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Research Article

Economic Policy Uncertainty and Sectoral Trading Volume in the U.S. Stock Market: Evidence from the COVID-19 Crisis

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We empirically analyze the impact of economic uncertainty due to the COVID-19 pandemic on the trading volume of each sector in the S&P 500 index. Wavelet coherence analysis is carried out using economic policy uncertainty data and the trading volume of each sector in the S&P 500 index from July 2004 to September 2020. Furthermore, we apply multifractal detrended fluctuation (MF-DFA) analysis to the trading volume series of all sectors. The wavelet coherence analysis shows that the COVID-19 pandemic has substantially influenced trading volume in all sectors. However, the impact of the pandemic is different from that during the global financial crisis in some sectors, such as information technology, consumer discretionary, and communication services. Because of the lockdown taken to suppress COVID-19, increased remote working and remote learning are the main reasons for these results. Additionally, according to the MF-DFA analysis, the trading volume of all the sectors has clear multifractal characteristics, and they are all nonpersistent. Specifically, trading volumes of the real estate and materials sector are highly correlated, whereas the trading volumes of industry and information technology sectors are comparatively less correlated.

1. Introduction

Trading volume has long been a major concern in finance. For example, many studies have reported that trading volume has a relationship with returns and the absolute value of returns (Crouch [1]; Copeland [2]; Karpoff [3]; Jones et al. [4]; Foster [5]; Kramer [6]; Wang and Yau [7]; Chen et al. [8]; Gagnon and Karolyi [9]; Lin [10]; Wang et al. [11]). According to these studies, there is a positive relationship between trading volume and stock returns. Similarly, the trading volume has also been investigated in terms of volatility (Karpoff [3]; Foster [5]; Lee and Rui [12]; Güner and Önder [13]; Li and Wu [14]; Wen and Yang [15]; Rossi and De Magistris [16]; Darolles et al. [17]; Clements and Neda [18]; Ftiti et al. [19]; Kao et al. [20]; Khuntia and Pattanayak [21]). One of the important motivations of these studies is that the volume of transactions represents the scale and rate of information flow to the stock market (Wang and Yau [7]; Clements and Neda [18]; Ftiti et al. [19]). That is, the trading volume captures the most important information about market participants' trading activities. Recently, several studies have investigated the relationship between changes in trading volume and uncertainty (Choi [22]; Rehse et al. [23]; Nagar et al. [24]; Chen et al. [25]; Chiah and Zhong [26]). In particular, Chiah and Zhong [26] and Chen et al. [25] examined how changes in the financial markets caused by the coronavirus disease 2019 (COVID-19) pandemic affect the trading volume. Meanwhile, numerous mathematical models are also used to investigate and control the COVID-19 pandemic. First, many studies describe the main features of the COVID-19 pandemic using the susceptible-infected-removed (SIR) models (Colombo et al. [27]; Tian et al. [28]; Alshomrani et al. [29]; Leung et al. [30]; Read et al. [31]; Wu et al. [32]; Yang et al. [33]). In these studies, the SIR-type models are fitted to the actual data, and the reproductive number was estimated (Read et al. [31]). Furthermore, the COVID-19 pandemic peaks and sizes are predicted based on the SIR-type models (Yang et al. [33]). Second, agent-based models have been used to capture the interaction structure of the underlying populations for the

COVID-19 pandemic (Adiga et al. [34]). For example, Agrawal et al. [35] build an agent-based simulator to study the impact of various nonpharmaceutical interventions in the COVID-19 pandemic and demonstrate the ability of simulators through several case studies. Gharakhanlou and Hooshangi [36] develop an agent-based model that simulates the spatio-temporal outbreak of COVID-19. Additionally, they simulate the transmission of COVID-19 between human agents based on one of the SIR-type models. Third, there are studies on developing new mathematical models for COVID-19. For example, Matouk [37] suggests a susceptible-infected model with a multi-drug resistance, called SIMDR. They also investigated the dynamic behavior of the SIMDR model for the COVID-19 pandemic. Mohammed et al. [38] examine the dynamic behavior of COVID-19 using Lotka–Volterra-based models. Particularly, their proposed models contain fractional derivatives, which present a more sufficient and realistic description of the COVID-19 phenomena. In this study, we examine the impact of economic uncertainty on the trading volume of the U.S. stock market. We employ the U.S. daily news-based economic policy uncertainty (EPU) index to measure economic uncertainty. To do that, we calculate industry-specific trading volume and investigate the relationship between the trading volume of each industry and EPU. Furthermore, we investigate the multifractal nature of the industry-specific trading volume. Based on this investigation, we analyze the fluctuations of trading volumes. Industry-specific trading volume is defined based on the trading volume of 11 S&P 500 index sectors. We apply wavelet coherence analysis to estimate the interdependence and causality between EPU and each sector's trading volume from January 2008 to September 2020. Furthermore, we examine the relationship between them in terms of several events during the sample period such as the global financial crisis (GFC) and COVID-19 pandemic. Recently, many studies have investigated the relationship between EPU and volatility of various financial assets, such as the stock market (Ko and Lee [39]; Liu and Zhang [40]; Li et al. [41]; Choi [42], oil Mei et al. [43]; Ma et al. [44]; Wen et al. [45], foreign exchange Juhro and Phan [46]; Bartsch [47]; Chen et al. [48], and cryptocurrency Demir et al. [49]; Wang et al. [50]; Cheng and Yen [51]). Unlike the previous literature, studies of the relationship between the trading volume and EPU are relatively scarce. To the best of our knowledge, this is the first report on the relationship between EPU and trading volume. Furthermore, we employ the multifractal detrended fluctuation analysis (MF-DFA) approach introduced by Kantelhardt et al. [52] to investigate long-range autocorrelations and describe the multifractal properties of the trading volume. Several studies show that stock markets are multifractal (Bacry et al. [53]; Kwapień et al. [54]; Zunino et al. [55]; Wang et al. [56]; Machado [57]; Choi [58]). The contributions of this study are threefold: first, it adds to the flourishing strand of the literature on the impact of COVID-19 on the U.S. stock market (Mazur et al. [59]; Sharif et al. [60]; Hanke et al. [61]; Smales [62]; Baker et al. [63]). Second, our study extends the literature by examining the change in trading volume at the industry level following extreme events. In particular, while some studies have examined the relationship between the effect of the COVID-19 pandemic and trading volume of individual stocks or the stock market in each country (Ortmann et al. [64]; Chiah and Zhong [26]), no studies have addressed the trading volume of each sector. Third, we inspect whether the trading volumes for all sectors have multifractal characters. The investigation of the multifunctional nature of the trading volume at the industrial level is also not adequately explored in the existing literature. The remainder of this study is organized as follows: Section 2 describes the data and reviews the wavelet coherence analysis and MF-DFA approaches. Section 3 presents the main findings. Finally, concluding remarks are provided in Section 4.

