Research Article

Economic Policy Uncertainty and Local Carbon Emission Trading: A Multifractal Analysis from US and Guangdong

Ruwei Zhao

School of Business, Jiangnan University, Wuxi, Jiangsu 214122, China

Correspondence should be addressed to Ruwei Zhao; zrwjnu@jiangnan.edu.cn

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This paper investigates the long-term dynamic cross-correlation evolution between US economic policy uncertainty index (USEPU) and Guangdong carbon emission trading price (GDCP) from the multifractal detrended cross-correlation analysis (MF-DCCA) perspective. With the calculation of correlation statistics and fluctuation function, the beginning procedures of MF-DCCA, we find that the cross-correlation between USEPU and GDCP is significant and presents power law property. Also, with the Hurst exponent, we find that the long-horizon correlations between series are persistent. Moreover, we perform Rényi exponent and spectrum singularity check. The empirical findings reveal that the all the correlations are of multifractality and the correlation of GDCP holds the highest degree.

1. Introduction

It is well acknowledged that climate change is the most challenging task the human being has ever encountered. As an effective solution for carbon emission reduction, carbon emission trading market has been widely accepted by many countries [1]. With this view, numerous studies contribute to the carbon emission trading field with regard to the mechanism and consequences of carbon emission trading market [2–14]. Also, as an ideal proxy for the measurement of macroeconomic fluctuation, economic policy uncertainty index has been commonly employed by the financial researchers [15–30]. Due to the huge impact of economic policy changes, several studies link economic policy uncertainty with carbon emissions to check the correlations between them. Adams et al. [31] took an investigation of economic policy uncertainty and carbon emission along with energy consumption through the autoregressive model. They find that compared with energy consumption, the influence of economic policy uncertainty to carbon emission can be ignored. Yu et al. [32] carried out a study regarding the economic policy uncertainty (EPU) and firm carbon emissions from provincial levels. They found that with rise in the economic policy uncertainty, firms intend to employ

cheap and low quality fossil fuels, which would result in an increase in carbon emission. However, these studies usually depict linear property between variables and take little concern over carbon emission trading market. Multiple research studies have recorded that it is hard for traditional statistical vehicle to discover the nonlinear correlation between series due to nonstationary evolution pattern of economic time series. [33–38]. With this view, researchers are trying to utilize multifractal analysis in modeling the nonlinear dynamic correlation between economic time series. Liu et al. [15] examined the cross-correlation between economic policy uncertainty and stock market volatility with multifractal analysis. They found that with the involvements of economic policy uncertainty and the multifractal model, the forecasting accuracy for future volatility can be greatly improved. Yao et al. [39] studied multifractal correlation among crude oil market, US stock market, and economic policy uncertainty. They found that the nonlinear long-range correlation between series is persistent and strong evidence for the existence of series correlation multifractality.

As the richest province of China, Guangdong weighs 10% of China total GDP and has been the economic champion among China's provinces over decades. Also, as a pioneer in China's reform and opening-up process and

neighboring province of Hong Kong, Guangdong is the first province opening for foreign investment. With decades of development, the US has been the largest trade partner of China, indicating that considerable Guangdong firms engage in the Sino-US trade. Besides, as the first batch of pilot provinces in carbon emission trading, Guangdong is of the longest history and largest volume in carbon emission trading. With this view, we connect US economic policy uncertainty index, as the representative of US macroeconomic policy change, with the Guangdong carbon emission trading price to check whether US policy changes would demonstrate impact to local carbon emission trading. Also, as a common statistical vehicle for multifractality, we employ the MF-DCCA to check whether cross-correlation multifractality exists between US policy uncertainty and Guangdong carbon emission trading. With significant cross-correlation statistics, we find the existence of long-horizon cross-correlation between US economic policy uncertainty and Guangdong carbon emission trading price. Additionally, we find that the cross-correlations between series are of power law property with the upward trend of fluctuation function with no regard to changes of scaling orders. Furthermore, we calculate the Hurst exponent to check the persistence of the correlation. We find that all the exponent values are above critical values, proving the persistence of correlation. Also, we find that none of the exponents are of constant values, confirming the cross-correlation multifractality. Moreover, we calculate the Rényi exponent and spectrum singularity as other checks for multifractality. We find that none of the Rényi exponent curves are of typical linear characters, confirming the multifractality existence. In addition, with the calculation of Hölder exponent difference, we find that Guangdong carbon price is of greatest difference, informing the richest multifractality.

