H	0.003	0.004	0.002	0.002
Freq M	0.091	0.014	0.031	0.034
Freq L	13.625	1.946	5.186	5.189

ID-EMV Infectious-disease equity-market-volatility tracker index, *ECO* Volatility of Wilder Hill clean energy index, *ERIX* Volatility of European renewable energy index, *S&P GCE* Volatility of S&P 500 global clean index, *D–Y* Diebold–Yilmaz approach, *Freq H* High-frequency band (Baruník–Křehlík), *Freq M* Medium-frequency band (Baruník–Křehlík method), *Freq L* Low-frequency band (Baruník–Křehlík)

low level of connectedness between ID-EMV and renewable energy stock returns. ID-EMV transmits the main spillover effects to ERIX (0.108%) returns, followed by ECO (0.062%) and S&P GCE (0.058%) returns. This result demonstrates that ID-EMV had a relatively stronger impact on the returns of the renewable energy stock market in Europe than in the USA and the world.

Using the Baruník–Křehlík methodology, we obtained the spillover effects that transmitted from ID-EMV to ECO, ERIX, and S&P GCE in the short, medium, and long terms, respectively. Table 3 shows that the total spillover effects were mainly focused on the short term (0.055%), while they were rarely found in the medium (0.001%) and long (0.003%) terms. This implies that shock information transmitted from economic uncertainty caused by the pandemic to renewable energy stock returns for only about one week. However, the differences between these terms are negligible.

The directional spillover effects from ID-EMV to renewable energy stock volatilities through the Diebold–Yilmaz approach and Baruník–Křehlík methodology are reported in Table 4. From the result of the former, total spillover effects from ID-EMV to all renewable energy stock volatilities were 5.225%, which was higher than that to returns (0.058%). Specifically, compared with the connectedness between ID-EMV and renewable energy stock returns, ID-EMV had a closer relationship with volatilities. Different from the results of returns, ID-EMV contributed the main spillover effects to the volatilities of ECO (13.719%), followed by those of S&P GCE (5.218%) and ERIX (1.964%). This result implies that ID-EMV had a significant influence on the renewable energy stock market in the USA compared to in Europe and the world. In addition, ID-EMV had higher connectedness with volatilities of each clean energy stock than it did with returns.

Similarly, the spillover effects of renewable energy stock volatilities were calculated using the Baruník–Křehlík methodology and are presented in Table 4. In contrast to the results of returns, volatilities received most total spillover effects in the long term (5.189%), followed by the medium (0.034%) and short (0.002%) terms. This implies that shocks transmitted from the ID-EMV had a long-lasting effect on renewable energy stock volatilities. This is an interesting finding that can be interpreted by the long memory in the volatilities of such stocks. This result agrees well with the previous literature (Tiwari et al. 2018; Balli et al. 2019; Gillaizeau et al. 2019) that the return spillovers in a system appear in the short term, while volatility spillovers are found in the long term when spillovers are decomposed into different frequency bands via the Baruník–Křehlík methodology. For example, Gillaizeau et al. (2019) identified connectedness in cross-market Bitcoin prices with both time- and frequency-domain mechanisms. They also found that overall volatility spillovers in the system were much higher in the long term than in the short term, while overall returns spillovers mainly focused on the short term.

5.2 Time-varying spillover analysis

It is well established that returns and volatilities vary over time, and the connectedness between ID-EMV and renewable energy stocks also changes over time. Thus, we applied a 400-day rolling window to capture the time-varying spillover effects of ID-EMV on returns and volatilities.