2. Data Description and Methodology

2.1. Data Description. The time series of EPU is obtained from https://www.policyuncertainty.com. This website presents data on the news-based EPU index proposed by Baker et al. [65]. The sample period runs from July 2004 to September 2020. The index measures EPU using information from keyword searches in 10 large newspapers and is normalized to the volume of news articles discussing EPU.

Figure 1 shows the monthly time series of EPU and total trading volume (the sum of the trading volume of all the shares included in the S&P 500 index) during the sample period and several events that shocked the market such as the Lehman bankruptcy, debt-ceiling crisis, trading tensions between the United States and China, and the COVID-19 pandemic. As can be seen, the EPU index during the pandemic is significantly higher than in other events. In addition, changes in total trading volume tend to be similar to changes in EPU. About 500 companies in the U.S. stock market are used to define the S&P 500 index, which has 11 sectors in total (we use the global industry classification standard). The market cap of the S&P 500 is 70–80% of total U.S. stock market capitalization. Consequently, the sectors of the index naturally become a classification criterion for the U.S. economy. To calculate the trading volume of each sector, we first define the daily average sectoral trading volume of the i-th sector at time t as follows:

$$r_{i,t} = \frac{1}{N(t)} \sum_{j=1}^{N(t)} V_{j,t}, \tag{1}$$

where $N(t)$ is the total number of stocks (the total number of shares (N) changes as the incorporated stock in the i-th sector changes) in the sector at time t and $V_{j,t}$ is the trading volume of the j-th stock in the i-th sector at time t. Because the EPU is calculated monthly, we define the monthly average trading volume (MATV) $\overline{r}_{i,m}$ for m,\{ m = July 2004, August 2004, ... September 2020\} as the sum of average daily trading volume in each month. Table 1 presents the summary statistics of MATV. In addition, the MATV in each sector is shown in Figure 2. According to Table 1andFigure 2, the MATV of the IT and financial industries is large and the fluctuation of MATV is also large. On the contrary, the MATV of the utilities and real estate

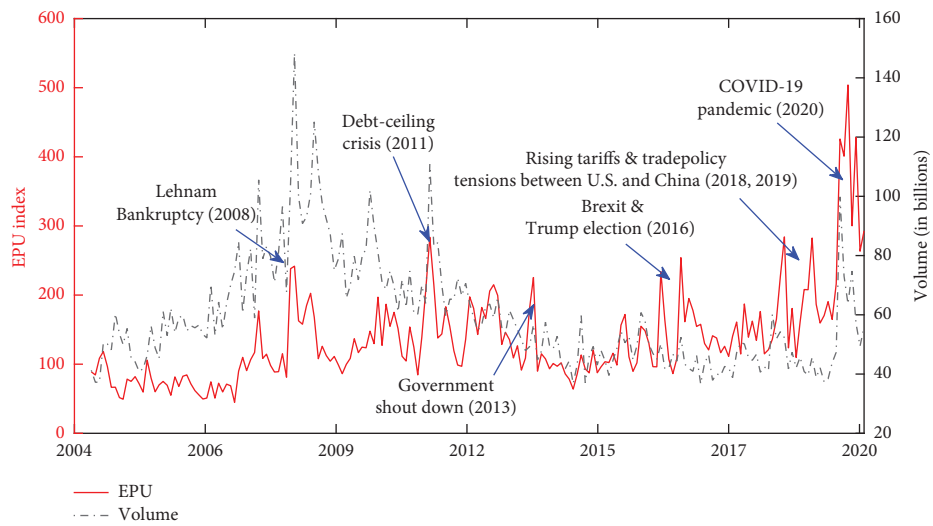

Figure 1: The monthly EPU index from July 2004 to September 2020. The events are based on those presented on the website.

Table 1: Summary statistics of MATV in the S&P 500 index. Here, the statistics are obtained based on scale-adjusted MATV (divided by 10 million).

Sectors	Observed	Mean	Maximum	Minimum	Standard deviation	Skewness	Kurtosis
Communication services	195	19.4914	33.7481	12.1475	3.8021	0.4977	0.4525
Consumer discretionary	195	10.9942	23.6278	6.5459	3.8239	1.1698	0.5081
Consumer staples	195	9.9723	24.7695	5.9175	2.8209	1.5751	3.8429
Energy	195	14.023	39.8828	7.8626	4.5355	2.1723	8.1248
Financial	195	13.3954	53.8857	3.5619	8.5303	1.9237	5.1907
Health care	195	8.1234	17.7929	4.5768	2.2544	1.2121	1.6574
Industrials	195	7.6887	23.1635	4.3141	3.0851	1.9966	5.0637
Information technology	195	33.5651	108.5334	11.6259	18.1847	0.8331	0.5104
Materials	195	6.8426	20.1044	3.0459	2.5255	1.509	4.2935
Real estate	195	3.8818	13.2393	1.0849	1.8127	1.7786	6.2873
Utilities	195	5.3573	10.6955	2.4811	1.3121	0.3104	1.9175

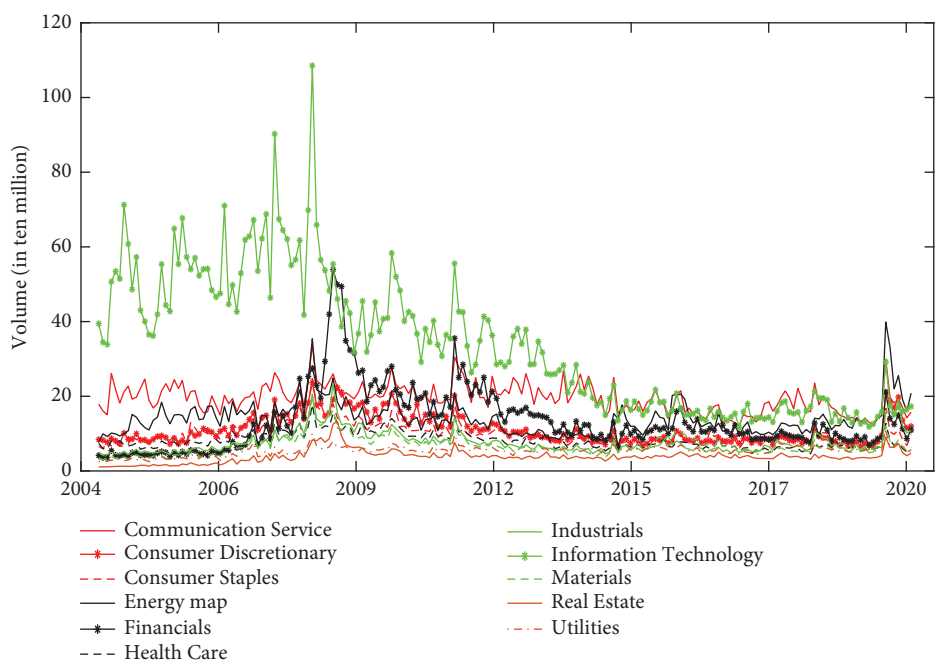

Figure 2: MATV ($\{\bar{r}_{i,m}, i = 1, 2, \cdot, 11\}$) from July 2004 to September 2020.