Our study enriches the current literature from two dimensions. First, we utilize the novel US economic policy uncertainty index as an indicator for the US macroeconomic policy fluctuation and link it with Guangdong carbon emission trading price from the multifractal perspective. Particularly, we find that long-horizon cross-correlation between US economic policy uncertainty and Guangdong carbon emission trading price exists. Moreover, with the Hurst and Rényi exponent, we find that the cross-correlation between series demonstrates solid evidence for the multifractality existence. From this point of view, our empirical findings are in line with prior economic research studies related to multifractality analysis [39–45]. Second, our study originated from the multifractal perspective, enabling in-depth investigation for the cross-correlation dynamics between economic policy uncertainty and carbon emission trading. Furthermore, as the most important economic zone in China, our findings would shed light on the carbon emission market risk management for not only Guangdong but also China policy makers and investors by avoiding the imported economic uncertainty.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 illustrates the multifractal cross-correlation methodology. Section 4 shows the empirical results. Section 5 concludes the paper.

2. Data

Our data consisted of US economic policy uncertainty index and Guangdong carbon emission price. US economic policy uncertainty index is developed by Baker et al. [20]. We directly download the index from the websites (<http://policyuncertainty.com>). As stated by the website, the US economic policy uncertainty index is constructed by counting article number of thousands of national and local newspapers archived in the Access World News' NewsBank service with three sets of terms. The first set refers to the terms economic or economy, such as monetary policy. The second set terms are uncertain or uncertainty, such as COVID-19. The third terms are related to government actions, such as deficit. The Guangdong carbon emission price is derived from the Wind Financial Services, a widely accepted financial data provider in China. For the US and Guangdong data pairing, we chose the sample time period from December 19, 2013, the earliest day of carbon emission trading, to April 29, 2021.

Table 1 presents the descriptive statistics of the US economic policy uncertainty index (USEPU) and Guangdong carbon emission trading price (GDGP). We can find from Table 1 that both GDGP and USEPU series present right-skew characters with greater averages of the GDGP and USEPU (22.57 and 120.82) over their medians (18.56 and 86.73). Also, the skewness of both series is positive (2.08 and 2.36), confirming the right-skew distribution findings. For the kurtosis, it is easy to find that the values of both series (7.89 and 9.45) are larger than 3, indicating sharp peak characteristics. Moreover, we utilize the prevailing Jarque-Bera tests to check whether both series demonstrate normality properties. We can find from Table 1 that JB statistics of both series (2555.47 and 3975.91) are much greater than zeros. As a result, the p values of JB tests are zeros, presenting strong evidence of the non-normal distribution existence.

Figures 1 and 2 present the evolution patterns of the Guangdong carbon emission trading price and US economic policy uncertainty index. As shown in Figure 1, the GDGP reaches its peak at the beginning of the series. After that, the GDGP series experience continuous drop and bounce back at 2018. On the contrary, in Figure 2, the USEPU series demonstrate moderate fluctuation from 2013 to 2019. However, entering 2020, the USEPU raises sharply, which may be caused by the uncertainty of US election and heavier situation of COVID-19. Furthermore, both series patterns show strong rejections to normality distributions with apparent sharp peaks and fat tails, which are consistent with statistics presented in Table 1.

3. Methodology

In this section, we employ the prevailing multifractal cross-correlation analysis (MF-DCCA) as an instrument to investigate whether multifractality exists between the Guangdong carbon emission trading price (GDGP) and US economic policy uncertainty index (USEPU). First, we utilize the cross-correlation statistics proposed by

TABLE 1: Descriptive statistics.

