

Research Article

Quantifying Cross-Correlations between Economic Policy Uncertainty and Bitcoin Market: Evidence from Multifractal Analysis

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We investigate the dynamic correlation between the Bitcoin price (BTC) and the U.S. economic policy uncertainty index (USEPU) from the perspective of multifractality. Utilizing the multifractal detrended cross-correlation analysis (MF-DCCA), we confirm a long-range cross-correlation between BTC and USEPU. Moreover, the empirical results of MF-DCCA show that the power-law properties and multifractal characteristics between BTC and USEPU are significant. We further examine the long-range dependency of cross-correlation between BTC and USEPU series via the Hurst exponent test and confirm the durable cross-correlation. Finally, we introduce another multifractal indicator and examine the extent of multifractality among time series. The empirical results indicate that the BTC series, USEPU series, and the cross-correlation of BTC-USEPU present apparent multifractality, where BTC shows the strongest degree of multifractality.

1. Introduction

In the context of the subprime mortgage crisis and the public's growing concerns over government policy changes, Bitcoin was introduced by Nakamoto [1]. Bitcoin is an adequately decentralized cryptocurrency depending on sophisticated protocols. Since then, the cryptocurrency market represented by Bitcoin has developed rapidly and aroused the widespread interest of regulators, scholars, and investors. A series of studies have conducted in-depth research on price formation [2–4], market efficiency [5–7], stylized facts [8, 9], and price dynamics of Bitcoin [10–14]. Additionally, because of Bitcoin's independence over authority and significant fluctuations in its prices, the debates over whether it is a safe-haven asset and its relationship with government policy changes have caused controversy [14–19]. Especially during the trade war and COVID-19, there has been a sudden increase in economic policy uncertainty (EPU).

Recent literature examines whether Bitcoin can hedge from uncertainty based on the wavelet-based quantile-on-quantile regressions, ordinary least-squares regressions, and the Bayesian Graphical Structural VAR model [20, 21]. They argue that Bitcoin has safe haven properties and can serve as a suitable hedge against different kinds of uncertainty. Wang et al. [22] also confirm this argument and find that EPU (this paper takes three indexes as proxies for EPU, including VIX, equity market uncertainty, and US EPU) exhibits generally weak risk spillover effects on Bitcoin. In contrast, Conlon and McGee [23] document that the downside risk of a portfolio containing Bitcoin increased significantly relative to investing in the S&P 500 alone during the Covid-19 pandemic. These studies usually focus on the linear properties between variables or simple nonlinear relationships. However, it has been widely accepted that the dynamic relationships between asset prices are inherently nonlinear and even multifractal [24–32]. Furthermore, various nonlinear cross-correlations between different time series have

been confirmed, including EPU and stock market volatility [33], online searches and Bitcoin [34, 35], different capital markets [36–41], and global stock markets [24, 26]. With this view, we attempt to study the dynamic correlation between Bitcoin price (BTC) and EPU from the perspective of multifractality.

Since the financial crisis, the impact of EPU on the economy and finance has also become a hot topic for scholars [42–46]. Based on the frequency of newspaper coverage, Baker et al. [47] proposed a novel EPU index and found that the U.S. EPU index (USEPU) is strongly linked to macro and micro variables such as stock market volatility and employment. At present, North America and Western Europe are the regions with the highest recognition of Bitcoin. The daily EPU data of the United States are publicly available. Therefore, we connect USEPU (the uncertainty of the U.S. economy and policy) with BTC to explore the joint dynamics between them. Some recent literature studies the impact of EPU on the Bitcoin market from the perspectives of risk spillovers, volatility effects, and dynamic correlations [48–51]. On the one hand, the empirical results of the impact of EPU on the Bitcoin market are relatively mixed. On the other hand, Wang et al. [50] demonstrated that there is a dynamic correlation between EPU and bit using the DCC-GARCH model. Inspired by these works of literature, we attempt to use the MF-DCCA method (traditional econometric methods mainly study the correlation between time series from a linear perspective; however, the characteristics of multifractality are common in socioeconomic systems. Also, it is not reliable and comprehensive to analyze financial markets with traditional linear analysis methods. The long memory of financial time series makes it unable to meet the application conditions of the traditional correlation coefficient method. On the contrary, by calculating the multifractal spectrum of the time series, the purpose of understanding the internal complex structure of the fractal can be achieved. Therefore, this paper adopts the widely recognized MF-DCCA method to study multifractal features) to examine the dynamic cross-correlations between them. As we know, the advantage of the MF-DCCA method is to measure the fractal characteristics of time series under different scales on the basis of eliminating local trends and further explore the cross-correlation and linear complex features between different time series [52–54].

Hence, we mainly adopt multifractal cross-correlation analysis (MF-DCCA) to investigate the multifractal characteristics between the USEPU series and the BTC series. The empirical evidence shows that there exists a long-range cross-correlation between the USEPU series and the BTC series. Moreover, using a log-log plot, we also find that no matter how the scaling order changes, the cross-correlations within the series demonstrate power-law character with the growing value of the fluctuation function. Furthermore, we calculate the Hurst exponent to test whether the cross-correlation between the BTC and USEPU series is enduring and find that it is persistent. Additionally, the results show that none of the Hurst exponent lines is constant, providing the preliminary evidence for multifractality. To confirm the

multifractality between BTC and USEPU, we calculate another proxy for multifractality and perform the spectrum singularity check. The empirical results indicate that neither the Rényi exponent nor the singularity spectral curve exhibits a typical linear shape, which confirms the existence of multifractality between BTC and USEPU. Finally, we calculate the Hölder exponent difference and find that the BTC series shows the strongest multifractality character with the largest value of the Hölder exponent difference.