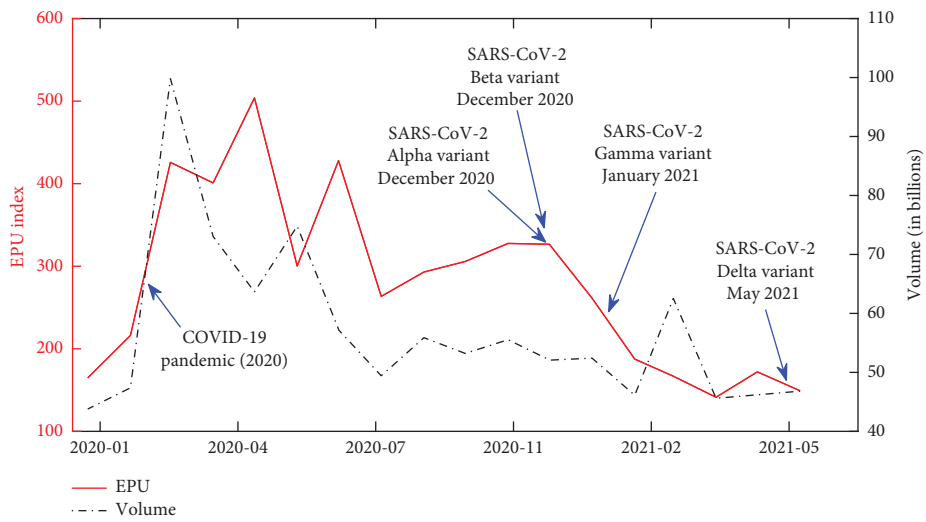

Figure 3: The monthly EPU index and total volume from January 2020 to July 2021.

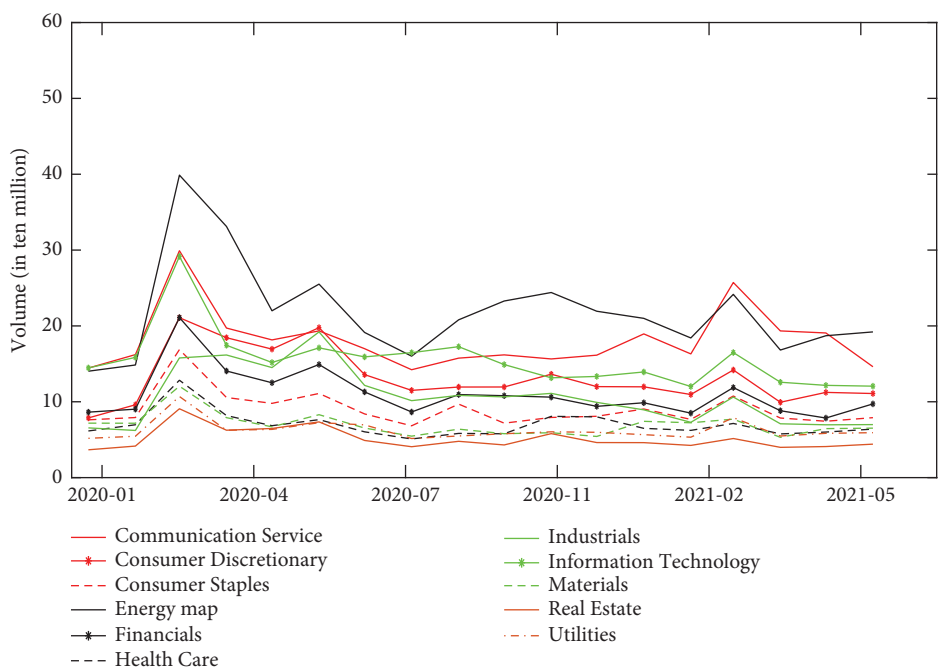

Figure 4: The MATV for 11 sectors from January 2020 to July 2021.

sectors is smaller than those of the other industries and their changes are also small. Furthermore, during both the GFC and the COVID-19 pandemic, there is a considerable change in trading volume in all sectors. According to the World Health Organization (WHO) ("Tracking SARS-CoV-2 variants" https://www.who.int/en/activities/tracking-SARS-CoV-2-variants), several COVID-19 variants have been observed, namely, alpha, beta, gamma, and delta. As they were all officially designated after December 2020, our sample data do not include the impact of the new COVID-19 variants on the EPU and the MATV. Therefore, we provide the extended EPU and MATV, that is, from January 2020 to June 2021, in Figures 3 and 4. In Figure 3, the designation date of COVID-19 variances is indicated. When looking at the plots, the EPU and the volume do not seem to have been significantly affected by the occurrence of COVID-19 variances. Furthermore, MATVs in all sectors do not appear to be significantly related to the COVID-19 variants. However, it is noteworthy that the MATV of the energy sector from January 2020, except for a few periods, is the largest among the MATVs of all sectors. This is largely different from the MATV results before 2020 in Figure 2. We use monthly EPU and the monthly sample data during the COVID-19 pandemic are not enough to apply to the wavelet coherency analysis. To solve this problem, a short-term sample data set is needed, such as weekly or daily data. Additionally, a longer study period may capture the impact of the new COVID-19 variants. These are opportunities for future studies.

2.2. Methodology

2.2.1. Wavelet Coherence Analysis. Using wavelet coherence analysis with the Morlet specification, we investigate the causality and interdependence between the EPU and trading volume. Based on this analysis, we make inferences in a time-frequency frame. From several studies (Ko and Lee [39]; Kristoufek [66]; Pal and Mitra [67]; Sharif et al. [60]), this can be briefly explained as follows: For time series $x(t)$, the continuous wavelet transform is given by the following equation:

$$W_x(\tau, s) = \int_{-\infty}^{\infty} x(t)\widetilde{\psi}^*_{\tau,s}(t)dt, \tag{2}$$

where s is the scaling factor adjusting the length of the wavelet and τ is the translation parameter adjusting the wavelet location in time. $\widetilde{\psi}^*_{\tau,s}(t)$ is the complex conjugate function of $\psi^*_{\tau,s}(t)$. In addition, $\widetilde{\psi}$ is found by scaling and shifting the mother wavelet ψ. According to Soares et al. [68], we choose the Morlet wavelet suggested by Goupillaud et al. [69] as the mother wavelet ψ:

$$\psi^*_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), s, \tau \in \mathbb{R}, s \neq 0. \tag{3}$$

