Asymmetric efficiency of cryptocurrencies during COVID19

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ABSTRACT

In this study, we examine the asymmetric efficiency of cryptocurrencies using 1-hour data of Bitcoin, Ethereum, Litecoin, and Ripple. In doing so, we utilize the asymmetric multifractal detrended fluctuation analysis (MF-DFA). We find significant asymmetric multifractality in the price of cryptocurrencies and that upward trends exhibit stronger multifractality than downward trends. Using the time-varying deficiency measure, we show that the COVID-19 outbreak adversely affected the efficiency of the four cryptocurrencies, given a substantial increase in the levels of inefficiency during the COVID-19 period. Bitcoin and Ethereum are the hardest hit, and at the same time, these two largest cryptocurrencies recovered faster at the end of March 2020 from their sharp dip towards inefficiency. The findings confirm previous evidence that market efficiency is time varying; also, unprecedented catastrophic events, such as the COVID-19 outbreak, have adverse effects of on the efficiency of leading cryptocurrencies.

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1. Introduction

The market efficiency of cryptocurrencies has been a hotly debated research topic in academia over the past four years. It has important implications for market participants and policymakers due to the emergence of cryptocurrencies as an alternative to government-backed currencies and as a new digital investment vehicle. Several studies have been conducted on the market efficiency of cryptocurrencies, but the academic literature has just started to reveal the shortcomings on several fronts. Firstly, previous studies generally consider the largest cryptocurrency, Bitcoin, and provide inconclusive results that switch between overall inefficiency [1–4] and efficiency during some periods (e.g., [5–8]).[1] Secondly, leading altcoins such as Ethereum, Ripple, and Litecoin,[2] show less evidence of market efficiency. Yet the scarce evidence is quite mixed, indicating that a few leading cryptocurrencies are gaining efficiency with time [8,10,11]. For example, using 1-min high-frequency data, Drozdz et al. [10] indicate that "the Bitcoin market, and possibly other cryptocurrencies, carry

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[1] Drozdz et al. [9] point to the dominance of Bitcoin in the cryptocurrency markets without ignoring the importance of other leading cryptocurrencies such as Ethereum and Ripple.

[2] Those altcoins mostly borrow their blockchain technology from Bitcoin. They compete with Bitcoin and are part of the digital investment vehicle.

concrete potential of imminently becoming a regular market". Thirdly, the efficiency of the cryptocurrency market seems to be unstable and subject to the impact of various events [8].[3]

However, there is a lack of evidence regarding the impact of unprecedented and catastrophic events, such as the COVID-19 outbreak, on the efficiency of leading cryptocurrencies. In this paper, we address this research gap by examining the effect of the COVID-19 on the efficiency of major cryptocurrencies with hourly price data. We use high-frequency data because Zargar and Kumar [4] find that inefficiency is more likely to be detected in intraday data than daily data. We utilize a distinct approach that involves the asymmetric multifractal detrended fluctuation analysis (MF-DFA) approach of Kantelhardt et al. [12]. In general, the asymmetric MF-DFA is especially useful when the data series under study is non-linear and multifractal in nature, and the market exhibits both up-trends and down-trends [13,14], i.e., bullish and bearish market states. Both features are common in the cryptocurrency markets (e.g., [15–17]), suggesting the need to treat the various market states differently while examining multifractality. Previous studies have shown that the degree of multifractality can be affected by crisis periods such as the global financial crisis (GFC) of 2008/2009 [13]. For example, by applying the multifractality approach, Rizvi and Arshad [18] indicate a deterioration in the efficiency of stock markets during the GFC.

Our main examination is further motivated as follows. On the one hand, the COVID-19 outbreak has induced a chaotic financial environment and triggered a global economic freeze that has led to a global recession. The risk shocks of the COVID-19 outbreak spread around the globe like a tsunami. It pushed up economic policy uncertainty and implied volatility to extremely high levels [19] and adversely affected financial markets.[4] Under normal conditions, investors are assumed to be fully informed, behave rationally, and make investment decisions based on public information. But crisis events such as COVID-19 can induce market overreaction, therefore disturbing the decision processes of investors. Such behavioral biases can alter market efficiency. Previous studies on financial markets (e.g., equities) show that market crash or crisis periods can result in market inefficiency. For example, Liao et al. [20] show that the level of stock market efficiency was disturbed by financial crises such as the GFC.

On the other hand, unlike the equity and futures, the markets of cryptocurrencies are immature, have weak regulatory frameworks, and less information disclosure. They involve a lot of speculative activities, evolve around anonymous and pseudonymous fundamentals, and are highly subject to psychological and sociological factors. Participants in the cryptocurrency markets are generally young individuals with a low level of education, an animal spirit, and their information is irregular. Therefore, the cryptocurrency markets are often criticized as highly risky. Furthermore, by far there exists no unified framework or model to determine the fair value of a cryptocurrency. These malfunctions can be magnified by catastrophic events, such as the COVID-19 outbreak. Such events can drive the cryptocurrency markets far away from the weak-form efficiency and lead to the possibility of predicting future cryptocurrency returns based on past information.

Compared to previous studies, our analysis can be related to Chu et al. [11] and Zargar and Kumar [4], both of which consider the Adaptive Market Hypothesis (AMH). The AMH extends the static view of market efficiency of Fama [21] by arguing that efficiency evolves over time and depends on the market environment. Like Chu et al. [11] and Zargar and Kumar [4], we also use a data frequency higher than daily (i.e., hourly). Nevertheless, our methodological and theoretical frameworks are different. Our focus is how the COVID-19 affects the market efficiency of a larger set of cryptocurrencies, including Bitcoin, Ethereum, Litecoin, and Ripple. In contrast, Zargar and Kumar [4] only examine Bitcoin and Chu et al. [11] on Bitcoin and Ethereum. Given the complexity of the cryptocurrency markets as reflected by the evidence of non-linearity and asymmetric multifractality [16,17], the asymmetric MF-DFA approach emerges as a suitable approach to study the market efficiency of leading cryptocurrencies in light of the COVID-19.[5]

Our current analysis offers several academic contributions. Firstly, our sample period covers the COVID-19 outbreak,[6] during which regular economic activities froze, market uncertainties spiked, and financial markets collapsed. Thus, we augment the literature on the effects of this unprecedented catastrophic event on financial markets [19,25,26] and cryptocurrency markets [27,28]. We confirm previous evidence that cryptocurrency market efficiency is not stable and varies with time [8,11]. Secondly, we apply the asymmetric MF-DFA approach to test the time-varying efficiency of leading cryptocurrencies. To the best of our knowledge, we are the first to provide evidence on the effect of the COVID-19 pandemic on the market efficiency of leading cryptocurrencies. Our analysis represents a nice extension to studies that examine market efficiency using statistical tests such as the serial correlation tests, runs test, variance ratio tests, and

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[3] For example, forking has been showed its ability to significantly decrease the level of efficiency in the cryptocurrency markets. Furthermore, Chu et al. [11] study the markets of Bitcoin and Ethereum and show the presence of a time-varying efficiency.