Our main contributions to the growing literature are twofold: first, different from the existing literature on the impact of EPU on BTC [48–51], our study is the first to study the dynamic relationship between BTC and EPU from the perspective of multifractality. Based on the MF-DCCA, we provide strong evidence for power-law cross-correlation and apparent multifractal features between USEPU and BTC. Our findings complement the existing studies on the impact of uncertainty on the Bitcoin market and provide a comprehensive understanding of their joint dynamics. Second, our study enriches the literature on multifractality analysis. The previous studies suggest that nonlinear correlations between EPU and traditional assets (stock, oil, and gold) are persistent [55, 56]. Unlike traditional assets, Bitcoin is a decentralized currency that is not dominated by any authority. However, contrary to intuitive expectations, EPU also exhibits robust multifractal characteristics with BTC. Moreover, BTC shows a continuous upward trend, especially after 2020, with a sharp rise and violent fluctuations. Our findings inform the dynamics, long-range autocorrelation, and multifractal characteristics of BTC. We expect that our study could shed light on the risk management of Bitcoin and help investors have a more comprehensive understanding of the innovative financial asset.

The remainder of this study is organized as follows. Section 2 introduces the data and discusses summary statistics of the BTC and USEPU series. In Section 3, we describe our research methodology, including cross-correlation analysis and MF-DCCA. Section 4 presents the detailed results and discusses the main empirical findings. Finally, we conclude in Section 5.

2. Data

Our sample is mainly composed of two-time series: the U.S. economic policy uncertainty index (USEPU) and Bitcoin price (BTC). Our selection of USEPU follows Baker et al. [47]. The index currently covers 27 major economies globally and has been adopted by many well-known institutions and academic research. As stated by the website, USEPU quantifies the coverage of various newspapers collected from Access World News's NewsBank source according to three sets of terms: (a) the terms related to "economic" or "economy" (e.g., "monetary policy"), (b) the terms related to "uncertain" or "uncertainty" (e.g., "COVID-19"), and (c) the terms related to "government actions" (e.g., "deficit"). We obtain data on the daily USEPU from the public website <https://policyuncertainty.com>, while the daily BTC is crawled from the website <https://finance.yahoo.com>,

which provides Bitcoin news, transaction data, and professional message. Since we study the relationship between U.S. economic policy uncertainty and Bitcoin price, the U.S. dollar is chosen as the exchange currency for Bitcoin (Bitcoin price data are usually the latest transaction price of Bitcoin against the US dollar). In this study, we conduct all of our analyses from September 2014 to August 2021.

Table 1 presents descriptive statistics of our data sample, which consists of 2,527 observations. Both USEPU and BTC series show right-skew characters, exhibiting greater averages of the USEPU and BTC (124.90 and 8551.19) compared with their medians (91.44 and 5067.11, respectively), and implying distributions within the series is right-skewed. The skewness (2.63 and 2.48) also shows more extreme values at the right end of the series. For the kurtosis, it is accessible that the values of USEPU and BTC are well over 3 (11.52 and 8.81). In other words, the data distributions are steeper than the normal distribution. Then, we conduct Jarque-Bera (JB) tests to test whether the series of USEPU and BTC demonstrates normality properties. The results reject the null hypothesis that the time series obeys a normal distribution since their JB statistics are much greater than 0 (10,540.42 and 6,148.18). The statistical results of the BTC and USEPU series provide strong evidence that neither series was normally distributed during our sample period.

Figures 1 and 2 document the overall fluctuations of BTC and USEPU, respectively. As a representative of virtual currency, BTC has shown a general upward trend, especially after 2017. As shown in Figure 1, from January 2020 to July 2021, BTC fluctuates significantly, which may be affected by government regulation of digital currencies, transaction demand, investor sentiment, etc. For USEPU in Figure 2, the series exhibits relatively stable fluctuations on average from 2014 to 2019. However, in early 2020, USEPU rises rapidly and then gradually normalizes. The sudden outbreak of COVID-19 and the US election may be the drivers of the violent fluctuations. From the evolution patterns of the BTC and USEPU series, we find that both series present fat-tailed characteristics, especially for the USEPU series, which is consistent with the results in descriptive statistics.

3. Methodology

To examine whether there is multifractality between BTC and USEPU, we follow Zhou [52] and conduct the prevailing MF-DCCA (multifractal cross-correlation analysis), which combines the advantages of DFA and DCCA. First, we conduct the DCCA proposed by Podobnik and Stanley [57] to examine the long-range characteristics of cross-correlations between BTC and USEPU series. Then, we apply the MF-DCCA to quantitatively analyze the power-law cross-correlation and multifractal features within BTC and USEPU series.

3.1. Cross-Correlation Analysis. Bitcoin is often seen as a safe haven due to its decentralized nature, and at the same time, Bitcoin has been an attractive risk asset in recent years. Hence, is there a linkage between Bitcoin's price and

TABLE 1: Descriptive statistics.