For the $x(t)$ and $y(t)$ time series, the cross-wavelet transform is defined as follows:

$$W_{xy}(\tau, s) = W_x(\tau, s)W^*_y(\tau, s). \tag{4}$$

From the cross-wavelet transform, the wavelet coherence between two series, $x(t)$ and $y(t)$, is given by Torrence and Webster [70]:

$$R^2(\tau, s) = \frac{\left|S\left(1/sW_{xy}(\tau, s)\right)\right|^2}{S\left(1/s|W_x(\tau, s)|^2\right)S\left(1/s|W_y(\tau, s)|^2\right)}, \tag{5}$$

where S is the smooth operator in time and scale. $R^2(\tau, s)$ is a squared correlation localized in time frequency and $0 \leq R^2(\tau, s) \leq 1$. Based on Bloomfield et al. [71], the phase difference from the phase angle obtained by the cross-wavelet transform is as follows:

$$\rho_{xy}(\tau, s) = \tan^{-1}\left(\frac{\mathrm{Im}\left[S\left(1/sW_{xy}(\tau, s)\right)\right]}{\mathrm{Re}\left[S\left(1/sW_{xy}(\tau, s)\right)\right]}\right), \tag{6}$$

$$\text{where } \rho_{xy} \in [-\pi, \pi],$$

where Re and Im are the real and imaginary parts of the smooth cross-wavelet transform, respectively. $\rho_{xy}(\tau, s)$ can explain the interdependence and causality between the two time series, $x(t)$ and $y(t)$, while the squared wavelet coherence does not know the direction of the relationship. Based on several studies (Flor and Klarl [72]; Cai et al. [73]; Funashima [74]), we can determine the connection between the two time series, $x(t)$ and $y(t)$, by understanding the scale of the phase difference, ρ_{xy}. If $\rho_{xy} \in (0, \pi/2)$, $x(t)$ and $y(t)$ have positive relations, and $x(t)$ leads $y(t)$. If $\rho_{xy} \in (-\pi/2, 0)$, $x(t)$ lags $y(t)$. For $\rho_{xy} \in (\pi/2, \pi)$, $x(t)$ and $y(t)$ have negative relations, but $x(t)$ lags $y(t)$. If $\rho_{xy} \in (-\pi, -\pi/2)$, the two time series also have negative relations, with $x(t)$ leading $y(t)$.

2.2.2. Multifractal Detrended Fluctuation Analysis. The MF-DFA method represents the multifractal properties of a financial time series. According to Kantelhardt et al. [52], the MF-DFA procedure consists of the following five steps (Wang et al. [75]). Let $\{x_k, k = 1, \ldots, N\}$ be a time series, where N is the length of the series:

(i) Step 1. Determine the profile

$$Y(i)(i = 1, 2, \ldots, N) \cdot Y(i) = \sum_{k=1}^{i}(x(k) - \overline{x}), \tag{7}$$

where

$$\overline{x} = \sum_{k=1}^{N} x\frac{(k)}{N}. \tag{8}$$

(ii) Step 2. Divide the profile $\{Y(i)\}(i = 1, 2, \ldots, N)$ into $N_s \equiv \mathrm{int}(N/s)$ nonoverlapping segments of equal length s. To cover the whole sample, repeat the same procedure from the end of the sample. In this way, $2N_s$ segments are obtained altogether:

$$\{Y[(\nu - 1)s + i]\}_{i=1}^{s}, \nu = 1, 2, \ldots, N_s,$$
$$\{Y[N - (\nu - N_s)s + i]\}_{i=1}^{s}, \nu = N_s + 1, N_s + 2, \ldots, 2N_s. \tag{9}$$

(iii) Step 3. Calculate the local trend for each of the $2N_s$ segments. For every segment, the local trend is estimated by a least-square fitting polynomial. Consequently, the variance is determined as follows:

$$F^2(s, \nu) = \begin{cases} \dfrac{1}{s}\displaystyle\sum_{i=1}^{s}\left\{Y[(\nu - 1)s + i] - \widehat{Y}^m_\nu(i)\right\}^2, & \nu = 1, 2, \ldots, N_s, \\ \dfrac{1}{s}\displaystyle\sum_{i=1}^{s}\left\{Y[N - (\nu - N_s)s + i] - \widehat{Y}^m_\nu(i)\right\}^2, & \nu = N_s + 1, N_s + 2, \ldots, 2N_s. \end{cases} \tag{10}$$

Here, $\widehat{Y}_{\nu}^{m}(i)$ is the fitting polynomial with order m in segment ν. In this study, we adopt a linear polynomial ($m = 1$) to prevent overfitting and facilitate the calculation (Lashermes et al. [76]; Ning et al. [77]).

(iv) Step 4. Average over all the segments. Then, we obtain the q-th order fluctuation function:

$$F_q(s) = \begin{cases} \left[\frac{1}{2N_s}\sum_{\nu=1}^{2N_s}\left(F^2(s,\nu)\right)^{q/2}\right]^{1/q}, & q \neq 0, \\ \exp\left[\frac{1}{4N_s}\sum_{\nu=1}^{2N_s}\ln\left(F^2(s,\nu)\right)\right], & q = 0. \end{cases} \tag{11}$$

(v) Step 5. Determine the scaling behavior of the fluctuation functions. Compare the log-log plots $F_q(s)$ with s for each value of q. If the series are long-range power-law correlated, $F_q(s)$ increases for high values of s. The power law is expressed as follows:

$$F_q(s) \propto s^{h(q)}, \tag{12}$$

where $h(q)$ represents the generalized Hurst exponent. Equation (12) can be written as $F_q(s) = a \cdot s^{h(q)} + b$. After taking the logarithms of both sides,

$$\log\left(F_q(s)\right) = h(q) \cdot \log(s) + c, \tag{13}$$

where c is a constant.

The exponent $h(q)$ depends on q. The time series is monofractal when $h(q)$ does not depend on q; otherwise, it is multifractal. For $q = 2, h(2)$ is identical to the Hurst exponent Calvet and Fisher [78]. Thus, the function $h(q)$ is called a generalized Hurst exponent. If $h(2) = 0.5$, the time series are not correlated, and it follows a random-walk process. When $0.5 < h(2)$, the time series is long-range dependent, and an increase (decrease) is more likely to be followed by another increase (decrease). $h(2) < 0.5$ means a nonpersistent series; that is, an increase (decrease) is more likely to be followed by a decrease (increase). According to Kantelhardt et al. [52], $h(q)$ relates to the multifractal scaling exponents $\tau(q)$ as follows:

$$\tau(q) = qh(q) - 1. \tag{14}$$

To estimate multifractality, we transform q and $\tau(q)$ to α and $f(\alpha)$ using a Legendre transform with the following equations:

$$\begin{aligned} \alpha &= \frac{d}{dq}\tau(q), f(\alpha) \\ &= \alpha(q)q - \tau(q), \end{aligned} \tag{15}$$

where $f(\alpha)$ is the multifractal spectrum or singularity spectrum, and α is the singularity strength. Furthermore, we define the degree of multifractality Δh as follows (Yuan et al. [79]; Antônio et al. [80]; Ruan et al. [81]):

$$\Delta h = \max(h(q)) - \min(h(q)). \tag{16}$$

In addition, we define the width of the multifractal spectrum $\Delta\alpha$ as follows (Wang et al. [82]; Antônio et al. [80]; Ruan et al. [81]):