[4] The US equity indices declined by more than 30% during the period of February 19 to March 23, 2020. Crude oil prices declined by more than 60% during the period of January 1 to March 23, 2020. During the same period, the Bitcoin price declined by 19%.

[5] The appeal and power of the asymmetric MF-DFA in studying market efficiency is well documented (e.g., [14,22]).

[6] The first case of COVID-19 was reported in China on December 16, 2019 by the Wuhan Centres for Disease Prevention & Control. Since the number of reported cases increased dramatically, Wuhan decided to lock down the whole city since January 23, 2020, and other provinces soon took a similar measure. On April 8, the lockdown in Wuhan was lifted. Meanwhile, developed economies such as Italy, Spain, UK, and the US have reported outbreaks consecutively, which led the WHO to declare that the outbreak "a global pandemic". Undoubtedly, the travel bans and business shutdown brought the global economy to a standstill and caused the financial market to panic as the confirmed cases surged [23]. The pandemic even caused the stocks whose firms or brand names containing "corona" to drop sharply in the price, even if these stocks had no bearing with the Chinese stock market before the pandemic [24].

unit root tests. Thirdly, we consider hourly rather than daily data. This choice is motivated by Zargar and Kumar [4], which highlight the differences in the efficiency results between daily and higher frequency data. Last, we extend related studies of symmetric multifractality (Bariviera, 2017; [29]) by differentiating upward and downward trends, and examine the sources of asymmetric multifractality regarding the long-range correlations and fat-tail distribution.

Although no two crises are alike, the examination of cryptocurrency market efficiency during the COVID-19 outbreak remains insightful and informative. It helps us draw lessons and might be useful in mitigating the adverse effects of similar events in the future. Furthermore, it helps better understands the efficiency of the immature and unregulated cryptocurrency markets. With hourly data and advanced models such as the asymmetric MF-DFA, we can also learn the behaviors of crypto-traders during the COVID-19 outbreak, which might provide informative indications for crisis management.

Our main results show strong evidence of inefficiency in the cryptocurrency markets, which seems to vary with time and strongly emerge during the COVID-19 pandemic. Among the four cryptocurrencies we examine, Bitcoin and Ethereum – the two largest cryptocurrencies – are the hardest hit during the outbreak. Meanwhile, they recovered faster than Litecoin and Ripple: at the end of March 2020, they restored efficiency from their sharp dip towards inefficiency.

The rest of the paper is given as follows. Section 2 describes the asymmetric MF-DFA approach. Section 3 presents the dataset and then discusses the empirical results. Section 4 concludes.

2. Asymmetric MF-DFA approach

The weak-from Efficient Market Hypothesis (EMH) implies that: if the market is efficient, then the price follows a martingale, of which a random walk is a special form. In many earlier studies on the US stock market, serial correlation, price reversal, and long-term dependence are found to exist in the prices, which run counter to the EMH [30,31]. These studies and some follow-up research in market efficiency rely on the existence of an equilibrium pricing relation. However, during a market turmoil—for example, the 2007/08 financial crisis and the recent outbreak of COVID-19—an equilibrium is difficult to define.

As an alternative to the EMH, Peters [32] proposed the fractal market hypothesis (FMH). According to Weron and Weron [33] and Onali and Goddard [34], the main ideas of FMH are as follows. First, there are short-term, medium-term, and long-term investors in the market, and they have different valuations for the information flow. For example, long-term investors focus more on the long-term performance, rather than the short-term fluctuations, of a stock. Second, when there is ample liquidity from the investors, the market is stable; otherwise, when there is a shortage of liquidity, market instability ensues. Following the FMH, if both the long- and short-term investors start to focus on the current interim fluctuations of the market, the market equilibrium breaks down.

Since investors with different investment horizons interact with each other, they should behave similarly if we scale the time horizon appropriately. As a result, asset prices should exhibit "self-affinity" or "self-similarity" in the same market state [35]. Empirically, many time series exhibit multifractality, that is, they behave similarly in normal times or during market turmoil, respectively, but not so across each regime [22,36]. There are two sources of this multifractality. First, the small and large fluctuations in a time series can be persistently correlated. Second, the distribution of the fluctuations may have fat tails. The multifractality of series can also be asymmetric: the magnitude of the multifractality differ in bull and bear markets, and both the two sources are able to generate such asymmetry [37].

To analyze the multifractality of the leading cryptocurrencies, we use the multifractal detrended fluctuation analysis (MF-DFA) proposed by Kantelhardt et al. [12].[7] Roughly put, MF-DFA looks at the case where different series share similarities on multiple dimensions after proper scaling. In general, MF-DFA is widely used to assess the long-memory property of a financial time series.

To conduct the MF-DFA, we apply the 5-step procedure of Kantelhardt et al. [12]. Denote our time series as $\{x(t), t = 1, \ldots, T\}$, where T is the length of our sample horizon; let $\bar{x}$ be the (sample) mean of $\{x(t)\}$. To account for the asymmetric multifractality in a series – that is, the positive and negative domain of a series may behave differently – we follow Benbachir and Alaoui [38] and Shahzad et al. [14] to use the asymmetric version of MF-DFA.

The first step is to calculate the "profile" of the time series $\{x(t)\}$. We abstract the mean of $\{x(t)\}$, i.e. $\bar{x}$, from each $x(t)$, and compute the cumulative sum from period 1 up to a period j

$$y(j) = \sum_{t=1}^{j} [x(t) - \bar{x}], \quad j = 1, \ldots, T \tag{1}$$

The profile, in fact, is the discretized version of integration with respect to time t.

The second step is to divide the profile $y(j)$ into a series of nonoverlapping segments (or windows). Each segment has a length of τ, so the total number of segments is $N_\tau = \text{int}(T/\tau)$, where the function $\text{int}(\cdot)$ denotes the integer part of T/τ. However, as is the usual case, T/τ may have a decimal part. If we discard them from the N_τ segments, it may mean nontrivial sample attrition. As a result, we divide the times series twice: one from period 1 to T, which leaves out the last $T - N_\tau \times \tau$ observations; the other from period T to 1, which leaves out the first $T - N_\tau \times \tau$ observations. This procedure

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[7] Kantelhardt et al. [12] extend the detrended fluctuation analysis (DFA) to the *multifractal* case, which is known as the MF-DFA approach.

delivers us $2N_\tau$ segments in total, which we illustrate in the following graph. The two shaded segments mark the tail part that we leave out.

