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Stock market trading volumes and economic uncertainty dependence: before and during Sino-U.S. trade friction

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ABSTRACT

This article mainly studies the interaction between the economic uncertainty and stock market trading volumes changes before and during Sino-U.S. trade friction using multifractal detrended fluctuation analysis (M.F.-D.F.A.) and multifractal detrended cross-correlation analysis (M.F.-D.C.C.A.). Our research aims to reveal whether the economic uncertainty increased by Sino-U.S. trade friction affects stock market trading volume more susceptible, as well as how policymaker strengthen risk management and maintain financial stability. The results show that the dynamic volatility linkages between economic uncertainty and stock market trading volumes changes are multifractal, and the cross-correlation of volatility linkages are anti-persistent. Through the rolling-windows analysis, we also find that the economic uncertainty and trading volumes are anti-persistent dynamic cross-correlated. This means that while economic uncertainty increases, trading volume decreases. Besides, Sino-U.S. trade friction has impact on the cross-correlated behaviour significantly, suggesting that stock markets' risks are relatively large and trading volumes changes are more susceptible by economic uncertainty during Sino-U.S. trade friction in the U.S. Our study complements existing literature about the stock markets trading volumes and economic uncertainty dependence relationship by multifractal theory's methods. The overall findings imply that the increased economic uncertainty caused by Sino-U.S. trade friction exacerbates financial risks, which are useful for policymakers and investors.

1. Introduction

Capital market has always been affected by economic uncertainty. As market sensitivity, economic uncertainty affects not only the efficiency of the stock market but also market's sentiment. And the direct reflection may be the markets' trading volume changes. This article will check the linkages between stock market trading volumes and economic uncertainty. Moreover, the Sino-U.S. trade friction effected capital

markets' instabilities, led to economic uncertainty increased, so we focus on the linkages between stock market trading volumes and economic uncertainty in two important periods: before and during Sino-U.S. trade friction periods. As the limitation of Efficient Market Hypothesis (E.M.H.), especially during times of uncertainty (Lo & MacKinlay, 1990; Jegadeesh & Titman, 1993), we explore the link between stock market trading volumes and economic uncertainty based on Fractal Market Hypothesis (F.M.H.).

F.M.H. proposed by Mandelbrot (1982) is the frontier of nonlinear theory while financial market cannot be adequately addressed by using the traditional E.M.H. Since then, many financial physics methods have been proposed to test the dynamic relationship between two financial time series. Peng et al. (1994) detected detrended fluctuation analysis (D.F.A.), then Kantelhardt et al. (2002) improved on it by proposing the multifractal form of D.F.A. (M.F.-D.F.A.). M.F.-D.F.A., also called multiscale fractal analysis, can describe the complex characteristics of financial time series changes in the capital market. This method became more persuasive through the generalised Hurst exponent, generalised fractal dimension, and multifractal spectral function. Podobnik and Stanley (2008) proposed detrended cross-correlation analysis (D.C.C.A.) to investigate power–law cross-correlations between nonstationary time series. Zhou (2008) then integrated D.C.C.A. into M.F.-D.F.A. to derive multifractal detrended cross-correlation analysis (M.F.-D.C.C.A.).

Numerous studies have detected the cross-correlations between two financial series. Fleming and Kirby (2011) documented the relationship characteristics of volume and volatility, showing a long memory of both volume and volatility. Guedes et al. (2017) analysed how each blue-chip company is adherent to its country index by D.C.C.A. cross-correlation coefficient. Alaoui et al. (2019) investigated the cross-correlation between Bitcoin prices and trading volumes, showing that Bitcoin prices changes and changes in trading volume mutually interact in a nonlinear way. Cai and Hong (2019) explored the volatility linkages between stock market trading volumes and investor fear gauges, showing that cross-correlations of large fluctuations are strongly anti-persistent in both short- and long-term. Hoque et al. (2019) showed that global economic policy uncertainty exerted negative effects on the overall stock market. Although existing studies have investigated on related topics, this study differentiated itself from past studied and contributes to the literature in the following ways. First, to the best of our knowledge, this is the first study that exams the stock markets trading volumes and economic uncertainty dependence relationship using multifractal theory's methods. Unlike the study of Prior research which examined financial markets usually by G.A.R.C.H., V.a.R., etc. based on E.M.H. (Dyhrberg, 2016; Jens, 2017; Drobetz et al., 2018; Nilavongse et al., 2020). We apply multifractal theory's methods to test the stock markets trading volumes and economic uncertainty dependence relationship considering the increasing complexity of the capital market. Second, after dividing sample into two important different periods: before and during Sino-U.S. trade friction periods, we re-exam volatility linkages of four pairs of financial time series for different periods, and then compare the multifractal characteristics of

volatility linkages for different periods to discover the impact of the Sino-U.S. trade friction on stock market trading volumes. Third, the negative impacts of the Sino-U.S. trade friction on stock market trading volumes provide several implications to maintain financial stability and sustain the momentum of stock market performances.

Since August 2017, the Office of the United States Trade Representative (U.S.T.R.) launched the '301 survey' in China. In March 2018, the U.S.T.R. published survey results, deeming that the Chinese government had unreasonable and discriminatory policies in measuring intellectual property protection, which caused at least $50 billion in annual losses to the U.S. economy. So since April, an additional 25% tariff has been levied on certain goods imported from China. Based on this survey, in March 2018, the U.S. government proposed protectionist measures against China, including large-scale tariffs on goods imported from China; the U.S.T.R. would file a lawsuit against Chinese practices in technology, violating World Trade Organization (W.T.O.) rules which licensing to the W.T.O.; the United States Department of Finance played an essential role in restricting investments by Chinese enterprises, to protect pivotal industries and technologies in the U.S. This represents the beginning of Sino-U.S. trade friction. This friction made investors more susceptible to policy uncertainty, as well as the capital market.

As the Sino-U.S. Trade friction has a significant influence on the capital market, we focus on the volatility linkages between trading volume changes of U.S. stock markets and economic uncertainty in two important periods: before and during the Sino-U.S. trade friction periods. We will test the feature of the volatility linkage between economic uncertainty and trading volume changes of some major stock markets (S&P500, Dow Jones Industrial Average [D.J.I.A.]) in different periods. By using the M.F.-D.C.C.A. method, we find the characteristic of multifractality for the cross-correlated degree between stock market trading volume changes and economic uncertainty. Through the rolling-windows method, the stock market trading volume and economic uncertainty dependence are re-examined. Since then, the characteristics of the volatility linkage has received attention based on the Sino-U.S. Trade friction. Karam and Zaki (2015) found a positive association between real GDP and both service and goods trading volume. The interaction term between goods and services trading volumes is negative, while the effect of service trading volumes on real G.D.P. is positive in the Middle Eastern and Northern Africa (M.E.N.A.) countries. Guo et al. (2017) found that considerable uncertainty resulted in reduced trading volume and higher price volatility in subsequent months through panel V.A.R. and causality analysis. Bahmani-Oskooee et al. (2019) showed that one-third of the commodities which account for a large share of Sino-U.S. trade were affected by significant long-term asymmetry. Though most studies examined the linkage between trading volume and economic factors, few studies paid attention to the characteristic of multifractality using M.F.-D.C.C.A. based on F.M.H. in before and during Sino-U.S. trade friction periods, respectively.