Variable	USEPU	BTC
Mean	124.90	8,551.19
Minimum	3.32	178.10
Median	91.44	5,067.11
Maximum	861.10	63,503.46
Std. Dev	107.19	12,625.76
Skewness	2.62	2.48
Kurtosis	11.52	8.81
Jarque-Bera	10,540.42	6,148.18
Probability	≤ 0.01	≤ 0.01
N	2527	2527

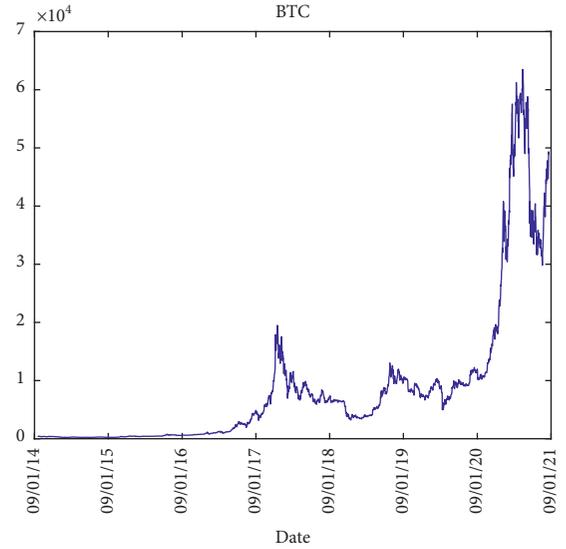


FIGURE 1: Evolution pattern of Bitcoin price (BTC).

economic policy uncertainty? To acquire a universal understanding of the cross-correlation properties, we initially introduce the cross-correlation statistic $Q_{cc}(m)$. Consider two equal-length series $\{x_k\}$ and $\{y_k\}$, where $k = 1, 2, \dots, N$. Specifically, $Q_{cc}(m)$ is defined as

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

Then, C_i represents the cross-correlation function and can be constructed through the following equation:

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

where m represents the degree of freedom; N is the length of the time series $\{x_k\}$ and $\{y_k\}$. If the value of $Q_{cc}(m)$ exactly matches the critical value of $\chi^2(m)$, a statistical cross-correlation cannot be found. Otherwise, we can infer that there is a statistically significant correlation.

3.2. MF-DCCA. Next, we apply the MF-DCCA to quantitatively analyze the power-law cross-correlation and multifractal features within BTC and USEPU series. Wang et al.

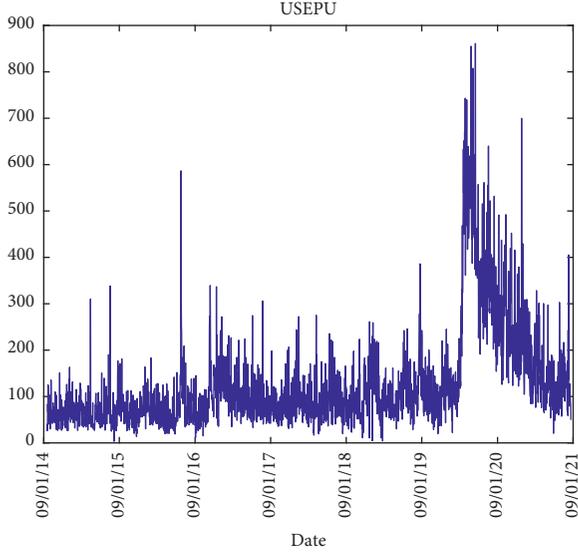


FIGURE 2: Evolution pattern of US economic policy uncertainty index (USEPU).

[41] established the widespread MF-DCCA method to investigate the multifractal power-law cross-correlation features between two nonstationary sequences with autocorrelation. Since the MF-DCCA method has been widely recognized, we only briefly introduce the steps as follows.

First, to remove the drift feature of each time series, we transform authentic series, $\{x_k\}$ and $\{y_k\}$, with a deduction of the constant shift (\bar{x} and \bar{y}), respectively. The full calculation operation has been demonstrated in the following equations:

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

Second, we break the detrended time series $X(i)$ and $Y(i)$ into N_s nonoverlapping equal parts with s observations to acquire a micro understanding of every single series. Taking N as the whole number of sample observations, the formation process of N_s is as follows:

$$Ns = \text{int}\left(\frac{N}{s}\right), \quad (4)$$

$\text{int}(\cdot)$ speaks on behalf of the integer function (because the time series length N may not always be an integer multiple of scale s , a relatively short portion will be discarded at the end of each profile. Hence, to include the remaining small segments, we do the same for the reverse order of the time series).

Third, with split N_s parts, we examine the local trend of every single part, ν . Specifically, the detrended covariance of every single part is marked as $F^2(s, \nu)$ and can be obtained from the following equations.

For $\nu = 1, 2, 3, \dots, N_s$, that is,

$$F^2(s, \nu) = \frac{1}{s} \sum_{i=1}^s [X_{(\nu-1)s+i} - \tilde{X}_{(\nu-1)s+i}] \cdot [Y_{(\nu-1)s+i} - \tilde{Y}_{(\nu-1)s+i}]. \quad (5)$$

For $\nu = N_s + 1, N_s + 2, N_s + 3, \dots, 2N_s$, we have

$$\begin{aligned} F^2(s, \nu) &= \frac{1}{s} \sum_{i=1}^s [X_{N-(\nu-N_s)s+i} - \tilde{X}_{N-(\nu-N_s)s+i}] \\ &\quad \cdot [Y_{N-(\nu-N_s)s+i} - \tilde{Y}_{N-(\nu-N_s)s+i}], \end{aligned} \quad (6)$$

where \tilde{X} and \tilde{Y} is the n th order polynomial fitness check of part ν .

Fourth, we average the local covariances of all detrended segments to get the q th order fluctuation function, $F_q(s)$. Thus, the fluctuation function can be constructed by the following equations:

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

when $q = 0$ and

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

It is evident that the movement of $F_q(s)$ is affected by the selection of q and s . To acquire a full perception of the multifractality within series, we carry out calculation processes from steps 2 to 4 on different scale s and then continue to the fifth and ending procedure.