1	2	$\cdots$	N_τ	Leave-out
$y(1)$	$y(\tau+1)$		$y(\tau(N_\tau-1)+1)$	$y(\tau N_\tau+1)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$y(\tau)$	$y(2\tau)$		$y(\tau N_\tau)$	$y(T)$
Leave-out	$2N_\tau$	$\cdots$	$N_\tau+2$	$N_\tau+1$
$y(1)$	$y(T-\tau N_\tau+1)$		$y(T-2\tau+1)$	$y(T-\tau N_\tau+1)$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$y(T-\tau N_\tau)$	$y(T-\tau(N_\tau-1))$		$y(T-\tau)$	$y(T)$

In addition, we impose $5 \le \tau \le N/4$. This is because when we need to fit two linear models over the segments. If τ is too large, we would miss out on important characteristics of the segment; if τ is too small, then the fitting would have poor finite sample property.

For the jth segment, let the kth element be $s_{j,k}$, with $k = 1, \ldots, \tau$; accordingly, the jth segment of the time series $\{x(t)\}$ is denoted as $S_j = \{s_{j,k}, k = 1, \ldots, \tau\}, j = 1, 2, \ldots, 2N_\tau$. Similarly, for the jth segment of length τ, let the kth profile be $y_{j,k}$; accordingly, the jth segment of the profile is written as $Y_j = \{y_{j,k}, k = 1, \ldots, \tau\}, j = 1, 2, \ldots, 2N_\tau$. That is,

$$s_{j,k} = \begin{cases} x((j-1)\tau+k), & j = 1, \ldots, N_\tau \\ x(T-(j-N_\tau)\tau+k), & j = N_\tau+1, \ldots, 2N_\tau \end{cases} \tag{2a}$$

$$y_{j,k} = \begin{cases} y((j-1)\tau+k), & j = 1, \ldots, N_\tau \\ y(T-(j-N_\tau)\tau+k), & j = N_\tau+1, \ldots, 2N_\tau \end{cases} \tag{2b}$$

For the jth segment of the time series, $S_j = \{s_{j,k}, k = 1, \ldots, \tau\}$, and the corresponding profile $Y_j = \{y_{j,k}, k = 1, \ldots, \tau\}$, fit two linear models by ordinary least squares (OLS), respectively:

$$\hat{s}_{j,k} = \alpha_j^s + \beta_j^s k \tag{3a}$$

$$\hat{y}_{j,k} = \alpha_j^y + \beta_j^y k \tag{3b}$$

where $\hat{s}_{j,k}$ is the fitted value for $s_{j,k}$, and $\hat{y}_{j,k}$ is the fitted value for $y_{j,k}$; α_j^s and α_j^y are the intercepts, while β_j^s and β_j^y are the slopes.

To capture the asymmetric multifractality, we distinguish between positive and negative β_j^ss. If $\beta_j^s > 0$, then over segment j, $x(t)$ is increasing in most of the cases, such that the profile will have a upward trend; by the same token, if $\beta_j^s < 0$, then over segment j, $x(t)$ in decreasing in most of the cases, such that the profile will have a downward trend.

For the jth segment ($j = 1, 2, \ldots, 2N_\tau$), specify the variance function as follows:

$$F_j(\tau) = \frac{1}{\tau} \sum_{k=1}^{\tau} (y_{j,k} - \hat{y}_{j,k})^2 \tag{4}$$

When $x(t)$ have positive or negative trends over some segments, it might possess the asymmetric cross-correlation scaling property. The original version of MF-DFA proposed by Kantelhardt et al. [12] features the *average variance function* (or *average fluctuation function*):

$$F_q(\tau) = \begin{cases} \left(\dfrac{1}{2N_\tau} \sum\limits_{j=1}^{2N_\tau} [F_j(\tau)]^{q/2} \right)^{1/q} & q \ne 0 \\[4mm] \exp\left(\dfrac{1}{2N_\tau} \sum\limits_{j=1}^{2N_\tau} \ln[F_j(\tau)]^{1/2} \right) & q = 0 \end{cases} \tag{5}$$

where $q = 2$ corresponds to the classic DFA procedure. To evaluate the degree of the asymmetry, we proceed to use two *directional variance functions*:

$$F_+^q(\tau) = \left(\frac{1}{M^+} \sum_{j=1}^{2N_\tau} \frac{\text{sign}(\beta_j^s)+1}{2} [F_j(\tau)]^{\frac{q}{2}} \right)^{1/q} \tag{6a}$$

$$F_-^q(\tau) = \left(\frac{1}{M^-} \sum_{j=1}^{2N_\tau} \frac{-(\text{sign}(\beta_j^s)-1)}{2} [F_j(\tau)]^{\frac{q}{2}} \right)^{1/q} \tag{6b}$$

where for the sake of simplicity, we omit the case when $q = 0$; M^+ and M^- are the number of segments with positive or negative trends, defined as follows

$$M^+ = \sum_{j=1}^{2N_\tau} \frac{\text{sign}\left(\beta_j^s\right) + 1}{2} \tag{7a}$$

$$M^- = \sum_{j=1}^{2N_\tau} \frac{-\left(\text{sign}\left(\beta_j^s\right) - 1\right)}{2} \tag{7b}$$

For Eqs. (6a) and (6b), we need to examine how different values of q affects the two-*directional fluctuation functions*. To pin down a value for q, we follow Kantelhardt et al. [12] and Shahzad et al. [14] to use a log–log plot, where the horizontal axis is the log of the window length τ while the vertical axis is the log of $F_q(\tau)$. If $x(t)$ has long-memory, then we expect that a power-law scaling:

$$F_q(\tau) \sim \tau^{H(q)} \tag{8}$$

where the function $H(q)$ is the scaling exponent or the generalized Hurst exponent. When $q = 2$, it reduces to the Hurst exponent. If $x(t)$ is *monofractal*, then $H(q)$ does not depend on the value of q. Recall a few cases with respect to the Hurst exponent: (i) if $0 < H < 0.5$, then $x(t)$ is not persistent; (ii) if $0.5 < H < 1$, $x(t)$ exhibits persistence; (iii) if $H = 0.5$, then $x(t)$ follows a random motion, which is a sufficient yet not necessary condition for market efficiency.