Variable	GDCP	USEPU
Mean	22.57	120.82
Median	18.56	86.73
Maximum	77.00	738.02
Minimum	8.10	10.92
Std. Dev.	11.97	103.60
Skewness	2.08	2.36
Kurtosis	7.89	9.45
Jarque-Bera	2555.47	3975.91
Probability	≤ 0.01	≤ 0.01
N	1491	1491

FIGURE 1: Evolution pattern of Guangdong carbon emission price (GDCP).

FIGURE 2: Evolution pattern of US economic policy uncertainty index (USEPU).

Podobnik and Stanley [46] to check the existence of the cross-correlation between the series in a qualitative way. Second, we apply the MF-DCCA approach to inspect if the correlations between series would vary conditionally on the changes of scaling orders, which would result in multifractality.

3.1. Cross-Correlation Analysis. To have a general view of cross-correlation between GDCP and USEPU, we first introduce a cross-correlation indicator proposed by Podobnik and Stanley [8]. The indicator C_i is constructed through the following equation:

$$C_i = \frac{\sum_{k=i+1}^N x_k y_{k-i}}{\sqrt{\sum_{k=1}^N x_k^2 \sum_{k=1}^N y_k^2}} \quad (1)$$

where $\{x_k\}$ and $\{y_k\}$ are responsible for two equal length time series.

With the involvement of cross-correlation indicator C_i , we further begin to construct the cross-correlation statistics. The detailed construction process is shown in the following equation:

$$Q_{cc}(m) = N^2 \sum_{i=1}^m \frac{C_i^2}{N-i}, \quad (2)$$

where C_i refers to the cross-correlation indicator, N is the total length of the series, and m means the degree of freedom. We can indicate from the equation that the cross-correlation statistics $Q_{cc}(m)$ would follow the $\chi^2(m)$ distribution with m degrees of freedom. To check if the cross-correlation between series is significant, we are required to compare the cross-correlation statistics $Q_{cc}(m)$ with chi-square critical value $\chi^2(m)$ under m degrees of freedom proposed by Podobnik and Stanley [46]. If the value of the cross-correlation statistics $Q_{cc}(m)$ is above the critical value of chi-square $\chi^2(m)$, we believe a significant cross-correlation exists between the two time series.

3.2. MF-DCCA. Zhou [47] proposed the prevailing multifractal cross-correlation analysis (MF-DCCA) methodology to check the nonlinear cross-correlation between detrended time series. The MF-DCCA, derived from the detrended fluctuation analysis, is constructed through following five steps:

Step 1. To eliminate the trending character of each series, we process the original time series $\{x_k\}$ and $\{y_k\}$, which are responsible for GDCP and USEPU, with a deduction of each series average, respectively. The detailed calculation process is presented by the following equation:

$$\begin{aligned} X(i) &= \sum_{k=1}^i (x_k - \bar{x}), \\ Y(i) &= \sum_{k=1}^i (y_k - \bar{y}), \end{aligned} \quad (3)$$

where $\bar{x}$ and $\bar{y}$ are the means of $\{x_k\}$ and $\{y_k\}$, $k = 1, 2, 3, \dots, N$. It is easy to deduce from equation (3) that $X(N)$ and $Y(N)$ are equal to zero.

Step 2. To have a microinvestigation of each series, we split the detrended profiles $X(i)$ and $Y(i)$ into N_s nonoverlapping segments with the equal time lengths of s . The length interval N_s is generated as follows:

$$N_s = \text{int} \frac{N}{s}, \quad (4)$$

where N is the total length of observation and int stands for the integer function, collecting the maximum integer toward the real number. Nevertheless, in some occasions, the total length N cannot be divided by scale s with no remainder, which would leave a short part segment at the end of each profile. Considering this scenario, we regenerate the segment with the length interval N_s from the last to the first value of the series for maximum usage of the whole time series. Thus, we can get two N_s segments for each time series with repeated generation process.

Step 3. With divided N_s segments, we start to investigate the local trend of each segment, v , through a polynomial fitness check. Therefore, the variance of each segment, denoted as $F^2(v, s)$, can be acquired through equations (5) and (6).