$$\Delta\alpha = \max(\alpha) - \min(\alpha). \tag{17}$$

A larger Δh value indicates a stronger degree of multifractality and a wider multifractal spectrum, implying a stronger degree of multifractality. As another important feature of the multifractal spectrum (Drożdż and Oświcimka [83]; Maiorino et al. [84]; Drożdż et al. [85]; Wątorek et al. [86]), we define the asymmetric parameter as follows:

$$\Theta = \frac{\Delta\alpha_L - \Delta\alpha_R}{\Delta\alpha_L + \Delta\alpha_R}, \tag{18}$$

where $\Delta\alpha_L = \alpha_0 - \alpha_{\min}, \Delta\alpha_R = \alpha_{\max} - \alpha_0$. Here, α_0 is the α value at the maximum of $f(\alpha)$. The asymmetric parameter estimates the asymmetry of the spectrum and determines the dominance of small and large fluctuations for the multifractal spectrum. When the asymmetric parameter $\Theta = 0$, both large and small fluctuations lead fairly to multifractality. In addition, $\Theta > 0$ exhibits left-sided asymmetry, which implies that subsets of large fluctuations contribute substantially to the multifractal spectrum. Conversely, $\Theta < 0$ exhibits right-sided asymmetry in the spectrum, thus indicating that smaller fluctuations constitute a dominant multifractality source.

3. Empirical Analysis

3.1. Wavelet Analysis. In this subsection, we provide the wavelet coherence between EPU and MATV for each sector to investigate the interdependence between them. Figures 5 and 6 present the estimated wavelet coherence and relative phasing of the two series represented by arrows. An explanation for wavelet coherence analysis is provided in previous studies (Torrence and Webster [70]; Tiwari [87]; Lu et al. [88]; Pal and Mitra [67]). Based on the wavelet coherence analysis results, our main findings are summarized as follows: first, in the figures, the red areas are mainly observed in the GFC and COVID-19 pandemic periods, which indicates strong interdependence between EPU and MATV. In other words, during the GFC and COVID-19 pandemic periods, the EPU and sectoral trading volume have noteworthy interdependence in most sectors. In times other than these two events, while several sectors display a common strong interconnection, the heavy linkage is short. Second, during the pandemic, in most sectors, the MATV has a different relationship with EPU than during the GFC. In particular, the red area in the consumer discretionary, energy, and utility industries is larger during the pandemic than in the GFC. Therefore, the pandemic has a greater influence on the MATV of industries than the GFC. Third, on the contrary, in the communication services, consumer staples, information technology, and materials sectors, the

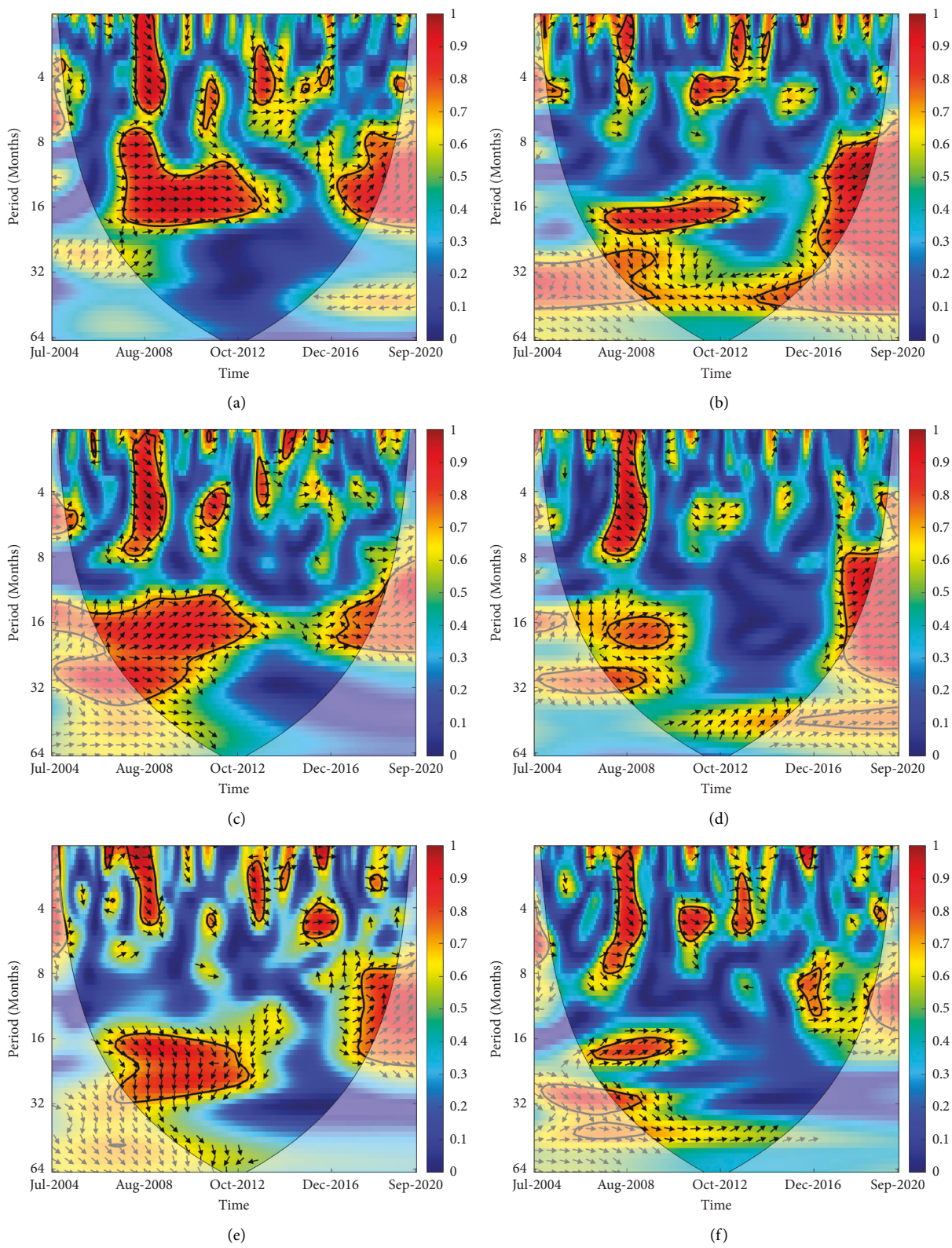

Figure 5: The wavelet coherence and phase plots between the EPU index and MATV for six sectors (communication services, consumer discretionary, consumer staples, energy, financial, and health care). (a) EPU and communication services. (b) EPU and consumer discretionary. (c) EPU and consumer staples. (d) EPU and energy. (e) EPU and financial. (f) EPU and health care.