There are two other measures of multifractality: one is the Rényi exponent—or the classic multifractal scaling exponent, and the other is the Hölder spectrum—or the singularity spectrum $f(\alpha)$ of the Hölder exponent α. Both can be written as a function of the generalized Hurst exponent. In fact, the relationship between the generalized Hurst exponent, $H(q)$, and the Rényi exponent $R(q)$ is:

$$R(q) = qH(q) - 1 \tag{9}$$

The generalized Hurst exponent relates to the Hölder exponent α and the Hölder spectrum $f(\alpha)$ via the Legendre transform, which we calculate as:

$$\alpha = H(q) + qH'(q) \tag{10a}$$

$$f(\alpha) = q[\alpha - H(q)] + 1 \tag{10b}$$

where α measures the degree of singularity, and $f(\alpha)$ captures the Hausdorff dimension of the fractal subset.

3. Data and empirical results

3.1. Data

The data we use for the empirical analysis consists of high-frequency 1-h prices of four major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP). Our sampling period is from July 1, 2017 to April 1, 2020. The availability of data determines the sample starting date. Compared with previous studies, our study focuses on a more recent period that covers a catastrophic event: the outbreak of the novel coronavirus (COVID-19).

Notably, the market capitalization of the four selected cryptocurrencies constitutes almost 81% of the market value of all cryptocurrencies. All the data is sourced from CryptoDataDownload.com on a 24-h basis. So, there are 24 prices each day, thus yielding a total of 24,121 observations. The observations are matched by their date/time information, which is timestamped at the UTC time.

The Bitcoin and its major counterparts have been regarded as a good hedge alongside gold. However, since they were born in the post-crisis period, they have not weathered any real stress tests. Kristoufek [28], by computing the quantile correlations of the Bitcoin with S&P500 index and with the VIX, found that Bitcoin has stronger corrections with the two benchmarks, thus cannot be regarded as a safe-haven asset. Following this line of research, we examine further if the efficiency of the cryptocurrency markets has decreased because of the COVID-19, and if the four cryptocurrencies bear the same magnitude of efficiency loss.

3.2. Results of asymmetric MF-DFA

As Lee et al. [13] argued, this asymmetric multifractality approach is especially useful when the market exhibits both up-trends and down-trends. Lee et al. [13] found that during the 2008/09 financial crisis, there is a significant increase in the degree of multifractality for stock indices. Similarly, in line with Rizvi and Arshad [18], we expect a decrease in efficiency in the cryptocurrency markets during the COVID-19 outbreak.

Fig. 1 is the log–log plot for four cryptocurrencies, BTC, ETH, LTC, and XRP. The horizontal axis is the log of time scale τ, while the vertical axis is the log of the average variance function $F_2(\tau)$, both with a base of two (i.e., in $\log_2(\cdot)$). The time range, τ, takes values from 64 to 4096, indicating time scales between the short- and long-run. Results of asymmetric
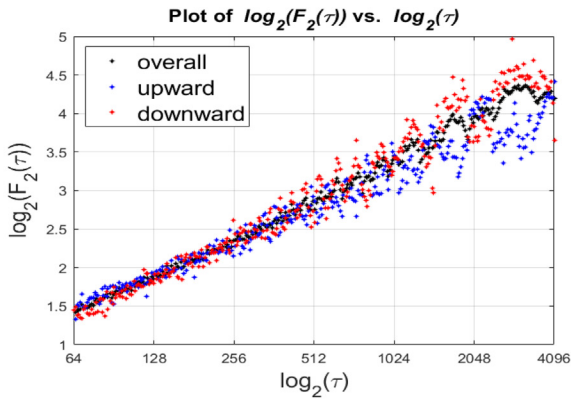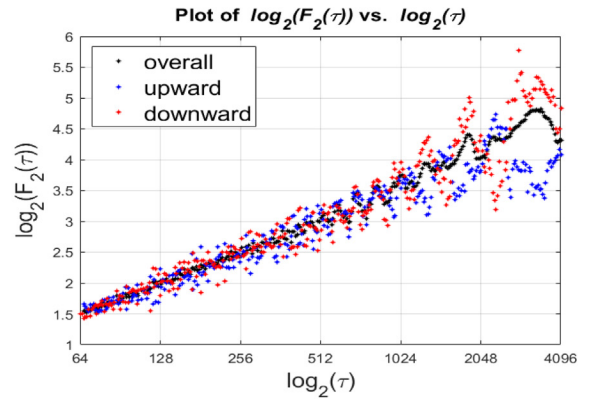
a). Bitcoin (BTC)
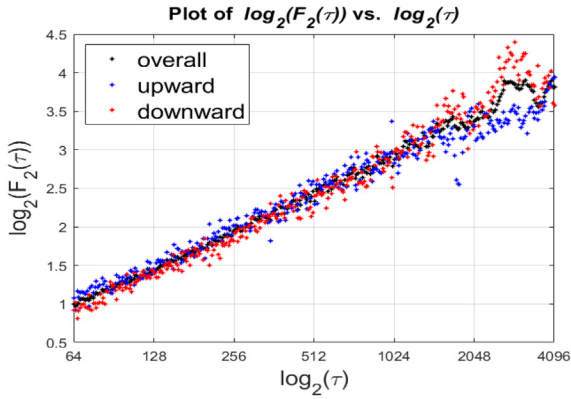
b). Ethereum (ETH)
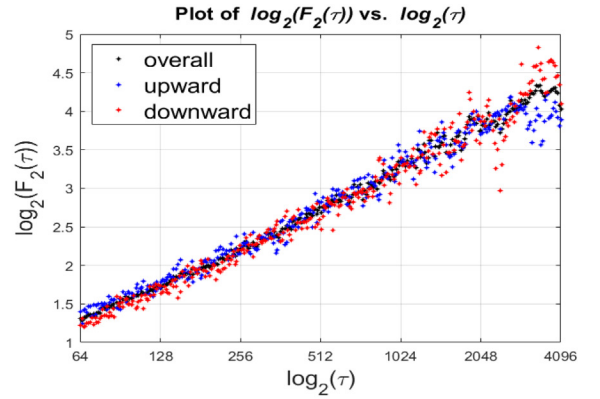
c). Litecoin (LTC)

d). Ripple (XRP)

Fig. 1. Log–log plot of the asymmetric MF-DFA functions for BTC, ETH, LTC, and XRP. Note: the y axis represents $\log_2 (F_2(\tau))$ while the x axis represents $\log_2(\tau)$, where τ is the time scale.

MF-DFA functions $F_2(\tau)$ versus the $\log_2(F_2(\tau))$ show similar trajectories at multiple frequencies. The black dots in each panel shows the overall case, the blue dots show the cases with upward trends, and the red dots show the cases with downward trends.