Fifth, with the multiselection of scale s , the scaling character of the fluctuation function $F_q(s)$ could be found through the gradient analysis for every single q . If a long-range multifractality feature can be discovered within the detrended series, the power-law relationship can be depicted by the following equation:

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

where $H_{xy}(q)$ is the generalized Hurst exponent, which is the slope of the $\log(F_q(s)) \sim \log(s)$ function graph (it is evident from equation (9) that the gradient of function varies with the scaling order q . Specifically, considering the case where q takes a value of 2, if the value of gradient $H_{xy}(2)$ is above 0.5, the cross-correlation between time series $X(i)$ and $Y(i)$ is persistent. If $H_{xy}(2)$ is lower than 0.5, the cross-correlation would be antipersistent).

To have a further study of multifractality within series, we begin to introduce another proxy, Rényi exponent. The proxy is designated as $\tau_{xy}(q)$ presented in the following equation:

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

Finally, we execute singularity spectrum analysis as an extra investigation to improve multifractality reliability.

Through the Legendre transformation, the singularity spectrum, $f_{xy}(\alpha)$, could be acquired and presented by the subsequent formulas, based on the involvement of the Rényi ($\tau_{xy}(q)$) and Hölder (α_{xy}) exponents, respectively.

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

where α_{xy} is defined as the Hölder exponent, representing the strength of the singularity spectrum. Therefore, we utilize the strength difference or the spectrum width of the Hölder exponent $\Delta\alpha_{xy}$ ($\Delta\alpha_{xy} = \alpha_{xy,\max} - \alpha_{xy,\min}$), as the measurement for multifractality degree. It is easy to learn from the equation that the greater value of $\Delta\alpha_{xy}$ would represent higher levels of multifractality.

4. Empirical Results

4.1. Cross-Correlation Test. Following the steps described in the previous section, we first conduct the cross-correlation test introduced in Section 3.1 and obtain general knowledge of the relationship between BTC and USEPU series. The results are presented in Figure 3. Specifically, the significance level is 5%, and the degrees of freedom range from 1 to $N - 1$. The green and red lines represent cross-correlation statistics $Q_{cc}(m)$ and the chi-square critical value $\chi^2(m)$. The pattern of Figure 3 implies that $Q_{cc}(m)$ of BTC and USEPU is always higher than $\chi^2(m)$ with a distinct gap. Thus, the pattern of Figure 3 preliminarily demonstrates a long-range cross-correlation between BTC series and USEPU series.

4.2. Multifractal Detrended Cross-Correlation Analysis. So far, our study has proven the long-range cross-correlation between BTC and USEPU through the cross-correlation test. Next, we utilize the MF-DCCA [52] to perform a comprehensive quantitative examination of the nonlinear characteristics. Following Zhang et al. [34], we assign values to q at intervals of 1, with a minimum value of -10 and a maximum of 10 . According to the statement in Section 3.2, we can infer that if $q < 0$, the time series exhibits weak volatility. In contrast, strong fluctuations are highlighted. The evolution trend of $F_q(s)$ for BTC and USEPU is plotted in Figure 4. The results show that no matter how q changes, all lines show a similar evolution pattern, moving upward as time length s gradually increases, implying a long-range power-law cross-correlation between BTC and USEPU.

Furthermore, to examine whether the cross-relationship between the BTC and USEPU series has persistent and multifractal characteristics, we further compute the Hurst exponent $H_{xy}(q)$. As shown in Figure 5, the Hurst exponents of the BTC-USEPU, BTC, and USEPU are significantly greater than 0.5 , which is the critical value. In other words, the correlation within the BTC series, the correlation within USEPU series, and the cross-correlation of BTC-USEPU are evidently persistent. From the trend of the curve, we can learn that Hurst exponents for the BTC-USEPU and the correlation within BTC decrease with the increase of q . For USEPU, the overall trend shows an S-shape curve that

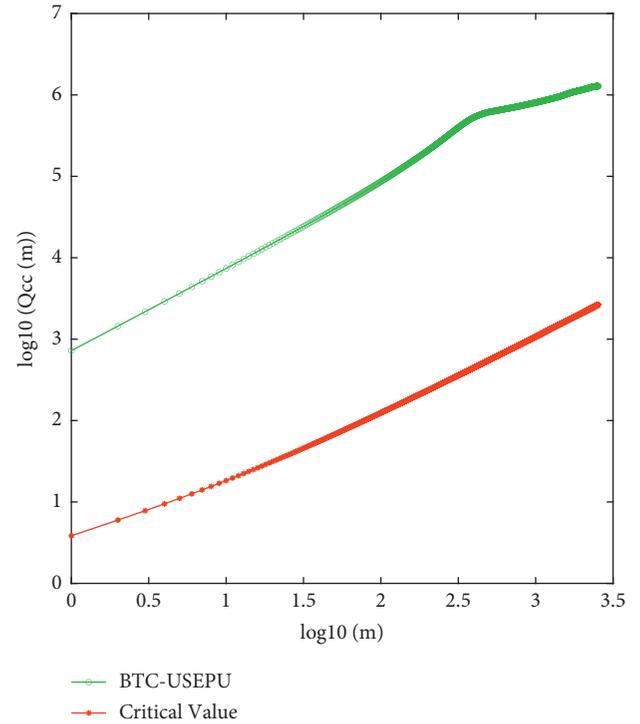


FIGURE 3: Log-log plot of $Q_{cc}(m)$ for BTC and USEPU.

gradually increases as q varies from -10 to -2 , peaks at $q = 6$, and then decreases. We can infer that the cross-correlations among the three pairs above are strictly multifractal. Specifically, when q is less than 0 , the Hurst exponent of the correlation within BTC is greater than BTC-USEPU and the correlation within USEPU. That is, correlation within BTC exhibits the highest degree of durability. When $q > 0$, the blue line (the correlation within USEPU) climbs abruptly, exceeding the Hurst index of BTC-USEPU. In general, the results of Figure 5 demonstrate the persistence of the cross-correlation between BTC and USEPU and provide preliminary evidence for multifractality.