If $v = 1, 2, 3, \dots, N_s$, the variance of segment v , $F^2(v, s)$, is as follows:

$$F^2(v, s) = \frac{1}{s} \sum_{i=1}^s |X((v-1)s+i) - p_v^n(i)| \bullet |Y((v-1)s+i) - p_v^n(i)|. \quad (5)$$

If $v = N_s + 1, N_s + 2, N_s + 3, \dots, 2N_s$, the variance of segment v , $F^2(v, s)$, is as follows:

$$F^2(v, s) = \frac{1}{s} \sum_{i=1}^s |X(N - (v - N_s)s + i) - p_v^n(i)| \bullet |Y(N - (v - N_s)s + i) - p_v^n(i)|, \quad (6)$$

where $p_v^n(i)$ is the n -th order polynomial fitness check of segment v .

Step 4. To have a measurement of nonlinear correlation between series, we calculate the q -th order of the fluctuation function by averaging variances of all the detrended segments. The construction processes of the fluctuation function are presented by equations (7) and (8).

If $q \neq 0$,

$$F_q(s) = \left[\frac{1}{2N_s} \sum_{v=1}^{2N_s} [F^2(v, s)]^{q/2} \right]^{1/q}. \quad (7)$$

If $q = 0$,

$$F_0(s) = \exp \left[\frac{1}{4N_s} \sum_{v=1}^{2N_s} \ln [F^2(v, s)] \right]. \quad (8)$$

It is easy to learn from equations (7) and (8) that the moving trend of fluctuation function $F_q(s)$ lies on the selection of the time length s under given value of q . In addition, to have a deep understanding of multifractal property between series, we repeat procedures from No. 2 to No. 4 upon various selections of s and finally draw forth our last fifth procedure.

Step 5. With the multiselection of time length s , fluctuation function $F_q(s)$ moving trend could be observed by the gradient of the log-log plot of $F_q(s)$ versus s conditional on various selections of scaling order q . If a long-term multifractal cross-correlation character could be detected between the detrended series $X(i)$ and $Y(i)$, the fluctuation function $F_q(s)$ would demonstrate a power law relationship as presented in the following equation:

$$F_q(s) \sim s^{H_{XY}(q)}, \quad (9)$$

where $H_{XY}(q)$ is on behalf of the gradient of the log-log plots of $F_q(s)$ conditional on the variation of scaling order q and $H_{XY}(q)$ is estimated by the ordinary least square regression.

We can learn from equation (9) that the gradient of fluctuation function, $H_{XY}(q)$, varies upon change of scaling order q . Also, when $q=2$, if the generalized scaling exponent $H_{XY}(2)$ is larger than 0.5, a long-term and consistent cross-correlation between detrended series $X(i)$ and $Y(i)$ would be confirmed. Nevertheless, if the scaling exponent of $H_{XY}(2)$ is smaller than 0.5, we believe the cross-correlation between detrended series $X(i)$ and $Y(i)$ is of no consistence. Also, if the scaling exponent $H_{XY}(2)$ equals 0.5, no significance of the cross-correlation between detrended series $X(i)$ and $Y(i)$ would be founded. With the consideration of the broad application, $H_{XY}(2)$ is widely recognized as the generalized Hurst exponent. With this view, we define that if the scaling exponent $H_{XY}(q)$ equals to a constant with no regard to any change of scaling order q , the cross-correlation between series is monofractal. Otherwise, we regard the cross-correlation between detrended series as multifractal. Moreover, we could learn from equations (3) and (5) that when q is larger than zero, the segment v works as a core factor in valuing fluctuation function $F_q(s)$ with the large variance of $F^2(v, s)$. With this view, when q is over zero, the exponent $H_{XY}(q)$ would be responsible for the large fluctuation scaling property. Conversely, when q is below zero, the exponent $H_{XY}(q)$ would be the indicator for the small fluctuation scaling property.