In this article, we use economic uncertainty index explored by Baker et al. (2016). Economic uncertainty index is a weighted average of three components. The first component quantifies the volume of news discussing policy-related uncertainty per
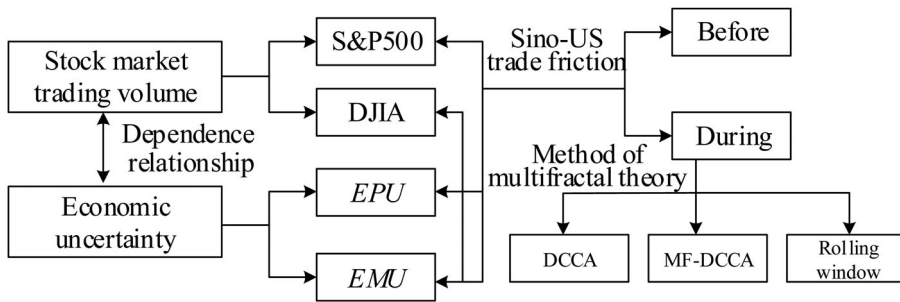
Figure 1. The basic framework of this study. *Source*: Authors' Design.

month since January 1985. The second component measures the level of uncertainty related to future changes in the tax code. This is done by using data from the Congressional Budget Office on the tax provisions which set to expire in the near future. Economic uncertainty index estimates the level of tax-related uncertainty every year by the discounted value of the revenue effects of all tax provisions which set to expire in the following 10 years. The third component captures forecasters' divergences about future monetary and fiscal policies. The authors use the Survey of Professional Forecasters provided by the Federal Reserve Board of Philadelphia to obtain forecasts of C.P.I., as well as purchases of goods and services by federal, state, and local governments. Several literatures ensured that economic uncertainty index did in fact capture aggregate policy uncertainty and equity market uncertainty (Gulen & Ion, 2016; Nguyen & Phan, 2017; Drobetz et al., 2018; Junttila & Vataja, 2018, Nguyen & Nguyen, 2019).

We put forward the research question on reveal whether the increased economic uncertainty caused by Sino-U.S. trade friction affects stock market trading volumes more susceptible, more irregular and disordered, as well as whether the increased economic uncertainty exacerbates financial risks. The key finding is useful for policy-makers and investors. The basic framework of this study is shown in Figure 1.

The rest of the article is organised as follows. Section 2 introduces the methodology. Section 3 describes the data to be used. Section 4 reports the analysis results. Section 5 concludes the article.

2. Methodology

Multifractal theory provides powerful tools to understand the complex nonlinear nature of time series in diverse field. Inspired by its striking analogy with hydrodynamic turbulence, from which the idea of multifractality originated, multifractal theory of financial markets has bloomed, forming one of the main directions of econophysics. To explore the volatility linkages between stock market trading volume changes and economic uncertainty, we apply some methods of multifractal theory to conduct a more essential analysis. D.C.C.A. and M.F.-D.C.C.A. methods can be expressed as follows.

Step 1. Imagine two time series $x(t)$ and $y(t)(t = 1, 2, \ldots, N)$, where N is the equal length of these two series. The 'profile' of each series is then determined as follows:

$$X_t = \sum_{k=1}^{t}(x_k - \overline{x}), Y_t = \sum_{k=1}^{t}(y_k - \overline{y}), t = 1, 2, ..., N. \tag{1}$$

Where $(\overline{x})$ and $(\overline{y})$ describe the average returns of the two time series $\S(t)$ and $y(t)$.

Step 2. The two series $x(t)$ and $y(t)$ are divided into $N_s = [N/s]$ non-overlapping segments of the same length s. Since the length N of the series is not always a multiple of the considered time scale s, a small part of the profile (1) may remain. To ensure that the complete information can be guaranteed in the time series, the same procedure is repeated starting from the opposite of the two series $x(t)$ and $y(t)$. Thus, $2N_s$ segments are obtained together.

Step 3. Define the local trends from an mth-order polynomial fit:

$$X_\lambda(j) = \alpha_k j^m + \alpha_{k-1} j^{m-1} + ... + \alpha_1 j + \alpha_0 \tag{2}$$

$$Y_\lambda(j) = \beta_k j^m + \beta_{k-1} j^{m-1} + ... + \beta_1 j + \beta_0. \tag{3}$$

Where $j = 1, 2, ..., s$, $\lambda = 1, 2, ..., 2N_s$, $m = 1, 2, ...$

Step 4. Calculate the local trends for each $2N_s$ segment by an mth-order polynomial fit. The detrended covariance is determined by:

$$F^2(s, \lambda) = \frac{1}{s}\sum_{j=1}^{s}|X_{(\lambda-1)s+j}(j) - X_\lambda(j)||Y_{(\lambda-1)s+j}(j) - Y_\lambda(j)|. \tag{4}$$

For each segment λ, $\lambda = 1, 2, ..., N_s$ and:

$$F^2(s, \lambda) = \frac{1}{s}\sum_{j=1}^{s}|X_{N-(\lambda-N_s)s+j}(j) - X_\lambda(j)||Y_{N-(\lambda-N_s)s+j}(j) - Y_\lambda(j)|. \tag{5}$$

For each segment λ, $\lambda = N_s + 1, N_s + 2, ..., 2N_s$. $X_\lambda(j)$ and $Y_\lambda(j)$ are the fitting polynomial of each profile with order m in segment λ, which is also referred to as M.F.-D.C.C.A.-m.

Step 5. Obtain the qth order fluctuation function from averaging all segments λ,

$$F_q(s) = \left\{ \frac{1}{2N_s}\sum_{\lambda=1}^{2N_s} F^2(s, \lambda)^{q/2} \right\}^{1/q}. \tag{6}$$

When $q = 0$, Eq. (6) can be re-expressed as follows:

$$F_0(s) = \exp\left\{ \frac{1}{4N_s}\sum_{\lambda=1}^{2N_s} ln[F^2(s, \lambda)] \right\}. \tag{7}$$

Step 6. Analyse the scaling behaviour of the fluctuation function by observing the log-log plot $F_q(s)$ against each value of q. If the two series $x(t)$ and $y(t)$ are long-range cross-correlated, we can derive that $F_q(s)$ has large values of s. Thus, a power–law relationship can be expressed as follows:

$$F_q(s) \sim s^{H_{xy}(q)}. \tag{8}$$

Eq. (8) can be rewritten as follows:

$$logF_q(s) = H_{xy}(q)log(s) + log(C). \tag{9}$$

Where C in Eq. (9) is a constant. The scaling exponent $H_{xy}(q)$, which is known as the generalised cross-correlation exponent, can be obtained by observing the slope of the log-log plot of $F_q(s)$ versus s using the method of ordinary least squares for each value of q. If $H_{xy}(q) > 0.5$, the cross-correlations between the two time series related to q are persistent, which demonstrates that an increase in one series is statistically likely to be followed by an increase in the other series. If $H_{xy}(q) < 0.5$, the cross-correlations between the two time series related to q are anti-persistent, which demonstrates that an increase in one series is statistically likely to be followed by a decrease in the other series. If $H_{xy}(q) = 0.5$, the two series are not cross-correlated with each other, which means that alterations in one series do not affect the behaviour of the other. When $q = 2$ in Eq. (8), the M.F.-D.C.C.A. method is simplified to D.C.C.A. If $\S(t)$ and $y(t)(t = 1, 2, \ldots, N)$ are the same series, the D.C.C.A. method can be simplified to D.F.A. further. The scaling exponent $H_{xy}(q)$ changes to $H(2)$, which is identical to the well-known Hurst exponent H.