To further demonstrate the existence of multifractality, we then investigate the pattern of Rényi exponents, including the cross-correlation of BTC-USEPU (red line), the correlation within the BTC series (green line), and the correlation within USEPU series (blue line). The results are presented in Figure 6. It is obvious that all three curves are distinct from typical linear shapes, confirming that BTC-USEPU cross-correlation conforms to multifractal characteristics.

Finally, we measure the degree of multifractality of the cross-correlation between BTC and USEPU using the singularity spectrum test, and the results are documented in Figure 7. The patterns indicate that all singularity spectrums are distinct from linear shapes, which is also consistent with the characteristics of multifractality. Furthermore, as shown in Table 2, we calculate the gap between minimum and maximum Hölder exponents ($\Delta\alpha$) to represent the degree of multifractality. The delta values of BTC-USEPU, USEPU, and BTC are 0.417 , 0.603 , and 1.008 , respectively. That is, BTC shows the strongest multifractality.

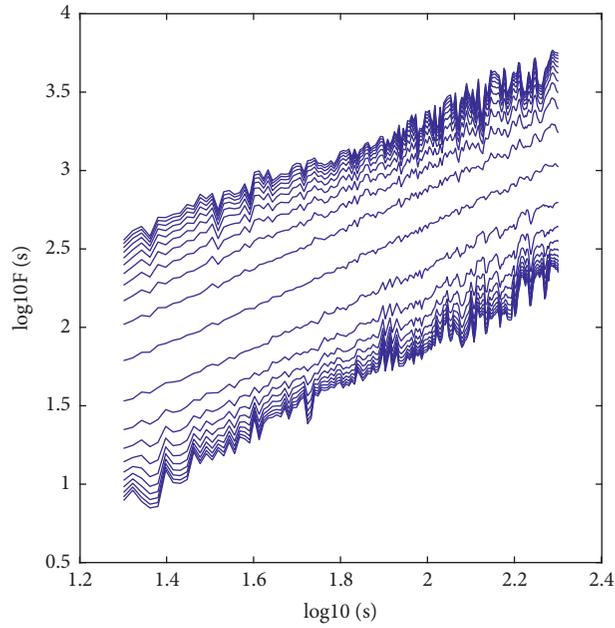


FIGURE 4: Log-log plot of $F_q(s)$ versus s for BTC and USEPU.

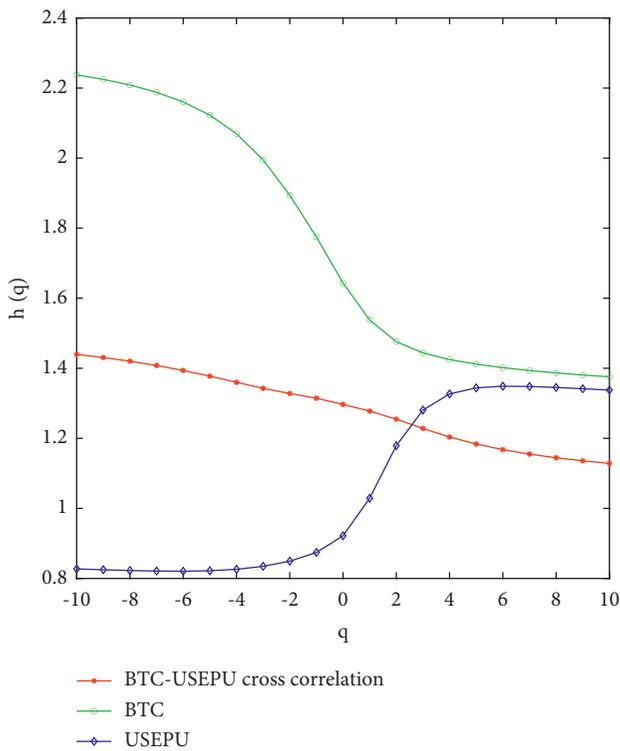


FIGURE 5: Generalized Hurst exponent of $h(q)$ versus q for BTC and USEPU cross-correlation, the correlation within BTC, and the correlation within USEPU.

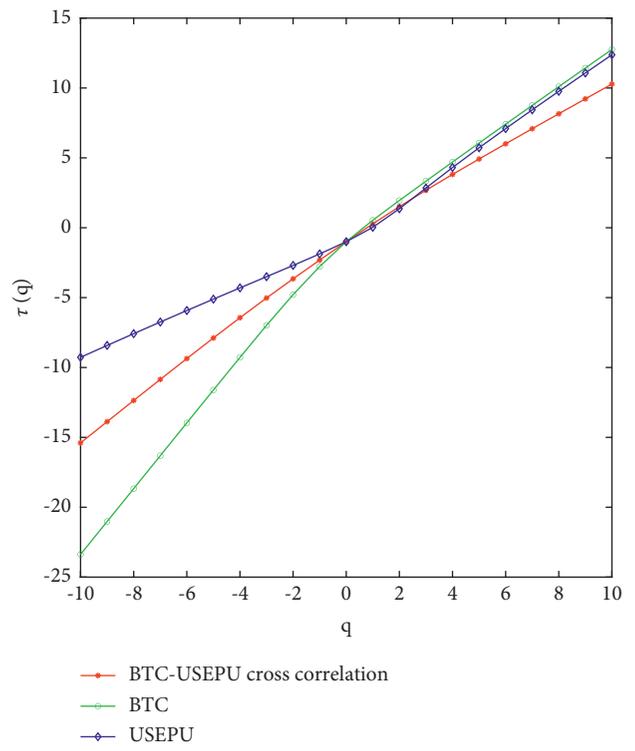


FIGURE 6: Rényi exponent of $\tau(q)$ versus q for BTC and USEPU cross-correlation, the correlation within BTC, and the correlation within USEPU.