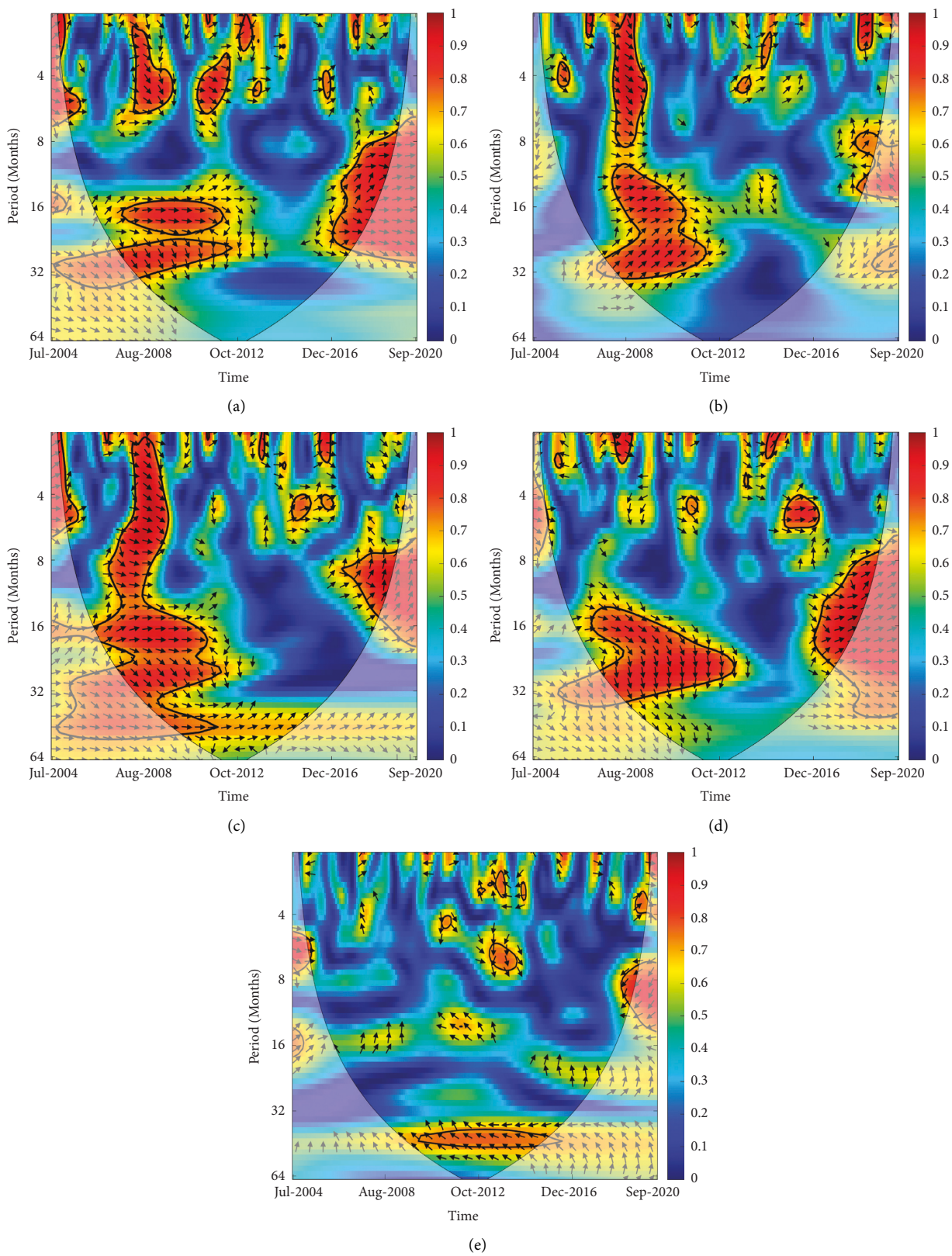

FIGURE 6: The wavelet coherence and phase plots between the +EPU index and MATV for five sectors (industrials, information technology, materials, real estate, and utilities). (a) EPU and industrials. (b) EPU and information technology. (c) EPU and materials. (d) EPU and real estate. (e) EPU and utilities.