With the Hurst exponent $H_{XY}(q)$, we start to construct the Rényi exponent, the key proxy for the multifractality investigation between series. The exponent is denoted as $\tau_{XY}(q)$. The calculation process is as follows:

$$\tau_{XY}(q) = qH_{XY}(q) - 1. \quad (10)$$

Moreover, to enhance the credibility of multifractality, we perform the singularity spectrum, marked by $f_{XY}(\alpha)$, as an additional check. With the Legendre transformation, the singularity spectrum, $f_{XY}(\alpha)$, can be obtained by the following equations, with the participation of the Rényi exponent, $\tau_{XY}(q)$, and the Hölder exponent α_{XY} . The detailed calculation process of $f_{XY}(\alpha)$ is as follows:

$$\begin{aligned} \alpha_{XY} &= \tau_{XY}'(q), \\ f_{XY}(\alpha) &= q\alpha_{XY} - \tau_{XY}(q), \end{aligned} \quad (11)$$

where α_{XY} is the Hölder exponent. As the key parameter in the singularity spectrum analysis, α_{XY} is the representative of the strength of the singularity spectrum. With this view, we employ the strength difference or the spectrum width, $\Delta\alpha_{XY}$, as the measurement for multifractality degree, where $\Delta\alpha_{XY} = \alpha_{XY\max} - \alpha_{XY\min}$. We can infer from the equation that a larger value of $\Delta\alpha_{XY}$ would indicate a larger degree of multifractality.

4. Empirical Results

4.1. Cross-Correlation Test. In this section, to have a basic knowledge of statistical correlation between Guangdong

carbon emission trading price and US economic policy uncertainty, we employ equations (1) and (2) to calculate the cross-correlation statistics, $Q_{cc}(m)$, as an instrument to investigate the correlation significance between series. Figure 3 shows the cross-correlation statistics, $Q_{cc}(m)$, and its corresponding chi-square critical value $\chi^2(m)$ at 5% significant level is depicted by green and red lines conditional on the degrees of freedom varying from 1 to $N-1$. We can find from Figure 3 that the cross-correlation statistic $Q_{cc}(m)$ demonstrates clear edge over its corresponding chi-square critical value $\chi^2(m)$ by noticeable distances between variables, which would strongly reject the null hypothesis and prove the long-term cross-correlation existence between GDGP and USEPU.

4.2. Multifractal Detrended Cross-Correlation Analysis.

With significant correlation statistics, $Q_{cc}(m)$, as presented in Figure 3, we could infer a long-term correlation between Guangdong carbon emission trading price and US economic policy uncertainty in a qualitative way. However, to have a detailed quantitative investigation of the nonlinear correlation character between Guangdong carbon emission trading price and US economic policy uncertainty, we utilize the multifractal detrended cross-correlation analysis proposed by Zhou [47] as the instrument. To perform the analysis, we first follow the work of Zhang et al. [48] by setting scaling order q from -10 to 10 with an interval of 1 . Also, we can infer from the illustration in Section 3.2 that if scaling order q is smaller than zero, we believe two time series demonstrate weak fluctuation. On the contrary, the time series show strong fluctuation. Figure 4 plots the log-log fluctuation function $F_q(s)$ evolution pattern conditional on the time length of s with scaling orders from -10 to 10 between Guangdong carbon emission trading price and US economic policy uncertainty (GDGP and USEPU). It is easy to find that all of the lines demonstrate similar evolution patterns by moving upward upon gradual increase in time length s with no regard to the changes of scaling orders, indicating a long-term power law correlation existence between GDGP and USEPU.

Also, to have an investigation of cross-correlation persistence and multifractality between Guangdong carbon emission trading price and US economic policy uncertainty series, we further calculate the Hurst exponent with the variation of scaling order q as presented in Figure 5. In Figure 5, we can find that the Hurst exponent values of the Guangdong carbon emission trading price and US economic policy uncertainty (GDGP-USEPU cross-correlation), the Guangdong carbon emission trading price (GDGP), and the US economic policy uncertainty (USEPU) are all above the critical values (0.5), providing strong evidence that the cross-correlation of GDGP-USEPU, the correlation within GDGP series, and the correlation within USEPU series are persistent. In addition, we can find from Figure 5 that GDGP-USEPU and GDGP present downward trend with decreased Hurst exponent values upon the rise of scaling order q . However, for USEPU, the line goes down with gradual increase in scaling order q from -10 to -2 . After that, the line

FIGURE 3: Log – log plot of the cross-correlation statistics ($Q_{cc}(m)$) for GDCP and USEPU.