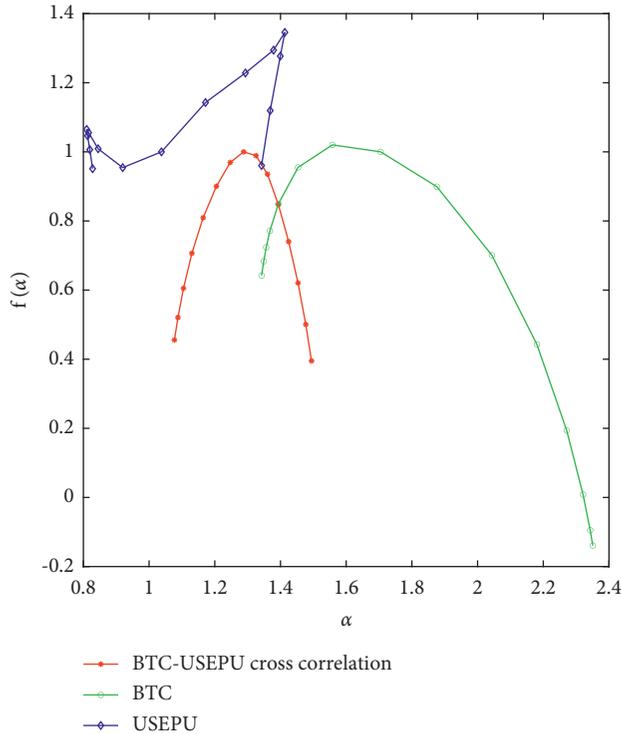


FIGURE 7: Spectrum singularity of $f(\alpha)$ versus α for BTC and USEPU cross-correlation, the correlation of BTC, and the correlation of USEPU.

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

	α_{\max}	α_{\min}	$\Delta\alpha = \alpha_{\min_{\max}}$
BTC	2.351	1.343	1.008
USEPU	1.413	0.810	0.603
BTC-USEPU cross-correlation	1.494	1.077	0.417

5. Conclusions

Our study examines the dynamic correlations between BTC and USEPU from September 2014 to August 2021. We mainly employ MF-DCCA to obtain a comprehensive insight into the long-range cross-correlation properties. First, we utilize cross-correlation analysis to preliminarily prove the long-range cross-correlation between BTC and USEPU. To further examine the nonlinear cross-correlation properties, we calculate the q th order fluctuation functions with an interval of one. All the curves demonstrate a similar evolution pattern, moving upward while time length s gradually increased, indicating the power-law properties and multifractal characteristics between BTC and USEPU. Then, we calculate the Hurst exponents to test the persistence of the cross-correlation, and the results support the existence of persistence. Moreover, we calculated another indicator of multifractality and performed a spectral singularity check to revalidate the multifractality between BTC and USEPU. Due to the unique design of Bitcoin's decentralization, the existing research on whether Bitcoin can be used as a safe-haven asset is still under discussion. Our findings inform the dynamics, long-range autocorrelation, and multifractal

characteristics of BTC. Also, we confirm the dynamic cross-correlation between BTC and USEPU. Based on the multifractal analysis of BTC and USEPU, our findings can provide valuable insights into the understanding of Bitcoin price dynamics and potential suggestions to market participants on the risk management of Bitcoin.

Data Availability

We affirm that the Bitcoin price and economic policy uncertainty data used to support the findings of this study are available at <https://finance.yahoo.com> and <https://policyuncertainty.com/> which is widely subscribed by the financial researchers, respectively.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

- [1] S. Nakamoto and A. Bitcoin, "A peer-to-peer electronic cash system, bitcoin," 2008, <https://bitcoin.org/bitcoin.pdf>.
- [2] P. Ciaian, M. Rajcaniova, and D. A. Kancs, "The economics of BitCoin price formation," *Applied Economics*, vol. 48, no. 19, pp. 1799–1815, 2016.
- [3] X. Li and C. A. Wang, "The technology and economic determinants of cryptocurrency exchange rates: the case of Bitcoin," *Decision Support Systems*, vol. 95, pp. 49–60, 2017.
- [4] A. Brauneis and R. Mestel, "Price discovery of cryptocurrencies: bitcoin and beyond," *Economics Letters*, vol. 165, pp. 58–61, 2018.
- [5] A. Urquhart, "The inefficiency of Bitcoin," *Economics Letters*, vol. 148, pp. 80–82, 2016.
- [6] S. Nadarajah and J. Chu, "On the inefficiency of Bitcoin," *Economics Letters*, vol. 150, pp. 6–9, 2017.
- [7] A. K. Tiwari, R. K. Jana, D. Das, and D. Roubaud, "Informational efficiency of Bitcoin-An extension," *Economics Letters*, vol. 163, pp. 106–109, 2018.
- [8] A. F. Bariviera, M. J. Basgall, W. Hasperué, and M. Naiouf, "Some stylized facts of the Bitcoin market," *Physica A: Statistical Mechanics and Its Applications*, vol. 484, pp. 82–90, 2017.
- [9] W. Zhang, P. Wang, X. Li, and D. Shen, "Some stylized facts of the cryptocurrency market," *Applied Economics*, vol. 50, no. 55, pp. 5950–5965, 2018.
- [10] B. M. Blau, "Price dynamics and speculative trading in bitcoin," *Research in International Business and Finance*, vol. 41, pp. 493–499, 2017.
- [11] W. Zhang, P. Wang, X. Li, and D. Shen, "Multifractal detrended cross-correlation analysis of the return-volume relationship of bitcoin market," *Complexity*, vol. 2018, Article ID 8691420, 2018.