The two groups of dots – red and blue – correspond to the downward and upward trends, respectively. As the two log directional average variance functions ($\log_2 (F_-^2(\tau))$ and $\log_2 (F_+^2(\tau))$) show, for BTC, LTC, and XRP, the asymmetry becomes most evident for the last few units of the time scale τ. The two directional average variance functions exhibit less pronounced deviations over lower frequencies, but the magnitude of deviation increases when the time scale is between 2048 and 4096. Our findings in Fig. 1 complement the earlier findings of Al-Yahyaee et al. [29,39] that cryptocurrency investors tend to pay more attention to persistence in the longer term, which results in evident asymmetric persistence when the time scale becomes larger.

We proceed to measure the excess asymmetry by

$$Df_q(\tau) = \log_2 \left(F_q^+ (\tau) \right) - \log_2 \left(F_q^- (\tau) \right)$$

where the expressions for $F_q^+ (\tau)$ and $F_q^- (\tau)$ are given in Eqs. (6a) and (6b), respectively.[8] Again, if $Df_q(\tau)$ is close to zero, then the multifractality is close to being symmetric. Otherwise, if $Df_q(\tau)$ has a large positive value, then the cryptocurrency market behaves more differently in market upturns versus in market downturns, then the positive trends of $x(t)$ generating higher cross-correlation than the negative trends.

Fig. 2 shows the excess asymmetry in multifractality for BTC, ETH, LTC, and XRP. In the figure, we can see large excessive asymmetric multifractality for all four cryptocurrencies. This strong asymmetry provides a strong rationale for using the

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[8] By Eq. (8) we have $F_q (\tau) \sim \tau^{H(q)}$, which means $F_q (\tau) = c_{q,\tau} \cdot \tau^{H(q)}$. Here, $c_{q,\tau}$ is a constant that might differ with each τ and q. If the multifractality is symmetric, we would expect $c_{q,\tau}$ and $H (q)$ to be very close for positive and negative variance measures, such that $Df_q(\tau)$ is close to zero.

a). Bitcoin (BTC)

b). Ethereum (ETH)

c). Litecoin (LTC)

d). Ripple (XRP)
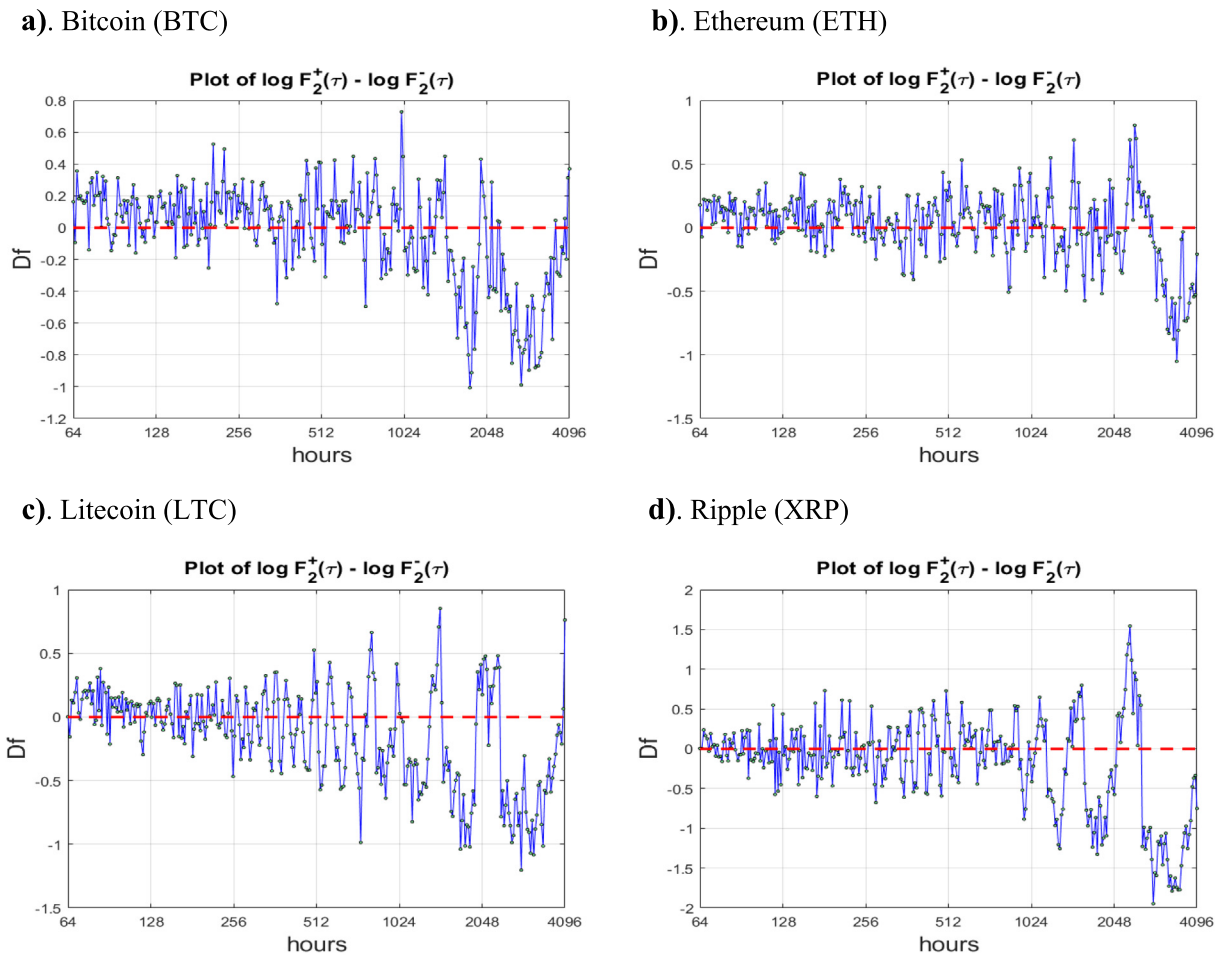
Fig. 2. Excess asymmetry in multifractality. **Note:** The horizontal axis shows the time scale τ, measured in hours and ranges from 5 to $T/4$, where T is the total length of hours in our sample. The vertical axis shows the difference between $\log_2(F_2^+(\tau))$ and $\log_2(F_2^-(\tau))$.

asymmetric MF-DFA approach. Among these four cryptocurrencies, LTC and XRP have a higher degree of asymmetry than BTC and ETH when τ tilts towards larger time scales.

Recall that when a time series exhibit *monofractality*, the generalized Hurst exponent should not vary with q. So, to further verify the *multifractality* of a time series, we check whether the three exponents changes as the value of q increases. Specifically, we examine how the overall trend $H(q)$, the upward trend $H_+(q)$, and downward trend $H_-(q)$ vary with q, where q ranges from -4 to 4. The results of the three curves are shown in Fig. 3.