The time-varying spillover effects from ID-EMV to overall renewable energy stock returns based on the Diebold–Yilmaz approach and Baruník–Křehlík methodology are depicted in Fig. 2. The results of dynamic spillover effects with the former show that there were several sharp increases during the sample period. The first occurred at the end of 2008, corresponding to the GFC. The second increase occurred during the 2014 crude oil price crash. COVID-19 may have caused the third significant increase, which appeared at the beginning of 2020. Consistent with our results, Li et al. (2016) supported that connectedness across assets is generally strengthened during periods of financial turmoil. Furthermore, the dynamic spillover effects from ID-EMV to all renewable energy stock returns in 2020 (about 72%) notably exceeded those in 2008 (about 5%), suggesting that the connectedness
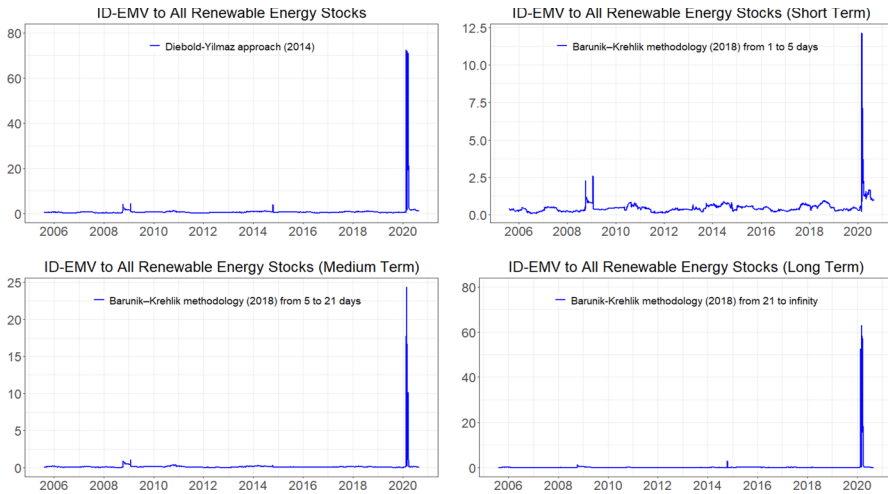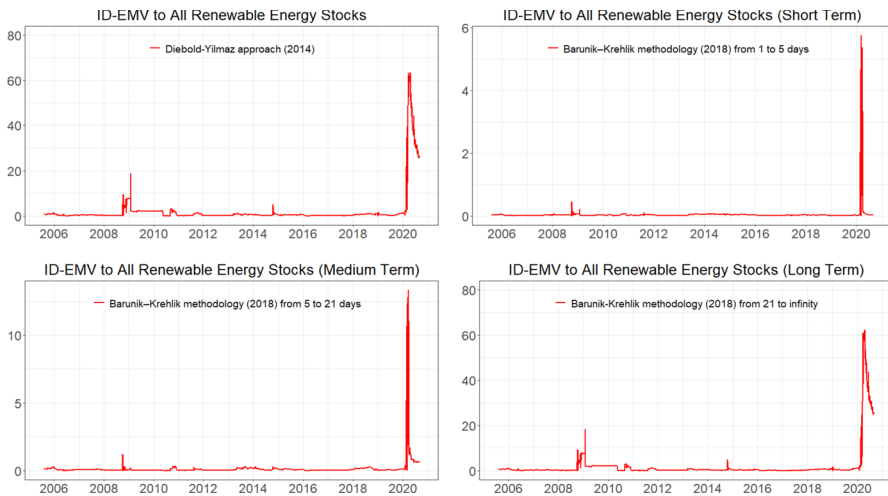
Fig. 2 Time-varying spillovers from ID-EMV to all renewable energy stock returns based on Diebold–Yilmaz approach and Baruník–Křehlík methodology

between the ID-EMV and returns was closer during COVID-19. In other words, this result implies that the impact of economic uncertainty resulting from COVID-19 on renewable energy stocks was much greater than that of the GFC.

Regarding the dynamic spillover effects computed by the Baruník–Křehlík methodology, we noticed several spillover effect fluctuations in each frequency band in 2008, 2014, and 2020, and the dynamic spillover effects during COVID-19 greatly exceeded those during the GFC. Such effects mainly appeared in the long term (about 65%), followed by the medium (about 25%) and short (about 12.5%) terms, which is contrary to the results of the full-sample analysis in Table 3. This highlights the importance of considering dynamic spillover effect analysis because this phenomenon could not be observed with full-sample analysis. In contrast, some previous studies (Tiwari et al. 2018; Trabelsi 2018; Liu et al. 2020) analyzed the connectedness among different assets using the Diebold–Yilmaz approach and Baruník–Křehlík methodology and observed that the dynamic spillover effects of returns primarily exist in the short term. This could be because ID-EMV can be regarded as a volatility index, and the spillover effects obtained herein refer to spillovers from asset volatilities to asset returns, while they were from asset returns to asset returns in the previous literature.