FIGURE 4: Log – log plot of $F(s)$ versus s for GDCP and USEPU.

starts to climb and reach its peak at $q=4$, showing an S-shaped curve. Also, when q is below zero, the Hurst exponent of GDCP is greater than that of GDCP-USEPU and USEPU, demonstrating the highest level of persistence. On the contrary, when q is above zero, the Hurst exponent of USEPU moves upward sharply and tops the three series correlations. Also, we can find from Figure 5 that none of the curves are flat, indicating the multifractality existence between series.

In addition, we calculate the Rényi exponents, another indicator of multifractality, with the cross-correlation of GDCP-USEPU, the correlation within GDCP series, and the correlation within USEPU series. As presented in Figure 6, we can find that none of three curves present typical linear

shapes, proving the existence of the multifractality character between GDCP and USEPU.

Finally, for the measurement of the multifractal richness of the cross-correlations between GDCP and USEPU, we perform another singularity spectrum check as shown in Figure 7. We can find that the none of the singularity spectrums, $f_{XY}(\alpha)$, demonstrate linear shapes, showing the multifractality between GDCP and USEPU. Moreover, we calculate the difference between min and max Hölder exponent, the delta, as the measurement for the multifractality degree, as presented in Table 2. It is easy to find that the GDCP delta of Hölder exponent is of the largest value (0.930), showing the strongest multifractality character.

FIGURE 5: Generalized Hurst exponent of $h(q)$ versus q for GDCP and USEPU cross-correlation, the correlation of GDCP, and the correlation of GDCP.

FIGURE 6: Rényi exponent of $\tau(q)$ versus q for GDCP and USEPU cross-correlation, the correlation of GDCP, and the correlation of USEPU.

FIGURE 7: Spectrum singularity of $f(\alpha)$ versus α for GDCEP and USEPU cross-correlation, the correlation of GDCEP, and the correlation of USEPU.

TABLE 2: Max, min, and delta values of the Hölder exponent.

	$\alpha_{\max}$	$\alpha_{\min}$	$\Delta\alpha = \alpha_{\max} - \alpha_{\min}$
GDCEP	2.041	1.111	0.930
USEPU	1.454	0.776	0.678
GDCEP-USEPU cross-correlation	1.261	1.044	0.218

5. Conclusions

In this paper, we take an investigation of the correlation between China's most prosperous carbon emission trading market and US economic policy uncertainty. To have a deep insight of the long-term cross-correlation property between series, we employ the prevailing multifractal detrended cross-correlation analysis as the instrument. We first calculate the cross-correlation statistics Q_{cc} and find sufficient evidence for the correlation significance between Guangdong carbon emission trading price (GDCEP) and US economic policy uncertainty (USEPU). Also, to have a more detailed understanding of the nonlinear cross-correlation property between GDCEP and USEPU, we calculate the fluctuation function and find that all the function values demonstrate linear shapes, proving the long-term power law cross-correlation between GDCEP and USEPU. In addition, we employ the Hurst exponent as the key parameter to check the persistence of correlation between GDCEP and USEPU. We find that the parameters are all over the critical values, confirming the correlation persistence between GDCEP and USEPU. Moreover, we calculate the Rényi exponent, the core factor in measuring the multifractality, to investigate the multifractal property between GDCEP and USEPU. We find that none of the Rényi exponents demonstrate typical

linear curves, supporting the multifractality character between GDCEP and USEPU. We further perform another spectrum singularity check as enhancement for the multifractality character between GDCEP and USEPU. We find that the delta values of the Hölder exponents are all far from zeros, confirming the existence of multifractality between GDCEP and USEPU. With this view, multifractality character enables deep insight for the forecast of future movement of the carbon trading price, which would provide substantial suggestions for the carbon trading management of investors.

Data Availability

We affirm that the carbon emission trading price and economic policy uncertainty data used to support the findings of this study are available at <http://policyuncertainty.com/> and Wind Financial Services which is widely subscribed by the financial researchers, respectively.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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