We can see that as q increases, all three measures—$H(q)$, $H_+(q)$ and $H_-(q)$—show a downward trend, which suggests that multifractality exists in the time series of all four cryptocurrencies of interest. Despite this common feature, there are nontrivial differences in these series. For BTC and ETH, when q is small (i.e., small average fluctuations), all three multifractality measures take similar values; as q approaches 4, the deviation of $H_+(q)$ from $H(q)$ is almost equal to the deviation of $H_-(q)$ from $H(q)$. But for LTC, when $q = -4$, $H_+(q)$ is smaller than $H(q)$ and $H_-(q)$. Conversely, for XRP, when $q = -4$, $H_-(q)$ is larger than $H(q)$ and $H_+(q)$. The magnitude of the Hurst exponents with respect to $q = 4$ suggests that investors bring the market to the stability in the long-term for all four markets. From an economic/financial standpoint, our findings can relate to the evidence provided by Al-Yahyaee et al. [29]. They find asymmetry in the relationship between the inefficiency in cryptocurrency markets with high volatility and low levels of liquidity in the markets. Our result is also consistent with Bouoiyour and Selmi [27], who looked at the return of the Bitcoin price index (BPI) from January 1, 2018 to February 15, 2020. They found that when the time scale $\tau > 20$, the generalized Hurst exponent is 0.6 at $q = -5$, which slowly decreases to around 0.3 when q approaches 5. Also, our results suggest that the inefficiency is more persistent with smaller q (small average fluctuations) and during downward periods (shown by the red line in each graph).

Fig. 4 shows the Hölder spectrum $f(\alpha)$ versus the Hölder exponent, α. Recall that well if a time series is monofractal, then $f(\alpha)$ would reduce to the Hurst exponent, such that $\alpha = H$, and $f(\alpha) = 1$. For all four cryptocurrencies, the Hölder spectrum shows an inverted parabola shape. This inverse U-pattern, again, validates our previous results of asymmetric

a). Bitcoin (BTC)   **b)**. Ethereum (ETH)

c). Litecoin (LTC)   **d)**. Ripple (XRP)
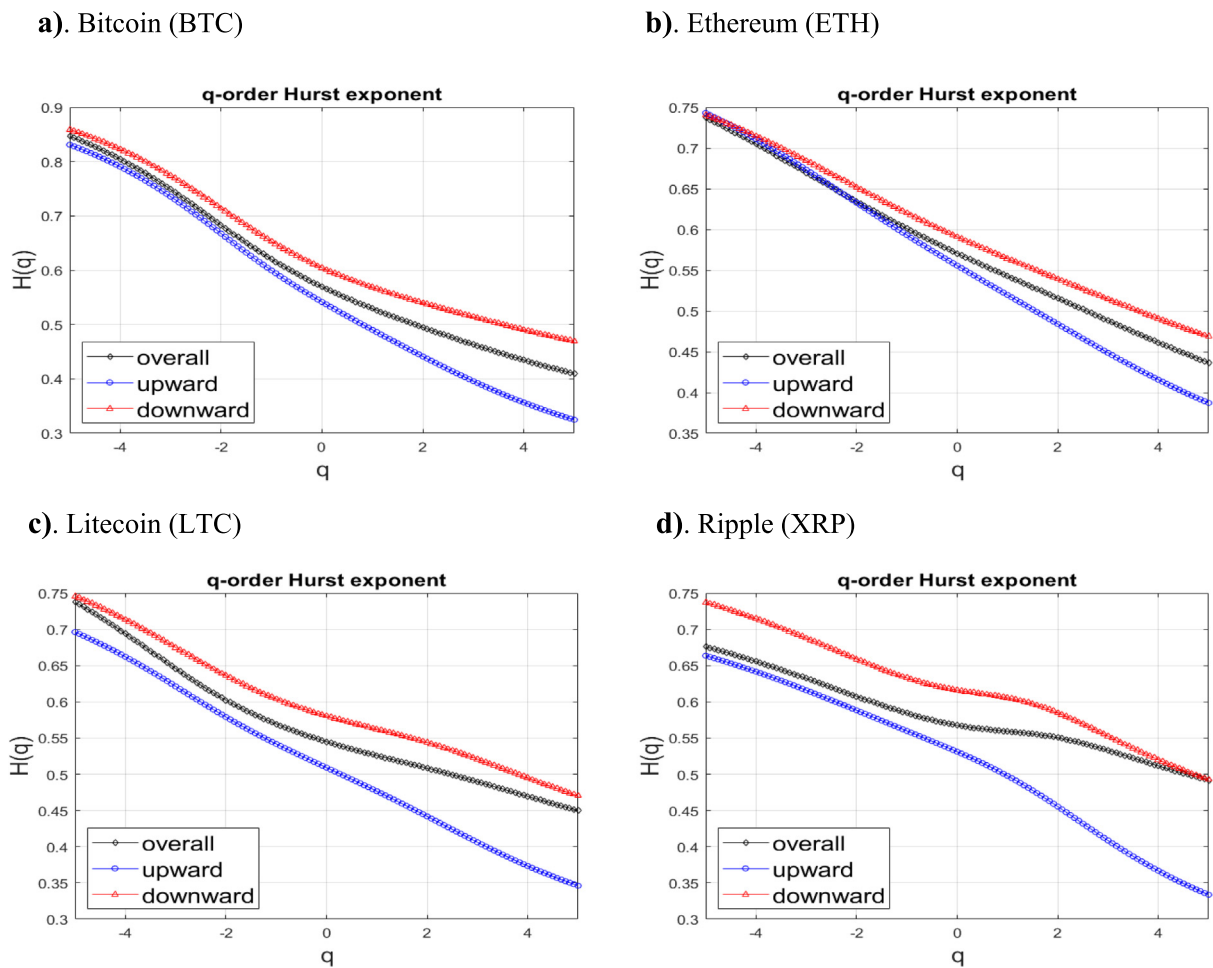
Fig. 3. The generalized Hurst exponents, $H(q)$, $H_+(q)$, and $H_-(q)$ for the four cryptocurrencies at different levels of q. Note: The horizontal axis is q, which ranges from -4 to 4; the vertical axis shows the values of $H(q)$, $H_+(q)$, and $H_-(q)$, which are represented by the black, blue, and red curves, respectively. If (i) $0 < H < 0.5$, then the time series $x(t)$ is not persistent; (ii) if $0.5 < H < 1$, $x(t)$ exhibits persistence; (iii) if $H = 0.5$, then $x(t)$ follows a random motion.

multifractality. For all four series, the range of α for the upward trend (the max minus the min value of α under the blue curve) is larger than that for the downward trend (the max minus the min value of α under the red curve), which implies that the upward trend has stronger multifractality than the downward trend. For our sample series, compared with LTC, BTC and ETH, XRP exhibits the strongest asymmetric multifractality.