The time-varying spillover effects of the ID-EMV on renewable energy stock volatilities are illustrated in Fig. 3. The results of the Diebold–Yilmaz approach and Baruník–Křehlík methodology reveal that the dynamic spillover effects of volatilities drastically fluctuated during the periods of crisis in 2008, 2014, and 2020, which is consistent with the results of the dynamic spillover effects of returns. The results of the Diebold–Yilmaz approach show that dynamic spillover effects reached a peak of about 64% in 2020, in contrast to only about 20% in 2008, confirming that the connectedness between renewable energy stocks and ID-EMV considerably increased during COVID-19. We also found that ID-EMV transmitted higher
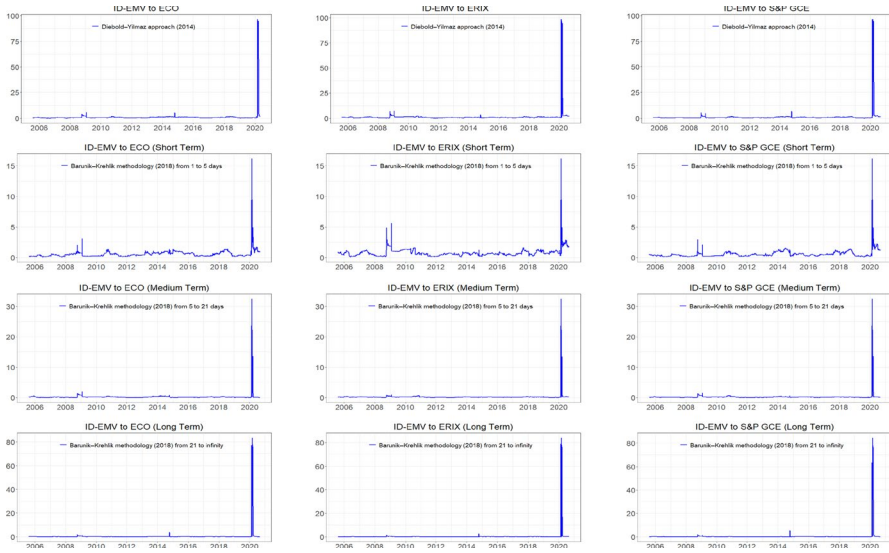
Fig. 3 Time-varying spillovers from ID-EMV to all renewable energy stock volatilities based on Diebold–Yilmaz approach and Baruník–Křehlík methodology

spillover effects to volatilities than it did to returns during the GFC, while it transmitted higher spillover effects to returns than to volatilities during COVID-19. This indicates that the impact of the ID-EMV index resulting from the GFC on renewable energy volatilities was more significant, and uncertainty due to COVID-19 had a more significant impact on renewable energy returns. Interestingly, the time-varying spillover effects reached a maximum in February 2020 and have gradually declined since then. This implies that the impact of COVID-19 on renewable energy stocks lasted for a long period and gradually decreased.

Our results indicate that the main dynamic spillover effects during the pandemic are concentrated in the long term, which is consistent with the full-sample results in Table 4. Furthermore, this result is in line with the related literature (Tiwari et al. 2018; Trabelsi 2018; Liu et al. 2020), which supports the notion that, based on the Baruník–Křehlík methodology, spillover effects from asset volatilities to asset volatilities are mainly focused on the long term.

Figures 4 and 5 capture the dynamic spillover effects from ID-EMV to ECO, ERIX, and S&P GCE returns and volatilities, respectively.[5] The figures show similar results to those in Figs. 2 and 3. Hence, we can assume that the results have universality. Therefore, the impact of economic uncertainty caused by the pandemic on renewable energy stock markets is similar in different regions.

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[5] Generalized impulse response of ECO, ERIX, and S&P GCE to ID-EMV (return and volatility) are depicted in Figures 6 and 7 in the Appendix.