If $H_{xy}(q)$ is independent of q, the cross-correlation between the two series is monofractal; otherwise, it is multifractal. To further measure the degree of multifractality, ΔH_{xy} can be described as $H_{max}(q) - H_{min}(q)$, the larger ΔH_{xy}, the greater the degree of multifractality, and vice versa.

Step 7. The Renyi exponent $\tau_{xy}(q)$ adopts a multifractal nature, so the exponent $\tau_{xy}(q)$ can be expressed as follows:

$$\tau_{xy}(q) = q H_{xy}(q) - 1 \tag{10}$$

If the scaling exponent function $\tau_{xy}(q)$ is linearly related to q, the cross-correlation between the two series is monofractal; otherwise, it is multifractal.

Step 8. Through the Legendre transformation, the singularity content of the time series can be deduced from the multifractal spectrum $f_{xy}(\alpha)$.

$$\alpha_{xy}(q) = \tau'_{xy}(q) = H_{xy}(q) + q H'_{xy}(q) \tag{11}$$

$$f_{xy}(\alpha) = q\alpha_{xy} - \tau_{xy}(q) = q[\alpha_{xy} - H_{xy}(q)] + 1. \tag{12}$$

Where $H'_{xy}(q)$ is the derivative of $H_{xy}(q)$ concerning q, $\tau'_{xy}(q)$ is the derivative of $\tau_{xy}(q)$ concerning q, and α is the Hölder exponent or singularity strength, which

Table 1. Descriptive statistic for daily changes of D.J.I.A., S&P500 volumes and *EPU*, *EMU*.

		Mean	Min	Max	S.D.	JB test	ADF	Observation
Full	$\Delta DJIA$	−0.00	−0.94	0.68	0.14	3059.60*	−79.45*	2547
	$\Delta SP500$	−0.00	−0.84	0.54	0.12	4452.40*	−80.16*	2547
	ΔEPU	−6.50	−291.72	351.78	53.45	1989.70*	−67.21*	2547
	ΔEMU	−2.75	−841.71	845.62	65.82	130030.00*	−71.29*	2547
Before	$\Delta DJIA$	−0.00	−0.94	0.68	0.14	1805.20*	−67.01*	1881
	$\Delta SP500$	−0.00	−0.84	0.53	0.11	2834.50*	−67.32*	1881
	ΔEPU	−6.08	−291.72	351.78	53.66	2106.10*	−56.34*	1881
	ΔEMU	−2.61	−841.71	845.62	64.59	128150.00*	−60.00*	1881
During	$\Delta DJIA$	−0.00	−0.69	0.66	0.14	1263.40*	−42.61*	666
	$\Delta SP500$	−0.00	−0.67	0.54	0.12	1487.00*	−43.44*	666
	ΔEPU	−7.67	−218.97	191.03	52.87	86.93*	−37.14*	666
	ΔEMU	−3.15	−558.71	571.69	69.23	14547.00*	−38.38*	666

Note: 'Min', 'Max', 'S.D.' denote Maximum, Minimum, Standard Deviation, respectively. J.B. test denotes Jarque–Bera test. A.D.F. denotes Augmented Dickey-Fuller test.
*Denotes the rejection of the null hypothesis at the significance level of 5%.
Source: Authors' calculations.

expresses the singularity and monofractality in time series. The width of the spectrum determines the strength of multifractality, obtained by $\Delta\alpha_{xy} = \max(\alpha_{xy}) - \min(\alpha_{xy})$. The broader the width of the spectrum, the higher the strength of multifractality, and vice versa. If a multifractal spectrum appears as a point, it is monofractal. The width of the spectrum α_{xy} can be fitted by the following function (Kantelhardt et al., 2003):

$$\alpha_{xy} = -\frac{1}{ln2} \times \frac{a^q lna + b^q lnb}{a^q + b^q}. \tag{13}$$

Where $\alpha_{xy}(-\infty) = -lna/ln2$ denotes the weakest singularity α_{min}, $\alpha_{xy}(+\infty) = -lnb/ln2$ reflects the strongest singularity α_{max}. Thus the $\Delta\alpha_{xy}$ can be estimated by the parameters a, b.

3. Data

We use daily S&P500 D.J.I.A stock market trading volume changes and economic uncertainty, containing economic policy uncertainty (*EPU*) and equity market uncertainty (*EMU*). The full sample data covered the period from 2 January 2009 to 31 October 2019, and each series contains 2547 observations. We started in 2009 because the financial crisis effected mostly past. In order to explore the differences of the linkages between stock market trading volume changes and economic uncertainty before and during Sino-U.S. trade friction, we divide the full sample into two important sub-periods: Before-period denotes the before-trade friction from 2 January 2009 to 31 December 2016, and during period denotes the during-trade friction from 2 January 2017 to 31 October 2019. The original data were derived from the Economic Policy Uncertainty website and Wind Data Services. Based on trading volume logarithmic changes measured by Podobnik et al. (2009), we set stock markets trading volume changes as follows:

$$\Delta VOL_t = log(VOL_t) - log(VOL_{t-1}) \tag{14}$$

Where VOL_t is the daily trading volume of each stock market. We set daily changes in EPU and EMU as follows:

$$\Delta EU_t = EU_t - EU_{t-1} \tag{15}$$

Where EU denotes EPU or EMU, respectively. The descriptive statistic results for ΔVOL_t and ΔEU_t are illustrated in Table 1.

Table 1 shows the descriptive statistics of daily trading volume changes of D.J.I.A., S&P500 and daily EPU changes, daily EMU changes. Each index of the mean value is close to zero, and each standard deviation is larger than zero. The Jarque-Bera statistical test shows the rejection of the null hypothesis of normality at the 5% significance level. Besides, the A.D.F. test shows the stationarity of daily EPU changes, daily EMU changes and daily trading volume changes of two kinds of stock markets. Trading volume changes and economic uncertainty demonstrate the clusters of small and large fluctuations.