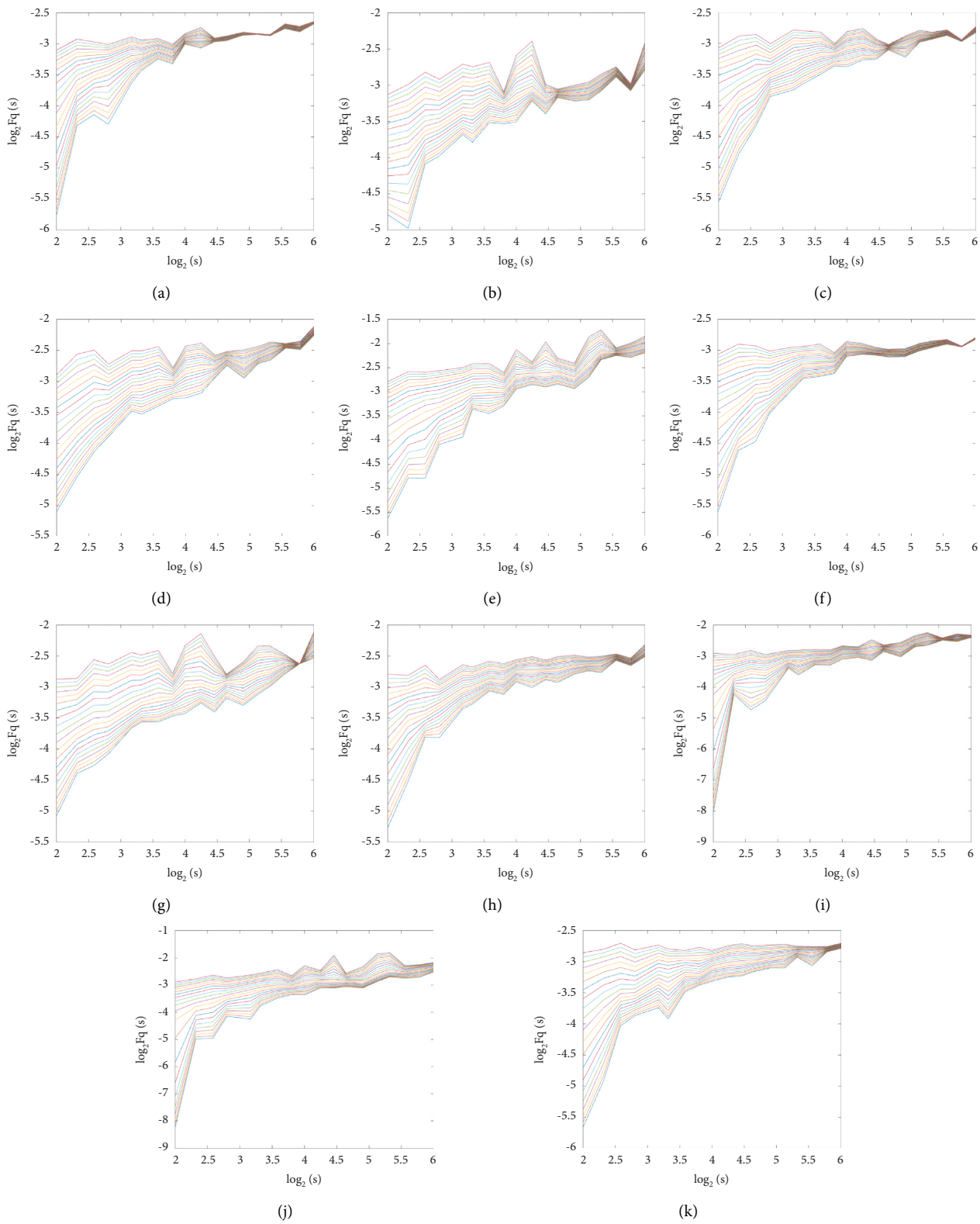

FIGURE 7: The curve of the multifractal fluctuation function $Fq(s)$ compared to s in a log-log plot of the MATV series for all the sectors during the GFC. (a) Communication service. (b) Consumer discretionary. (c) Consumer staples. (d) Energy. (e) Financials. (f) Health care. (g) Industrials. (h) Information technology. (i) Materials. (j) Real estate. (k) Utilities.

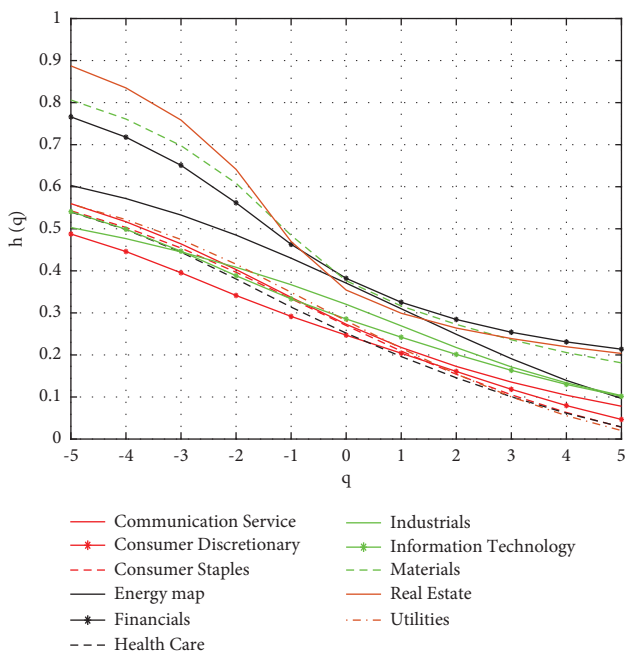

Figure 8: Generalized Hurst exponents $h(q)$ of the MATV series.

impact of the GFC on trading volume is greater. One of the reasons may be that some sectors such as technology and e-commerce are more profitable than before because of the pandemic ("Winners from the pandemic Big tech's covid-19 opportunity," The Economist, https://www.economist.com/leaders/2020/04/04/big-techscovid-19-opportunity).

3.2. Multifractal Analysis. In this subsection, we apply MF-DFA to the MATV series to investigate the fractal nature of the MATV series, based on the degree of multifractality (Δh) and the width of the multifractal spectrum ($\Delta\alpha$). First, we display the log-log plots of $F_q(s)$ compared to s for all the MATV series for $q = -5, -4.5, \ldots, 4.5, 5$, corresponding to the curve from the bottom to the top when the polynomial order $m = 1$ in Figure 7. According to the plots, we obtain the presence of different scaling laws and exponents.

Second, we further show the generalized Hurst exponents of the MATV series, as shown in Figure 8. As shown in Figure 8, the generalized Hurst exponent of the MATV series decreases as q increases from -5 to 5 in all sectors. This implies that the MATV of all sectors has obvious multifractal features. Additionally, all sectors' Hurst exponents ($= h(2)$) are smaller than 0.5. This indicates that the MATV series of all sectors are nonpersistent.

Third, Figure 9 and Table 2 illustrate the multifractal spectra and the degree of multifractality and width of the multifractal spectra of all the MATV series, respectively. Regarding the degrees of multifractality ($\Delta\alpha$ and Δh) given in Table 2, the real estate and materials sectors have the first and second-largest degrees of multifractality, respectively. Meanwhile, the industry and information technology sectors have the first and second smallest degree of multifractality, respectively. This implies that the MATV of the real estate and materials sectors is more highly correlated, whereas the MATV of the industry and information technology sectors is less correlated. Finally, all MATV series have negative asymmetric parameters Θ. In other words, the small fluctuations in MATV are more leading multifractality sources than the large fluctuations in the MATV series of all sectors.

4. Concluding remarks

We present empirical evidence on the relationship between economic uncertainty about the COVID-19 pandemic and trading volume at the sector level. Furthermore, we compare the effect of this pandemic with the impact of the GFC in the United States. We employ the wavelet coherence analysis to measure the interrelation and causality between EPU and trading volume of each sector. According to the MF-DFA analysis, we examine the multifractality of the trading volume for all sectors. The empirical results provide a number of interesting conclusions. First, we find a strong positive correlation between EPU and MATV in all sectors in the middle term during the pandemic. In addition, the phase patterns indicate that EPU leads MATV in all sectors. Second, in terms of the impact of the market shock, some industries show different characteristics during the pandemic compared with the GFC. For example, in industries based on Internet technology such as the IT and communication services sectors, the impact of EPU is relatively small. Third, the impact of COVID-19 on the trading volume of the consumer discretionary and material sectors is longer and shorter than that during the GFC, respectively. According to an article ("Consumer discretionary and IT stocks are "egregiously expensive," strategist says," CNBC, https://www.cnbc.com/2020/12/04/avoid-expensive-consumer-discretionary-and-it-stocks-strategist-says.html), IT and consumer discretionary stocks have performed strongly since the outbreak of the COVID-19 pandemic, with more people working remotely and spending time at home due to lockdown restrictions. In particular, the MSCI World Consumer Discretionary Price Index has rocketed by 85% since mid-March 2020, while the MSCI World Information Technology Price Index has soared by over 75%. On the contrary, unlike during the GFC, there has been no sharp drop in housing prices during the pandemic; rather, housing prices have risen because of the Federal Reserve's unprecedented monetary easing (Zhao [89]). Moreover, the materials sector is generally affected by the housing market. Therefore, these factors seem to have caused the difference in the materials sector. Finally, based on the MF-DFA results, the MATV of all the sectors has obvious multifractal features, and the small fluctuations in the MATV are a more dominant multifractality source. In addition, the MATV of the real estate and materials sectors is more highly correlated; meanwhile, the MATV of the industry and information technology sectors is less correlated. Our study contributes insights into the influence of the COVID-19 pandemic on the trading volume of the sectors in the U.S. stock market. The findings demonstrate that overall COVID-19 has affected trading volume considerably. However, some industries are not affected to the same degree as during the GFC. The reason for this difference could be