Fig. 4 Time-varying spillovers from ID-EMV to ECO, ERIX, S&P GCE returns based on Diebold–Yilmaz approach and Baruník–Křehlík methodology. *Note*: *ID-EMV* Infectious-disease equity-market-volatility tracker index, *ECO* Returns of Wilder Hill clean energy index, *ERIX* Returns of European renewable energy index, *S&P GCE* returns of S&P 500 global clean index
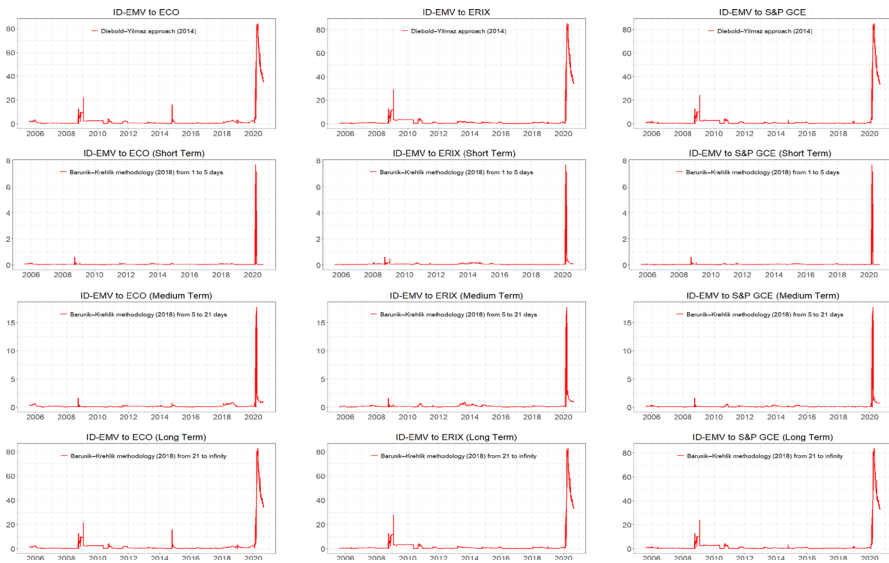
Fig. 5 Time-varying spillovers from ID-EMV to ECO, ERIX, S&P GCE volatilities based on the Diebold–Yilmaz approach and Baruník–Křehlík methodology. *Note*: *ID-EMV* infectious-disease equity-market-volatility tracker index. *ECO* Volatility of Wilder Hill clean energy index. *ERIX* Volatility of European renewable energy index, *S&P GCE* volatility of S&P 500 global clean index

6 Conclusions

This study mainly investigated the spillover effects of economic uncertainty indices on renewable energy stock markets in the time and frequency domains by employing the Diebold–Yilmaz approach and Baruník–Křehlík methodology. In particular, we applied a newly established ID-EMV index as a proxy for economic uncertainty caused by the pandemic, and three indices, ECO, ERIX, and S&P GCE that represent renewable energy markets in the USA, Europe, and the world, respectively. Furthermore, the aforementioned approach and methodology are new frameworks that can reveal the intensity and direction of spillover effects between ID-EMV and renewable energy stock returns and volatilities. A rolling window was employed to examine the time-varying spillover effects during the recent financial crises (i.e., the GFC in 2008 and COVID-19 in 2020).

The major empirical results are summarized as follows.

First, the total spillovers transmitted from economic uncertainty to renewable energy stock volatilities caused by the pandemic were much higher than the returns. This indicates that economic uncertainty has a significant influence on renewable energy stock volatilities compared to returns.

Second, in the frequency-domain analysis, the main total spillovers from economic uncertainty to renewable energy stock returns are concentrated at a high frequency, while the main total spillovers to renewable energy stock volatilities appear at low frequencies. These findings are consistent with previous research (Tiwari et al. 2018; Balli et al. 2019; Gillaizeau et al. 2019), which demonstrated that information transmission from economic uncertainty to renewable energy stock returns is faster than that to volatilities for only about one week, while the shocks of economic uncertainty have a long-lasting effect on renewable energy volatilities.

Third, renewable energy stock returns and volatilities are highly sensitive to economic uncertainty shocks under financial turmoil. There were some sharp increases in the time-varying spillover effects of returns and volatilities during periods of financial turmoil or extreme events, which suggests that connectedness across assets generally strengthens during periods of financial turmoil, and this is also supported by the related literature (Li et al. 2016).

Fourth, compared to the impact of the ID-EMV index resulting from the GFC on renewable energy stock returns and volatilities, the uncertainty caused by COVID-19 had a more significant impact on returns and volatilities.

Fifth, the results of the dynamic frequency-domain analysis revealed that during COVID-19, the main time-varying spillover effects on returns from the resulting economic uncertainty were concentrated in the long term (low frequency), which is contrary to the results of previous studies (Tiwari et al. 2018; Trabelsi 2018; Liu et al. 2020). This may be explained by the fact that the ID-EMV is a volatility tracker that could be regarded as a volatility index, and the spillover effects we calculated can be seen as those from asset volatilities to asset returns, while they are from asset returns to asset returns in the previous literature. Additionally, most time-varying spillover effects from uncertainty to volatilities during

COVID-19 appeared in the long term, which is in line with the related literature (Tiwari et al. 2018; Trabelsi 2018; Liu et al. 2020). These findings confirm that shocks caused by COVID-19 in terms of economic uncertainty affect renewable energy stock returns and volatilities and last for a long period of time.