4. Empirical results

4.1. Volatility linkages across time using D.C.C.A. analysis

The DCCA coefficient is a method to investigate how the coefficient varies with different time scales. Then Reboredo et al. (2014), Wang et al. (2017) adopt the D.F.A. to quantify the level of dynamic relationship between two different financial series. The coefficient ρ_{DCCA} is expressed as follows:

$$\rho_{DCCA} = \frac{F_{DCCA}^2(s)}{F_{DFA1}(s)F_{DFA2}(s)} \tag{16}$$

Where $F_{DCCA}^2(s)$、$F_{DFA1}(s)$、$F_{DFA2}(s)$ are calculated using Eqs. (4, 5) while $q=2$, polynomial order $m=1$ in this article. The value of ρ_{DCCA} ranges from -1 to 1. If $\rho_{DCCA} = 0$, there is no cross-correlation between the two time series. If $\rho_{DCCA} \neq 0$, it is shown the existence of cross-correlation between the two time series. Different values of ρ_{DCCA} based on different values of window size s are shown in Figure 2.

As seen in Figure 2, with each different s ($8 \leq s \leq N/4$), the values of D.C.C.A. coefficient ρ_{DCCA} of $\Delta DJIA(\Delta SP500)$- ΔEPU are all within the range from -1 to 0, and ρ_{DCCA} of $\Delta DJIA(\Delta SP500)$- ΔEMU are all within the range from 0 to 1. Because of the finite size of time series, even if there is no cross-correlation, ρ_{DCCA} is not equal to 0. This cross-correlation coefficient test is used to show the existence of cross-correlation. Therefore, in order to find out whether the cross-correlation is long-range or anti-correlation, the D.C.C.A. method and its variants are needed to apply in our study.
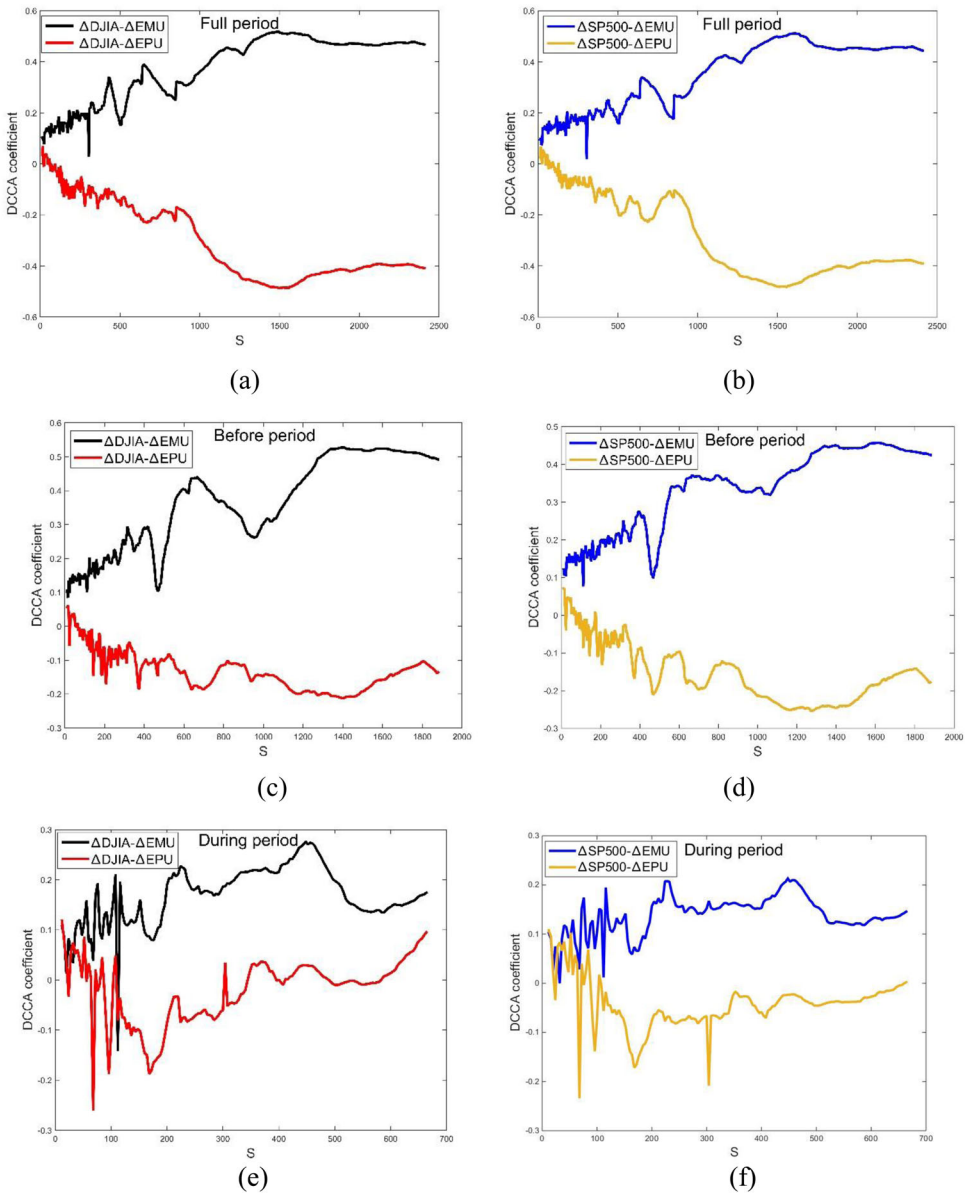
Figure 2. D.C.C.A. coefficient ρ_{DCCA} between stock market volume changes and economic uncertainty changes with different Sino-U.S. trade friction periods ([a, b] full period, [c, d] before period, [e, f] during period). The black curve expresses the D.C.C.A. coefficient between daily D.J.I.A. stock market trading volume changes and economic market uncertainty changes, the red curve expresses the D.C.C.A. coefficient between daily D.J.I.A. stock market volume changes and economic policy uncertainty changes, and the blue curve denotes the D.C.C.A. coefficient of $\Delta SP500$-ΔEMU, the yellow curve denotes the D.C.C.A. coefficient of $\Delta SP500$-ΔEPU.
Source: Authors' calculations.

4.2. Volatility linkages across time using M.F.-D.C.C.A. analysis

In order to further observe the volatility linkages between trading volume changes of stock markets and economic uncertainty, we adopt the M.F.-D.C.C.A. to model the scaling behaviour of volatility cross-correlation between different time series in a quantitative way using the full period, before and during the Sino-U.S. trade friction periods, respectively.

From Eqs. (1–9), we set $-10 \leq q \leq 10$, $8 \leq s \leq N/4$, polynomial order $m = 1$, and calculate the slope of the fluctuation function $F_q(s)$ by ordinary least squares to obtain the Hurst exponents, the cross-correlations between daily trading volume changes of stock markets and daily changes economic uncertainty for the full sample and sub-samples are shown in Table 2.