We continue to pin down the source of multifractality in the cryptocurrencies – either from long-range correlations or from the fat-tail distributions – by applying two methods to each time series. The first treatment, which aimed to see the contribution of long-range correlations, is called *shuffling*. That is, we randomly switch the order of the observations and compare the multifractality measures of the original series versus the shuffled series. The second method is called *phase randomization*, which aims to disrupt the non-linearities in the phases. That is, we move to the frequency domain and apply the Fourier phase-randomization method to the series and call the phase-shuffled series as the "surrogate series" [40]. We then compare the multifractality measures of the original series and the surrogate series. We denote the measures of asymmetric scaling for original series, the shuffled series, and the surrogate series as $\Delta H_{\pm}^{orig}$, $\Delta H_{\pm}^{shuf}$, and $\Delta H_{\pm}^{surr}$.

For each measure, we compute the difference between the Hurst exponent for the upward trend $H_+(q)$ and the downward trend $H_+(q)$, say $\Delta H_{\pm}(q) = |H_+(q) - H_-(q)|$. If $\Delta H_{\pm}(q)$ approaches zero, the time series $x(t)$ is close to being symmetric; otherwise, if $\Delta H_{\pm}(q)$ increases with q, then the time series $x(t)$ exhibits stronger asymmetry.

Fig. 5 plots the for the $\Delta H_{\pm}(q)$ measure for the original series $\Delta H_{\pm}^{orig}$ (in black), the shuffled series $\Delta H_{\pm}^{shuf}$ (in blue), and the surrogated series $\Delta H_{\pm}^{surr}$ (in red). Again, the four cryptocurrencies behave differently. For BTC, the $\Delta H_{\pm}(q)$ of the original series is low, so there is little evidence that the asymmetric multifractality comes from the long-range correlations or fat-tail distribution. For ETH, both the shuffled series and the surrogated series have a lower $\Delta H_{\pm}(q)$ than the original
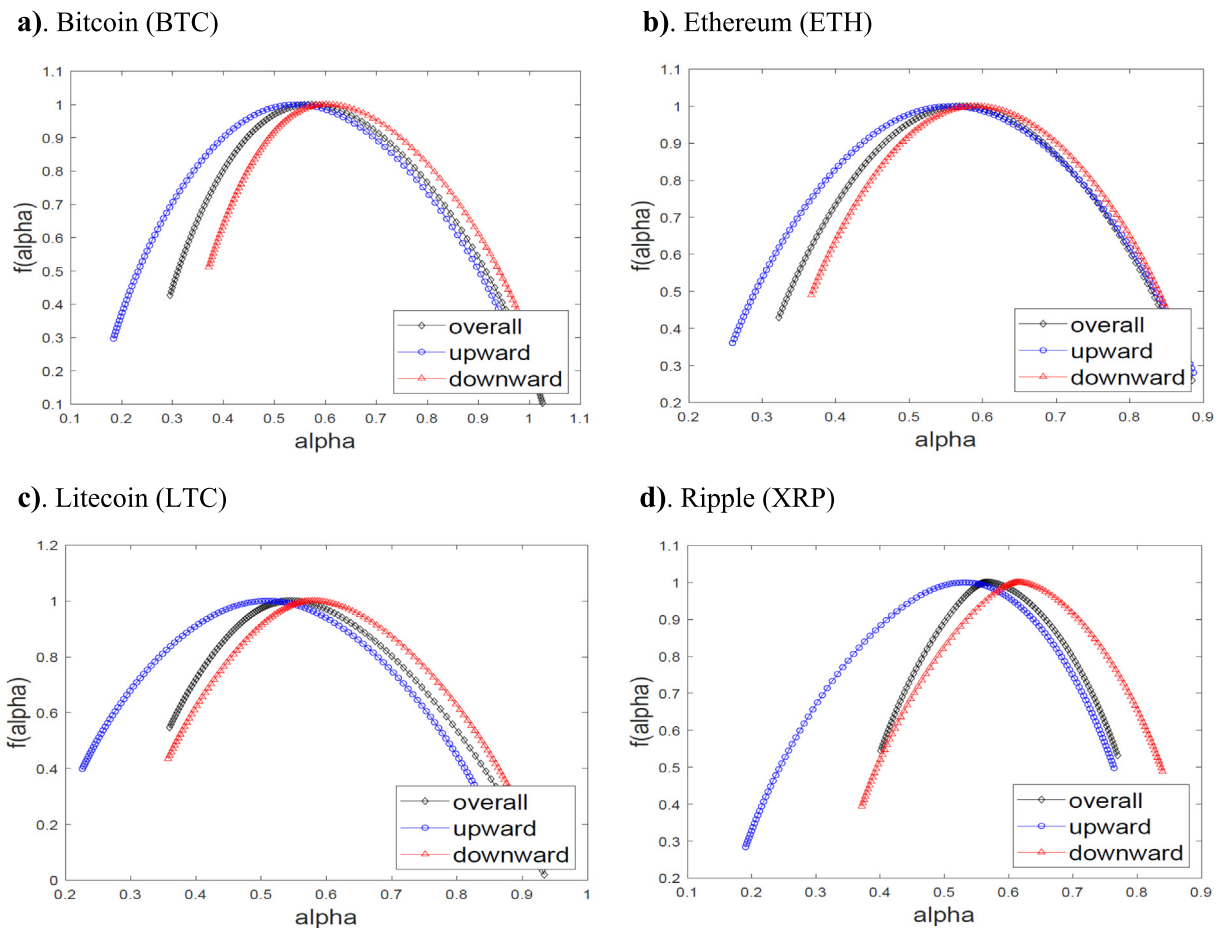
a). Bitcoin (BTC)

b). Ethereum (ETH)

c). Litecoin (LTC)

d). Ripple (XRP)

Fig. 4. The multifractal spectra $f(\alpha)$ versus α where q ranges from -5 to 5.

series, which means the asymmetry comes both from long-range correlations and fat-tail distribution. For LTC, at $q < 0$ (small fluctuations), both the shuffled series and the surrogated series have a lower $\Delta H_{\pm}(q)$ than the original series, so the asymmetric multifractality comes from both long-range correlations and fat-tail distributions. At $q > 0$ (large fluctuations), only the shuffled series is lower than the original series, so the asymmetric multifractality comes from fat-tail distributions. For XRP, at all levels of q, both the shuffled series and the surrogated series have a lower $\Delta H_{\pm}(q)$ than the original series, implying that both long-range correlations and fat-tail distributions contribute to the asymmetric multifractality.