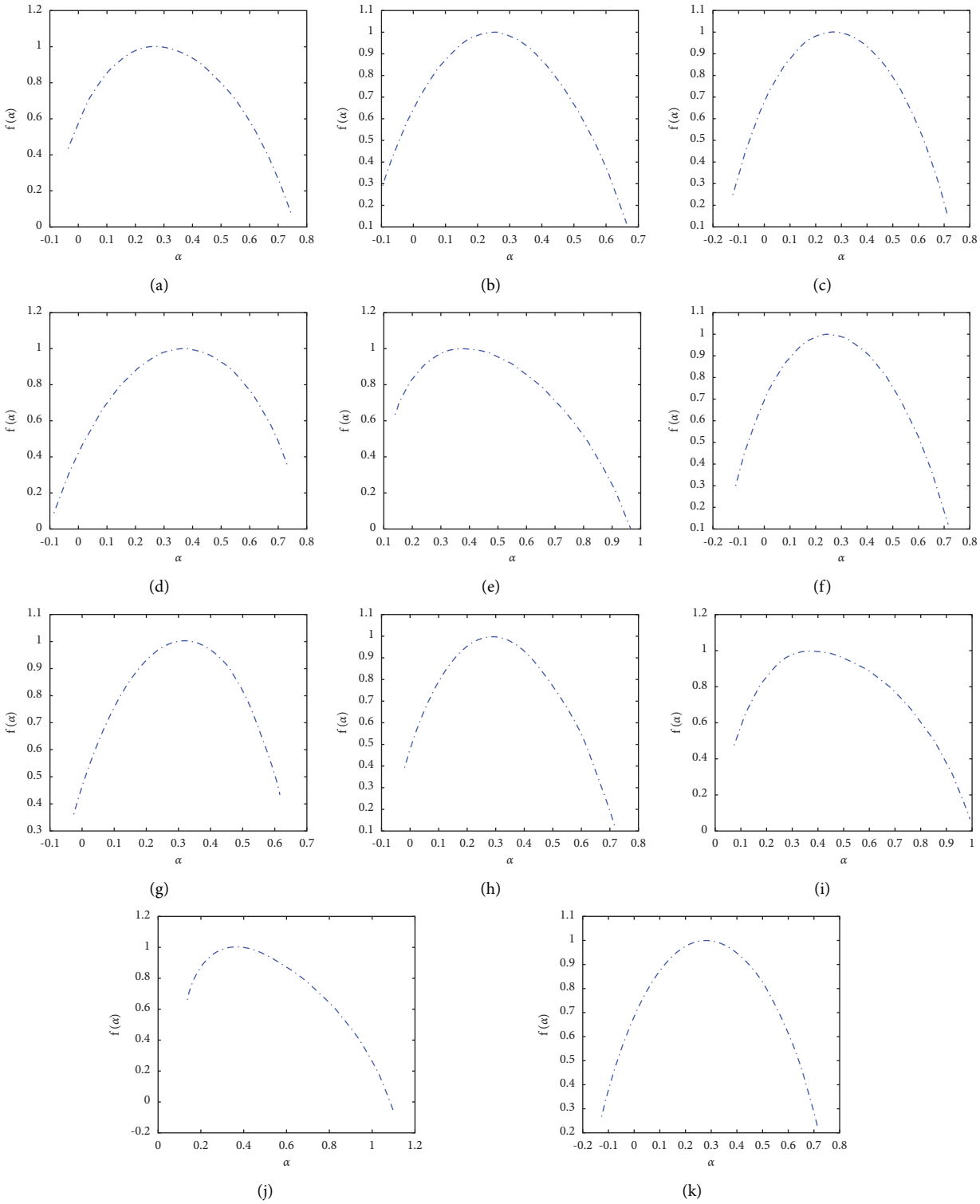

Figure 9: The multifractal spectra of each MATV series for all the sectors. (a) Communication service. (b) Consumer discretionary. (c) Consumer staples. (d) Energy. (e) Financials. (f) Health care. (g) Industrials. (h) Information technology. (i) Materials. (j) Real estate. (k) Utilities.

the lockdown taken to prevent the spread of COVID-19 as well as the implementation of a 0% interest rate and unlimited quantitative easing (Donthu and Gustafsson [90]; Zhang et al. [91]). Moreover, our findings show that the trading volume series for all sectors has a multifractal nature. Compared to the existing literature that mainly conducted multifractal analysis on the trading volume of the financial market (Bolgorian and Raei [92]; Stosic et al. [93]; Zhang

Table 2: The width of the multifractal spectrum $\Delta\alpha$ in equation (17) and degree of multifractality Δh for the MATV for all the sectors.

Sector	α_{max}	α_{min}	α_0	$\Delta\alpha$	Δh	Θ
Communication service	0.7323	−0.027	0.2179	0.7593	0.4818	−0.355
Consumer discretionary	0.6544	−0.0853	0.2041	0.7398	0.441	−0.2175
Consumer staples	0.7014	−0.1123	0.2092	0.8138	0.5147	−0.2098
Energy	0.7278	−0.0745	0.3099	0.8023	0.5065	−0.0419
Financials	0.9589	0.1443	0.3252	0.8146	0.5524	−0.5558
Health care	0.7071	−0.1023	0.1961	0.8094	0.5112	−0.2628
Industrials	0.6086	−0.0174	0.2692	0.626	0.3997	−0.0843
Information technology	0.7078	−0.0115	0.2422	0.7193	0.4391	−0.2948
Materials	0.9872	0.0828	0.3163	0.9044	0.6251	−0.4836
Real estate	1.0968	0.14	0.2992	0.9567	0.6838	−0.6673
Utilities	0.706	−0.1207	0.216	0.8267	0.5385	−0.1854

et al. [94]), this study has another contribution to examining the multifractal nature of the trading volume at the industry level. Finally, we mention a few directions for future research. First, as the COVID-19 pandemic has not been officially terminated, the data used in this study cannot reflect all the effects of the COVID-19 pandemic on the trading volume. Therefore, with the official closure of the COVID-19 pandemic, it is necessary to conduct a study on the entire COVID-19 pandemic period. If so, we can inspect the effect of the new variants of COVID-19 on the trading volume. Second, here, the multiplicity properties of the trading volume of sectors were investigated. According to the previous literature (Ané and Ureche-Rangau [95]; Cheng et al. [96]; Boudt and Petitjean [97]; Ong [98]; Ma et al. [99]; Ftiti et al. [100]), the trading volume is known to be highly related to the price and volatility of stocks. Future studies should examine the fractal relationship between trading volume and stock price or volatility based on an industrial level. Finally, as another measure for complexity, the entropy measure might be applied to the trading volume. The entropy measure properly describes the chaotic structure of the time series and it has been broadly used for financial data (Maasoumi and Racine [101]; Bentes and Menezes [102]; Stosic et al. [103]; Ahn et al. [104]; Machado [57]). Therefore, a study on the entropy measure for the trading volume can enhance our findings.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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