In Table 2, the Hurst exponent $H_{xy}(2)$ for $\Delta DJIA(\Delta SP500)\text{-}\Delta EPU$ is 0.1788(0.1724) with full sample, and $H_{xy}(2)$ for $\Delta DJIA(\Delta SP500)\text{-}\Delta EMU$ is 0.2011(0.1995), showing that the cross-correlations of stock markets (S&P500, D.J.I.A.) daily trading volume changes and economic uncertainty movements are anti-persistent. The exponent for $\Delta DJIA(\Delta SP500)\text{-}\Delta EPU$ (ΔEMU) all satisfy $H_{xy}(2) < 0.5$ before and during the Sino-U.S. trade friction periods, which also shows anti-persistent volatility linkages between daily trading volume changes of stock markets and economic uncertainty movements before and during periods. These mean that while economic uncertainty increases, stock market trading volume decreases for different periods. Besides, the scaling exponent for the during-trade friction period is smaller than the before-trade friction period. Such cross-correlations can be expressed as follows:

$$|H(2)_{during} - 0.5| > |H(2)_{full} - 0.5| > |H(2)_{before} - 0.5| \tag{17}$$

Therefore, the linkage between stock market trading volume changes and economic uncertainty appears to get the strongest across during Sino-U.S. trade friction period. Partly due to increasing uncertainty for the U.S. economy during the Sino-U.S. Trade friction, so the strongest volatility linkage has reflected.

If the exponents $H(q)$ depend on q, the volatility linkages between the two series are multifractal. To investigate the dependence of the scaling exponents on different values of q, the degree of multifractality is quantified by the method of the value $\Delta H(q)$, which obtains the largest value of $H(q)$ minus the smallest value of $H(q)$ based on Eq. (9). The larger the value ΔH of volatility linkages between two financial time series, the stronger is the multifractality. As shown in Table 2, the strongest multifractal volatility linkages is $\Delta SP500\text{-}\Delta EMU(\Delta H(q) = 0.4118)$, and the lowest multifractal volatility linkages is $\Delta DJIA\text{-}\Delta EPU(\Delta H(q) = 0.2228)$ for the full period. After dividing the sample into two important sub-sample, the strongest multifractal volatility linkage is $\Delta DJIA\text{-}\Delta EMU(\Delta H(q) = 0.4202)$ during the Sino-U.S. trade friction time, and the lowest multifractal volatility linkages is $\Delta DJIA\text{-}\Delta EPU(\Delta H(q) = 0.2182)$ before period. This means the relationship of $\Delta DJIA\text{-}\Delta EMU$ for the during-trade period is the most, and $\Delta DJIA\text{-}\Delta EPU$ for the before-trade period is the least irregular and disordered in these four financial time series. Based on the historical trend, predicting the future is most ineffective by relationship of $\Delta DJIA\text{-}\Delta EMU$ for the during-trade period.

Table 2. $H_{xy}(q)$ for volatility linkages of trading volumes changes and economic uncertainty.

	Δ DJIA-Δ**EPU**			Δ SP500-Δ**EPU**			Δ DJIA-Δ**EMU**			Δ SP500-Δ**EMU**		
q	full	before	During	full	before	during	full	before	during	full	before	during
−10	0.3351	0.3523	0.3471	0.3669	0.3552	0.3300	0.4504	0.4630	0.4088	0.4668	0.4536	0.4110
−9	0.3264	0.3446	0.3388	0.3577	0.3486	0.3220	0.4397	0.4527	0.3862	0.4550	0.4530	0.3956
−8	0.3165	0.3356	0.3292	0.3470	0.3408	0.3127	0.4273	0.4409	0.3774	0.4412	0.4507	0.3680
−7	0.3051	0.3249	0.3182	0.3344	0.3315	0.3019	0.4130	0.4272	0.3669	0.4252	0.4364	0.3392
−6	0.2923	0.3121	0.3056	0.3193	0.3201	0.2892	0.3966	0.4116	0.3544	0.4065	0.4200	0.3288
−5	0.2780	0.2969	0.2912	0.3012	0.3059	0.2746	0.3780	0.3939	0.3393	0.3853	0.4011	0.3162
−4	0.2628	0.2792	0.2752	0.2800	0.2881	0.2579	0.3569	0.3742	0.3213	0.3615	0.3797	0.3010
−3	0.2475	0.2602	0.2576	0.2573	0.2674	0.2394	0.3335	0.3525	0.3002	0.3356	0.3560	0.2824
−2	0.2329	0.2430	0.2388	0.2368	0.2478	0.2195	0.3082	0.3297	0.2761	0.3082	0.3308	0.2600
−1	0.2189	0.2283	0.2190	0.2195	0.2312	0.1987	0.2820	0.3063	0.2493	0.2808	0.3053	0.2343
0	0.2054	0.2154	0.1985	0.2039	0.2159	0.1771	0.2558	0.2828	0.2203	0.2539	0.2800	0.2059
1	0.1920	0.2037	0.1771	0.1884	0.2011	0.1550	0.2293	0.2588	0.1897	0.2271	0.2538	0.1759
2	**0.1788**	**0.1930**	**0.1547**	**0.1724**	**0.1867**	**0.1328**	**0.2011**	**0.2338**	**0.1581**	**0.1995**	**0.2257**	**0.1450**
3	0.1661	0.1832	0.1309	0.1552	0.1726	0.1111	0.1710	0.2075	0.1264	0.1715	0.1959	0.1148
4	0.1545	0.1739	0.1071	0.1375	0.1588	0.0905	0.1414	0.1813	0.0963	0.1449	0.1667	0.0871
5	0.1443	0.1651	0.0856	0.1204	0.1456	0.0717	0.1151	0.1568	0.0696	0.1215	0.1403	0.0633
6	0.1357	0.1572	0.0673	0.1053	0.1335	0.0551	0.0934	0.1352	0.0469	0.1021	0.1179	0.0436
7	0.1284	0.1502	0.0519	0.0924	0.1226	0.0407	0.0760	0.1170	0.0281	0.0864	0.0994	0.0274
8	0.1222	0.1441	0.0390	0.0815	0.1131	0.0284	0.0621	0.1018	0.0125	0.0738	0.0842	0.0142
9	0.1169	0.1388	0.0280	0.0723	0.1049	0.0179	0.0507	0.0891	−0.0005	0.0635	0.0715	0.0032
10	0.1123	0.1341	0.0186	0.0645	0.0977	0.0090	0.0414	0.0784	−0.0114	0.0550	0.0610	−0.0059
ΔH	**0.2228**	**0.2182**	**0.3285**	**0.3024**	**0.2575**	**0.3210**	**0.4090**	**0.3846**	**0.4202**	**0.4118**	**0.3926**	**0.4169**

Note: ΔH is the degree of multifractality.
Source: Authors' calculations.

In the view of overall, the value ΔH with different periods all satisfy $\Delta H_{during} > \Delta H_{full} > \Delta H_{before}$. The value ΔH of volatility linkages between different stock markets trading volumes and equity market uncertainty across before Sino-U.S. trade friction period are all smaller than the during-trade friction period, showing stock markets trading volumes is more affected by economic uncertainty, the more irregular and disordered volatility linkages lead to increase stock markets' risk during Sino-U.S. trade friction.