- [12] A. Cretarola and G. Figà-Talamanca, "Detecting bubbles in Bitcoin price dynamics via market exuberance," *Annals of Operations Research*, vol. 299, no. 1, pp. 459–479, 2021.
- [13] B. Jia, J. W. Goodell, and D. Shen, "Momentum or reversal: which is the appropriate third factor for cryptocurrencies?" *Finance Research Letters*, vol. 45, Article ID 102139, 2022.
- [14] D. Shen, A. Urquhart, and P. Wang, "Bitcoin intraday time series momentum," *Financial Review*, vol. 57, pp. 319–344, 2021.
- [15] S. Wu, M. Tong, Z. Yang, and A. Derbali, "Does gold or Bitcoin hedge economic policy uncertainty?" *Finance Research Letters*, vol. 31, pp. 171–178, 2019.
- [16] M. Fama, A. Fumagalli, and S. Lucarelli, "Cryptocurrencies, monetary policy, and new forms of monetary sovereignty," *International Journal of Political Economy*, vol. 48, no. 2, pp. 174–194, 2019.
- [17] T. V. H. Nguyen, B. T. Nguyen, K. S. Nguyen, and H. Pham, "Asymmetric monetary policy effects on cryptocurrency markets," *Research in International Business and Finance*, vol. 48, pp. 335–339, 2019.
- [18] S. Corbet, C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya, "Cryptocurrency reaction to fomic announcements: evidence of heterogeneity based on blockchain stack position," *Journal of Financial Stability*, vol. 46, Article ID 100706, 2020.
- [19] C. Chen, L. Liu, and N. Zhao, "Fear sentiment, uncertainty, and bitcoin price dynamics: the case of COVID-19," *Emerging Markets Finance and Trade*, vol. 56, no. 10, pp. 2298–2309, 2020.
- [20] E. Bouri, P. Molnár, G. Azzi, D. Roubaud, and L. I. Hagfors, "On the hedge and safe haven properties of Bitcoin: is it really more than a diversifier?" *Finance Research Letters*, vol. 20, pp. 192–198, 2017.
- [21] E. Demir, G. Gozgor, C. K. M. Lau, and S. A. Vigne, "Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation," *Finance Research Letters*, vol. 26, pp. 145–149, 2018.
- [22] G. J. Wang, C. Xie, D. Wen, and L. Zhao, "When Bitcoin meets economic policy uncertainty (EPU): measuring risk spillover effect from EPU to Bitcoin," *Finance Research Letters*, vol. 31, 2019.
- [23] T. Conlon and R. McGee, "Safe haven or risky hazard? Bitcoin during the COVID-19 bear market," *Finance Research Letters*, vol. 35, Article ID 101607, 2020.
- [24] F. Ma, Y. Wei, and D. Huang, "Multifractal detrended cross-correlation analysis between the Chinese stock market and surrounding stock markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 392, no. 7, pp. 1659–1670, 2013.
- [25] X. Zhuang, Y. Wei, and B. Zhang, "Multifractal detrended cross-correlation analysis of carbon and crude oil markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 399, pp. 113–125, 2014.
- [26] M. Dai, J. Hou, J. Gao, W. Su, L. Xi, and D. Ye, "Mixed multifractal analysis of China and US stock index series," *Chaos, Solitons & Fractals*, vol. 87, pp. 268–275, 2016.
- [27] W. Zhang, Y. Li, Z. Zhang, and D. Shen, "The dynamic cross-correlations between foreign news, local news and stock returns," *Physica A: Statistical Mechanics and Its Applications*, vol. 509, pp. 861–872, 2018.
- [28] X. Xiong, K. Xu, and D. Shen, "Dynamic cross-correlations between investors' attention and CSI300 index futures," *Fluctuation and Noise Letters*, vol. 18, no. 04, Article ID 1950022, 2019.
- [29] S. Zou and T. Zhang, "Multifractal detrended cross-correlation analysis of the relation between price and volume in European carbon futures markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 537, Article ID 122310, 2020.
- [30] R. Zhao, "Economic policy uncertainty and local carbon emission trading: a multifractal analysis from US and guangdong," *Complexity*, vol. 2021, Article ID 8091394, 2021.
- [31] X. Ge and A. Lin, "Multiscale multifractal detrended partial cross-correlation analysis of Chinese and American stock markets," *Chaos, Solitons & Fractals*, vol. 145, Article ID 110731, 2021.
- [32] Y. Li, J. Goodell, and D. Shen, "Does happiness forecast implied volatility? Evidence from nonparametric wave-based Granger causality testing," *The Quarterly Review of Economics and Finance*, vol. 81, pp. 113–122, 2021.
- [33] Z. Liu, Y. Ye, F. Ma, and J. Liu, "Can economic policy uncertainty help to forecast the volatility: a multifractal perspective," *Physica A: Statistical Mechanics and Its Applications*, vol. 482, pp. 181–188, 2017.
- [34] Z. Zhang, Y. Zhang, D. Shen, and W. Zhang, "The cross-correlations between online sentiment proxies: evidence from Google Trends and Twitter," *Physica A: Statistical Mechanics and Its Applications*, vol. 508, pp. 67–75, 2018.
- [35] Y. Li, J. W. Goodell, and D. Shen, "Comparing search-engine and social-media attentions in finance research: evidence from cryptocurrencies," *International Review of Economics & Finance*, vol. 75, pp. 723–746, 2021.
- [36] G. Cao, L. Xu, and J. Cao, "Multifractal detrended cross-correlations between the Chinese exchange market and stock market," *Physica A: Statistical Mechanics and Its Applications*, vol. 391, no. 20, pp. 4855–4866, 2012.
- [37] H.-Y. Wang and T.-T. Wang, "Multifractal analysis of the Chinese stock, bond and fund markets," *Physica A: Statistical Mechanics and Its Applications*, vol. 512, pp. 280–292, 2018.
- [38] R. Zhao and Y. Cui, "Dynamic cross-correlations analysis on economic policy uncertainty and US dollar exchange rate: AMF-DCCA perspective," *Discrete Dynamics in Nature and Society*, vol. 2021, Article ID 6668912, 2021.
- [39] G. Gajardo, W. D. Kristjanpoller, and M. Minutolo, "Does Bitcoin exhibit the same asymmetric multifractal cross-correlations with crude oil, gold and DJIA as the Euro, Great British Pound and Yen?" *Chaos, Solitons & Fractals*, vol. 109, pp. 195–205, 2018.
- [40] M. A. Naeem, S. Farid, R. Ferrer, and S. J. H. Shahzad, "Comparative efficiency of green and conventional bonds pre- and during COVID-19: an asymmetric multifractal detrended fluctuation analysis," *Energy Policy*, vol. 153, Article ID 112285, 2021.
- [41] G. Wang, Y. Tang, C. Xie, and S. Chen, "Is bitcoin a safe haven or a hedging asset? Evidence from China," *Journal of Management Science and Engineering*, vol. 4, no. 3, pp. 173–188, 2019.
- [42] Ľ. Pástor and P. Veronesi, "Political uncertainty and risk premia," *Journal of Financial Economics*, vol. 110, no. 3, pp. 520–545, 2013.
- [43] J. Brogaard and A. Detzel, "The asset-pricing implications of government economic policy uncertainty," *Management Science*, vol. 61, no. 1, pp. 3–18, 2015.
- [44] W. Kang, K. Lee, and R. A. Ratti, "Economic policy uncertainty and firm-level investment," *Journal of Macroeconomics*, vol. 39, pp. 42–53, 2014.
- [45] H. Gulen and M. Ion, "Policy uncertainty and corporate investment," *Review of Financial Studies*, vol. 29, no. 3, pp. 523–564, 2016.