Lastly, the impact of economic uncertainty caused by the pandemic on renewable energy stock markets in the USA, Europe, and the world was found to be similar. This indicates that the impact of COVID-19 on renewable energy stocks in different regions is almost the same.

The findings have important economic implications. Associations between renewable energy stocks and economic uncertainty vary across time and investment horizons, and they are strengthened when extreme events occur. Understanding these associations may help investors with different investment horizons make wiser decisions, respond quickly, and change asset portfolios during COVID-19. Speculators and institutional investors should fully consider the long-run volatility and external risk spillovers caused by economic uncertainty so that they can adjust their positions and employ hedge instruments to reduce the risk. Passive investors should continue to adopt the diversification strategy and adjust the weight of the portfolio appropriately. Since COVID-19 continues to spread worldwide, policymakers should remain vigilant of the risk spillover and economic uncertainty in the financial market. Our results indicate that COVID-19 has a significant impact on renewable energy stocks, which will last for a long period. Thus, policymakers should consider the profound effects on stock markets and adopt financial and macroeconomic policies to improve the stability of the financial system and reduce risks.

Appendix

See Tables 5, 6 and Figs. 6, 7.

Table 5 Spillovers from ID-EMV to returns: Diebold–Yilmaz under the different forecast horizons

	ID-EMV to ECO	ID-EMV to ERIX	ID-EMV to S&P GCE	To
H = 200	0.067	0.108	0.057	0.058
H = 300	0.067	0.108	0.057	0.058
H = 400	0.067	0.108	0.057	0.058

ID-EMV Infectious-disease equity-market-volatility tracker index, *ECO* Returns of Wilder Hill clean energy index. *ERIX* Returns of European renewable energy index, *S&P GCE* Returns of S&P 500 global clean index

Table 6 Spillovers from ID-EMV to volatilities: Diebold–Yilmaz under the different forecast horizons

	ID-EMV to ECO	ID-EMV to ERIX	ID-EMV to S&P GCE	To
H = 200	13.503	2.193	5.305	5.250
H = 300	13.472	2.217	5.312	5.250
H = 400	13.469	2.220	5.313	5.250

ID-EMV Infectious-disease equity-market-volatility tracker index, *ECO* Volatility of Wilder Hill clean energy index, *ERIX* Volatility of European renewable energy index, *S&P GCE* Volatility of S&P 500 global clean index
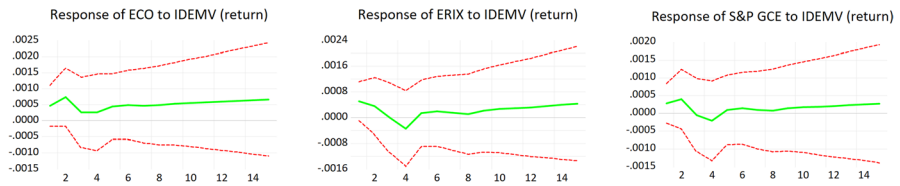
Fig. 6 Generalized impulse response (cumulative) of ECO, ERIX, and S&P GCE to ID-EMV (return). *Note*: *ID-EMV* Infectious-disease equity-market-volatility tracker index, *ECO* Returns of Wilder Hill clean energy index, *ERIX* Returns of European renewable energy index, *S&P GCE* Returns of S&P 500 global clean index
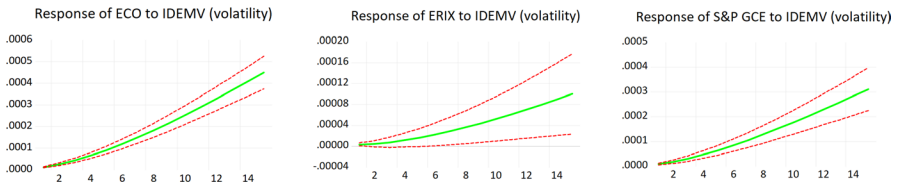
Fig. 7 Generalized impulse response (cumulative) of ECO, ERIX, and S&P GCE to ID-EMV (volatility). *Note*: *ID-EMV* Infectious-disease equity-market-volatility tracker index, *ECO* Volatility of Wilder Hill clean energy index, *ERIX* Volatility of European renewable energy index, *S&P GCE* Volatility of S&P 500 global clean index

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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