The above results show that the volatility linkages of small and large fluctuations are anti-persistent. In other words, the increase in the trading volume of the stock market will be accompanied by a decline in changes in economic uncertainty. We can also see $H_{xy}(q)$ changes versus different values of q, which means the value of $H_{xy}(q)$ is dependent on q, the volatility linkages between daily trading volume changes of stock markets and economic uncertainty movements for the before- and during-trade friction period are multifractal. An anti-persistent cross-correlation between each daily trading volume change in the stock market and each economic uncertainty movement is established. This is consistent with our perception of the market, while the equity market and policy uncertainties goes up, investors are more cautious, and the trading volume tends to be smaller, and vice versa. During the Sino-U.S. trade friction, economic uncertainty has increased, so the anti-persistent cross-correlated between trading volumes and economic uncertainty is stronger than the before-trade friction period.

The Renyi exponent $\tau(q)$ can be calculated using Eq. (10). Figure 3 shows $\tau_{xy}(q)$ versus different values of q for the before-, during-trade friction period and the full period. As seen from Figure 3, the value of $\tau_{xy}(q)$ is non-linearly dependent on q for
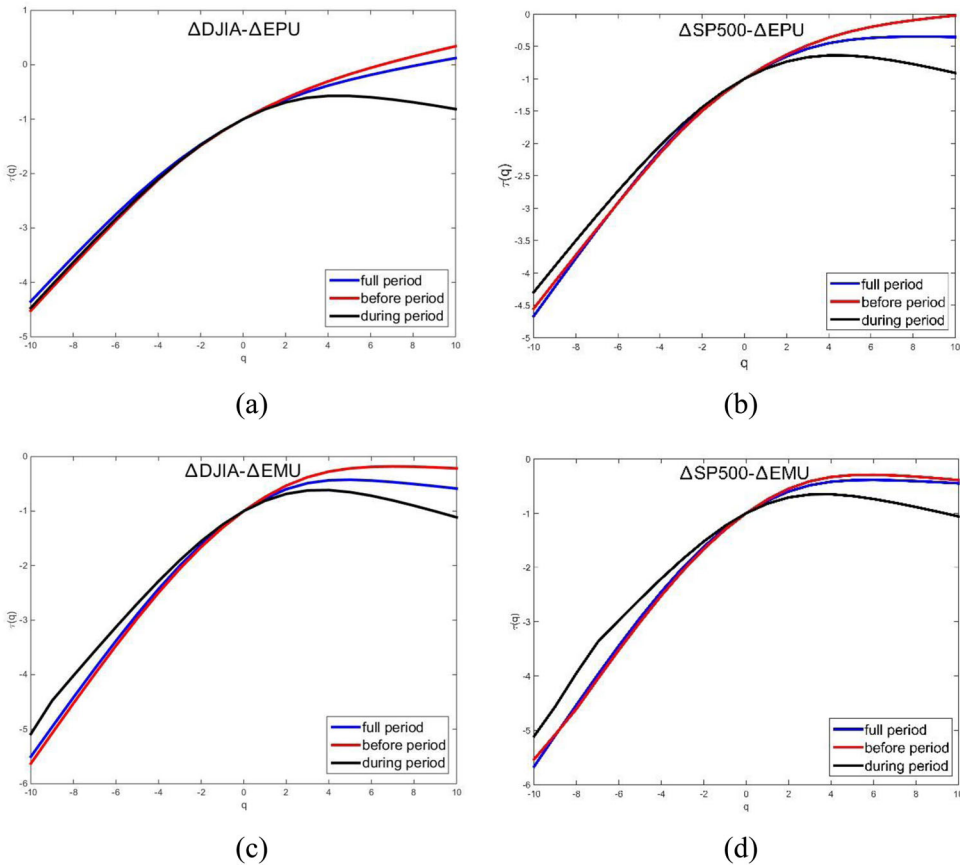
Figure 3. The Renyi exponent $\tau_{xy}(q)$ versus q for daily trading volume changes of stock markets and daily changes in two different measurement economic uncertainty. (a) denotes $\tau_{xy}(q)$ of $\Delta DJIA$-ΔEPU for different periods, (b) denotes $\tau_{xy}(q)$ of $\Delta SP500$-ΔEPU for different periods, (c) denotes $\tau_{xy}(q)$ of $\Delta DJIA$-ΔEMU for different periods, (d) denotes $\tau_{xy}(q)$ of $\Delta SP500$-ΔEMU for different periods. The blue curves denote the $\tau_{xy}(q)$ for the full period, the red curves denote the $\tau_{xy}(q)$ for the before-Sino-U.S. trade friction period, the black curves denote the $\tau_{xy}(q)$ for the during-Sino-U.S. trade friction period using M.F.-D.C.C.A.
Source: Authors' calculations.

different periods, which also confirms that stock markets trading volume changes and each economic uncertainty movement has a multifractal volatility linkage. These results are further evidence of what we have previously obtained.

Figure 4 shows that the multifractal spectra of the two different financial time series is 'bell-type', indicating that the cross-correlation between stock markets trading volume changes and economic uncertainty movements has multifractal characteristics. The strength of multifractality can be estimated by the width of the multifractal spectrum and can be calculated by the value of $\Delta\alpha$ in Table 3.