- [46] D. Zhang, L. Lei, Q. Ji, and A. M. Kutan, "Economic policy uncertainty in the US and China and their impact on the global markets," *Economic Modelling*, vol. 79, pp. 47–56, 2019.
- [47] S. R. Baker, N. Bloom, and S. J. Davis, "Measuring economic policy uncertainty," *Quarterly Journal of Economics*, vol. 131, no. 4, pp. 1593–1636, 2016.
- [48] P. Wang, W. Zhang, X. Li, and D. Shen, "Is cryptocurrency a hedge or a safe haven for international indices? A comprehensive and dynamic perspective," *Finance Research Letters*, vol. 31, pp. 1–18, 2019.
- [49] L. Fang, E. Bouri, R. Gupta, and D. Roubaud, "Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin?" *International Review of Financial Analysis*, vol. 61, pp. 29–36, 2019.
- [50] P. Wang, X. Li, D. Shen, and W. Zhang, "How does economic policy uncertainty affect the bitcoin market?" *Research in International Business and Finance*, vol. 53, Article ID 101234, 2020.
- [51] T. L. D. Huynh, M. Wang, and V. X. Vo, "Economic policy uncertainty and the Bitcoin market: an investigation in the COVID-19 pandemic with transfer entropy," *Singapore Economic Review*, vol. 66, pp. 1–27, 2021.
- [52] W. X. Zhou, "Multifractal detrended cross-correlation analysis for two nonstationary signals," *Physical review. E, Statistical, nonlinear, and soft matter physics*, vol. 77, no. 6, Article ID 066211, 2008.
- [53] G. Cao, Y. Han, Q. Li, and W. Xu, "Asymmetric MF-DCCA method based on risk conduction and its application in the Chinese and foreign stock markets," *Physica A: Statistical Mechanics and its Applications*, vol. 468, pp. 119–130, 2017.
- [54] S. Li, X. Lu, and X. Liu, "Dynamic relationship between Chinese RMB exchange rate index and market anxiety: a new perspective based on MF-DCCA," *Physica A: Statistical Mechanics and its Applications*, vol. 541, Article ID 123405, 2020.
- [55] C. Z. Yao, C. Liu, and W. J. Ju, "Multifractal analysis of the WTI crude oil market, US stock market and EPU," *Physica A: Statistical Mechanics and Its Applications*, vol. 550, Article ID 124096, 2020.
- [56] S. Papadamou, N. A. Kyriazis, and P. G. Tzeremes, "Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets," *The North American Journal of Economics and Finance*, vol. 56, Article ID 101343, 2021.
- [57] B. Podobnik and H. E. Stanley, "Detrended cross-correlation analysis: a new method for analyzing two nonstationary time series," *Physical Review Letters*, vol. 100, no. 8, Article ID 084102, 2008.