According to Figure 4, the span of spectra for the during-trade friction period is larger than the before-trade friction period. That means cross-correlations of different linkages show stronger multifractality during the Sino-U.S. trade friction. The Sino-U.S. trade friction has severely exacerbated economic uncertainty. During the trade
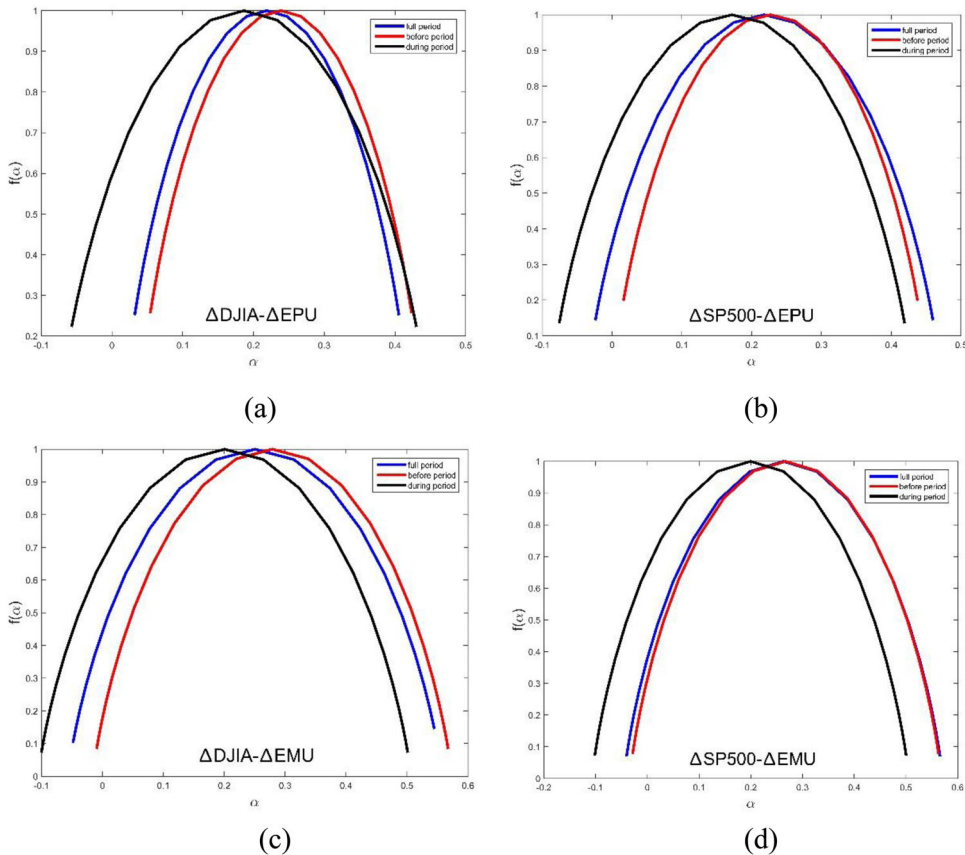
Figure 4. Nonlinear relationship of $f_{xy}(\alpha)$ versus α for daily stock market trading volume changes and daily changes of economic uncertainty movements. (a) denotes $f_{xy}(\alpha)$ versus α of $\Delta DJIA$-ΔEPU for different periods, (b) denotes $f_{xy}(\alpha)$ versus α of $\Delta SP500$-ΔEPU for different periods, (c) denotes $f_{xy}(\alpha)$ versus α of $\Delta DJIA$-ΔEMU for different periods, (d) denotes $f_{xy}(\alpha)$ versus α of $\Delta SP500$-ΔEMU for different periods. The blue, red, black curves denote $f_{xy}(\alpha)$ for the full period, the before-Sino-U.S. trade friction period, the during-Sino-U.S. trade friction period by M.F.-D.C.C.A., respectively.
Source: Authors' calculations.

friction, the cross-correlation between changes in U.S. stock market trading volume and economic uncertainty is more complex to affect each other.

In looking at Figure 4 and Table 3, we find that stock markets trading volume changes and economic uncertainty all have multifractal features. For the full period, the strongest multifractal strength is $\Delta SP500$-ΔEMU, and the weakest multifractal strength is $\Delta DJIA$-ΔEPU as previously obtained, meaning that the volatility of $\Delta SP500$-ΔEMU is the most dramatic, and the fluctuation of $\Delta DJIA$-ΔEPU is the least dramatic. For the before- and during-trade friction periods, the widths of spectra $\Delta \alpha$ for the before-trade friction period are all smaller than the during-trade friction period as previously obtained, showing during the Sino-U.S. trade friction, trading volumes in two different stock markets are more affected by economic uncertainty. The widths of spectra $\Delta \alpha$ across time satisfy the following relation:

Table 3. Estimated parameters of the multifractal spectrum.

Time series	α_{min}	α_{max}	$\Delta\alpha$	α_{min}	α_{max}	$\Delta\alpha$	α_{min}	α_{max}	$\Delta\alpha$
	Full			Before			During		
$\Delta DJIA$-ΔEPU	0.0149	0.4228	**0.4078**	0.0367	0.4410	**0.4044**	−0.0759	0.4491	**0.5250**
$\Delta DJIA$-ΔEMU	−0.1057	0.5066	**0.6122**	−0.0158	0.5737	**0.5895**	−0.0566	0.5575	**0.6140**
$\Delta SP500$-ΔEPU	−0.0342	0.4699	**0.5041**	0.0025	0.4515	**0.4490**	−0.0854	0.4288	**0.5142**
$\Delta SP500$-ΔEMU	−0.1070	0.5057	**0.6128**	−0.0342	0.5688	**0.6030**	−0.0454	0.5711	**0.6166**

Source: Authors' calculations.

$$\Delta\alpha_{during} > \Delta\alpha_{full} > \Delta\alpha_{before}. \tag{18}$$

It shows that the strongest multifractal characteristics time is the during-trade friction period, this is the further evidence of what we have previously obtained that the cross-correlated is more susceptible to each other during the Sino-U.S. trade friction. The Sino-U.S. trade friction increases economic uncertainty, more irregular and more disordered volatility linkage lead to ineffective to predict the future, so stock market risks are relatively higher for the during-trade friction period than the before-trade friction period.

4.3. Volatility linkages across time using rolling-window analysis

The rolling-windows method is often used to further investigate the volatility linkage between two financial time series. The windows length can be adjusted to suitable segments that fit the research needs. Inoue et al. (2017) used macroeconomic time series to provide evidence that the choice of estimated window size is sensitive and proposed that an optimal size should be used for forecasting. Cai and Hong (2019) set the length of each window at approximately one year to research the cross-correlations between crude oil and investor fear gauges. We fix the length of each window at 230 that each stock market with business days (approximately one year), set the rolling step as one day, and calculate the scaling exponents for the four pairs of series in each window when $q = 2$. The results are shown in Figure 5.

Figure 5 show that all scaling exponents are less than 0.5, indicating the strong anti-persistent cross-correlations between daily stock markets trading volume changes and economic uncertainty. The scaling exponents are almost the smallest value during the trade friction, showing the strongest multifractal characteristics of volatility linkages between trading volumes and economic uncertainty for the during-trade friction period. That means during the Sino-U.S. trade friction, stock market trading volumes are significantly affected by economic uncertainty more strongly. The Sino-U.S. trade friction indeed makes the future economic situation more complicated.
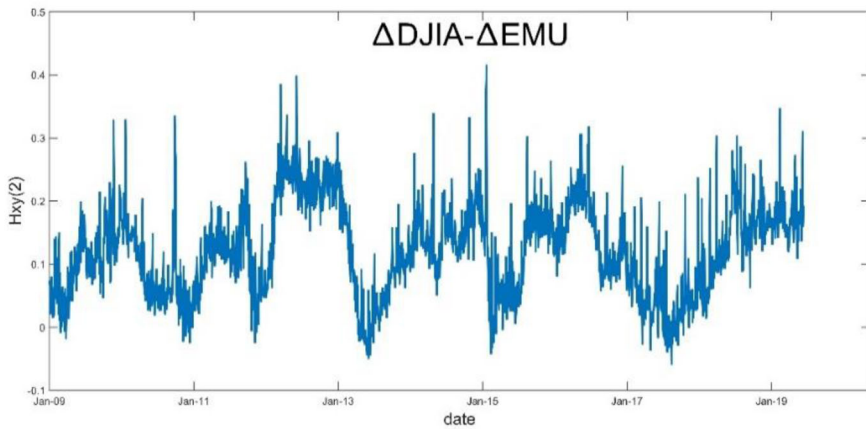
5. Conclusion

In this article, the volatility linkages between stock markets trading volume changes and economic uncertainty movements are investigated using D.C.C.A. and M.F.-D.C.C.A. analyses. The main findings of the study are as follows. First, the empirical results show that the volatility linkages between daily stock markets trading volume
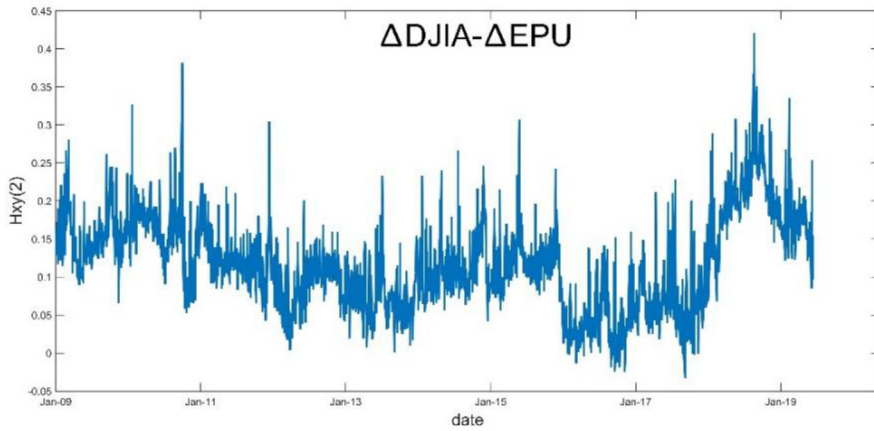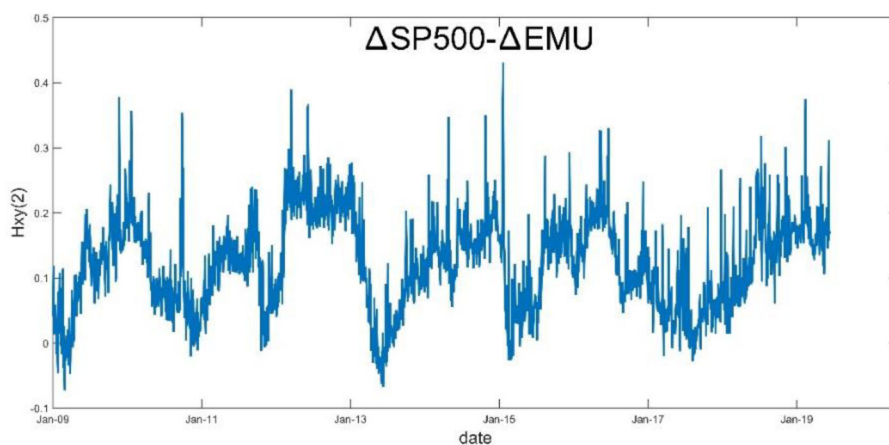
(a)
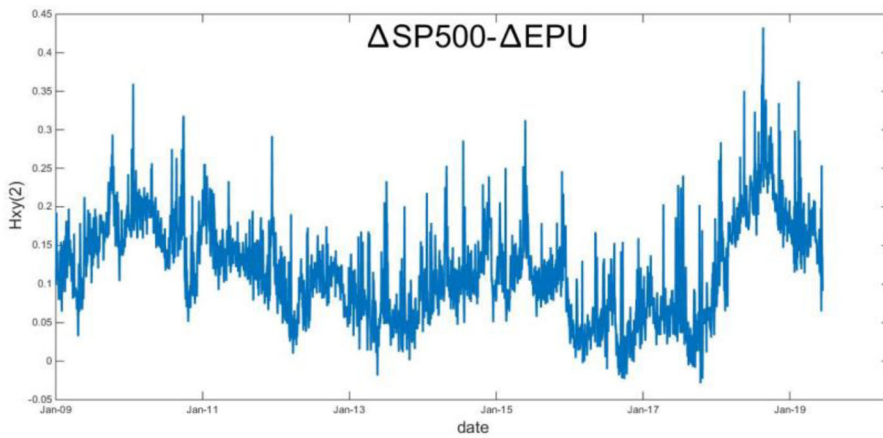
(b)

(c)

Figure 5. Scaling exponents for $q = 2$ with window moving. (a) denotes $H_{xy}(2)$ of $\Delta DJIA\text{-}\Delta EPU$, (b) denotes $H_{xy}(2)$ of $\Delta SP500\text{-}\Delta EPU$, (c) denotes $H_{xy}(2)$ of $\Delta DJIA\text{-}\Delta EMU$, (d) denotes $H_{xy}(2)$ of $\Delta SP500\text{-}\Delta EMU$ with window moving, respectively.
Source: Authors' calculations.

(d)

Figure 5. continued.

changes and daily economic uncertainty movements are multifractal anti-persistent, the strongest multifractal volatility linkages is $\Delta SP500\text{-}\Delta EMU$, and the lowest multi-fractal volatility linkages is $\Delta DJIA\text{-}\Delta EPU$. So the volatility linkages of $\Delta SP500\text{-}\Delta EMU$ is the most irregular and disordered in four pairs of financial time series. Based on the historical trend, predicting the future is most ineffective by relationship of $\Delta SP500\text{-}\Delta EMU$ for the full period. Second, after dividing the full period into two important sub-periods: the before-trade friction and during-trade friction periods, the strongest multifractal volatility linkage is $\Delta DJIA\text{-}\Delta EMU$ during the Sino-U.S. trade friction, and the lowest multifractal volatility linkages is $\Delta DJIA\text{-}\Delta EPU$ before the trade friction. Both the qualitative and the quantitative analyses confirmed that the during-trade friction period has stronger multifractal characteristics, showing more affected between daily stock markets trading volume changes and daily economic uncertainty across the during-trade friction period. The Hurst exponents and the multifractal spectra also explore that the period of trade friction is a stronger period of multifractal characteristics, showing that the cross-correlation is more susceptible to each other during Sino-U.S. trade friction period. The Sino-U.S. trade friction increases economic uncertainty, makes the future economic situation more compli-cated and more difficult to predict. Finally, rolling-window analysis indicates that the daily stock market trading volume changes and daily economic uncertainty move-ments are all anti-persistent cross-correlated, and volatility linkages of different pairs of financial time series is almost stronger during-trade frictions, which also indicates that the Sino-U.S. trade friction indeed makes the future economic situation more uncertain, and the risks for the stock market for the during-trade friction period are greater than the before-trade friction period.

The above results provide several implications to policymakers and investors. The negative impacts of the Sino-U.S. trade friction on stock market trading volumes sug-gest that in times of heightened economic uncertainty, policy makers should sustain the momentum of stock market performances, regulate financial market to maintain

financial stability. For example, policymakers can provide investment incentives to boost investors' participations in the capital market, establish a stability capital market fund by benchmarking it to a certain safety level, reduce trade imbalance, etc. These are all useful to avoid financial markets' systemic risks.

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Disclosure statement

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