Last, we examine the market efficiency of the four cryptocurrencies using the market deficiency measure (MDM) proposed by Wang et al. [41]:

$$MDM = \frac{1}{2}\left(|H(-4) - 0.5| + |H(4) - 0.5|\right)$$

where we choose $H(-4)$ to represent small fluctuations and $H(4)$ to represent large fluctuations. If the MDM takes a value that is close to zero, we say that the market of a cryptocurrency is efficient; otherwise, if the MDM is greater than zero, then the market of a cryptocurrency may be inefficient. Rizvi et al. [42] has used this MDM measure to rank the efficiency of 22 markets. Shahzad et al. [14] also use this measure to study the stock market indices for clean energies.

Recall that our sample period includes the recent boom-and-bust cycles for cryptocurrency markets, including the recent COVID-19 pandemic. To capture the time-varying nature of the MDM and account for possible structural changes, we calculate a rolling window deficiency measures based on a fixed window of 10,000 hourly observations and a step size of 24 h.

Fig. 6 is an illustration of the MDM for all four cryptocurrencies, where the black, blue, and red trajectories correspond to the MDM measure for the overall trend, the upward, and the downward trend. The markets showed large upside inefficiency than the downside, especially towards the end of the sample period showing the COVID-19 impact, where the upward trend (the blue curve) rises above the downward trend (the red curve).
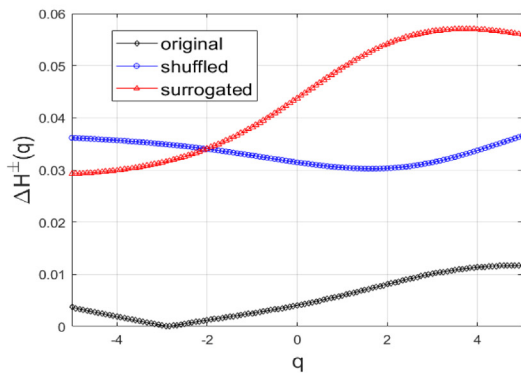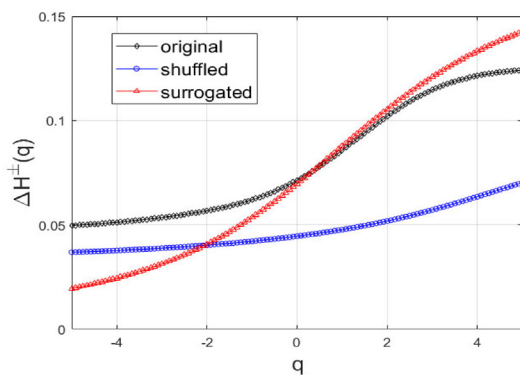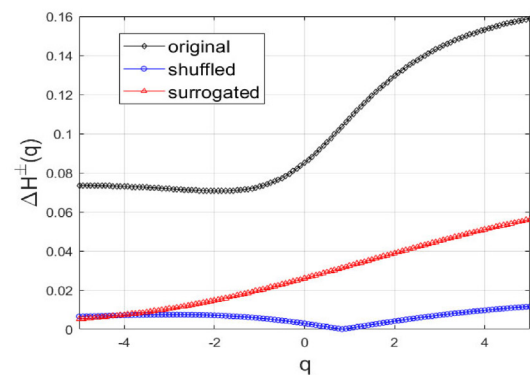
a). Bitcoin (BTC)   b). Ethereum (ETH)
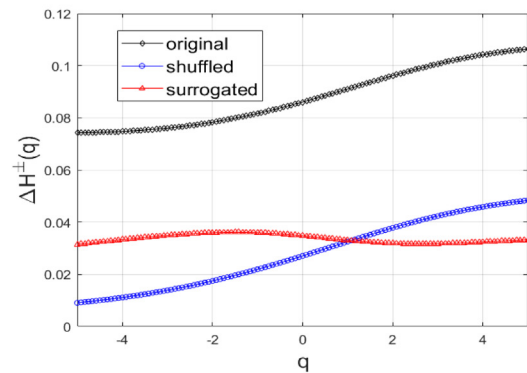

d). Litecoin (LTC)   e). Ripple (XRP)

Fig. 5. $\Delta H_{\pm(q)}(q)$ of the original, shuffled, and surrogated series.

Overall, the results show similar patterns of inefficiency without underestimating the complexity and dynamics of cryptocurrency market efficiency. Although the four cryptocurrencies show evidence of deteriorating efficiency during the COVID-19 period, Bitcoin (BTC), and to a less extent Ethereum (ETH), moved away faster from inefficiency levels and becomes much closer to efficiency levels. The inefficiency rises at the start of the rolling sample from November 2018 until April 2019. During this period, the prices of the cryptocurrencies fell but the connectedness among cryptocurrencies increased [43,44]. After that, the four cryptocurrencies entered a period of relatively low inefficiency, until at the end of our sample period. The drastic increase of inefficiency from March 2020 is related to the recent outbreak of the COVID-19. The surge in MDM measure potentially provides evidence to the herding behavior in the cryptocurrency market. Our results are partly consistent with previous evidence showing that the efficiency of the cryptocurrency markets is unstable and subject to various events (e.g., [8]). Our findings are also somewhat in line with Gajardo et al. [15], who show that Bitcoin does not behave like a typical commodity or currency.

4. Conclusion

The short history of Bitcoin and other leading cryptocurrencies do not offer researchers an opportunity to examine their market efficiency during major catastrophic events on a scale similar to the COVID-19 outbreak. The latter represents an unprecedented catastrophic event in contemporary economic history. It has frozen the global economy and disturbed the financial markets, leading to a chaotic financial environment.

In this paper, the effect of the COVID-19 on the efficiency of four leading cryptocurrencies is examined via the application of an asymmetric MF-DFA method. According to the empirical results, cryptocurrency price returns exhibit, somewhat, a significant presence of long-range dependence that intensified during the COVID-19, pointing to inefficiency. On a cryptocurrency-by-cryptocurrency basis, the results show that the COVID-19 outbreak adversely affected the efficiency of leading cryptocurrencies, with Bitcoin and Ethereum being the hardest hit. At the same time, these two largest cryptocurrencies recovered faster at the end of March 2020 from their sharp dip towards inefficiency.

a). Bitcoin (BTC)   **b)**. Ethereum (ETH)

c). Litecoin (LTC)   **d)**. Ripple (XRP)
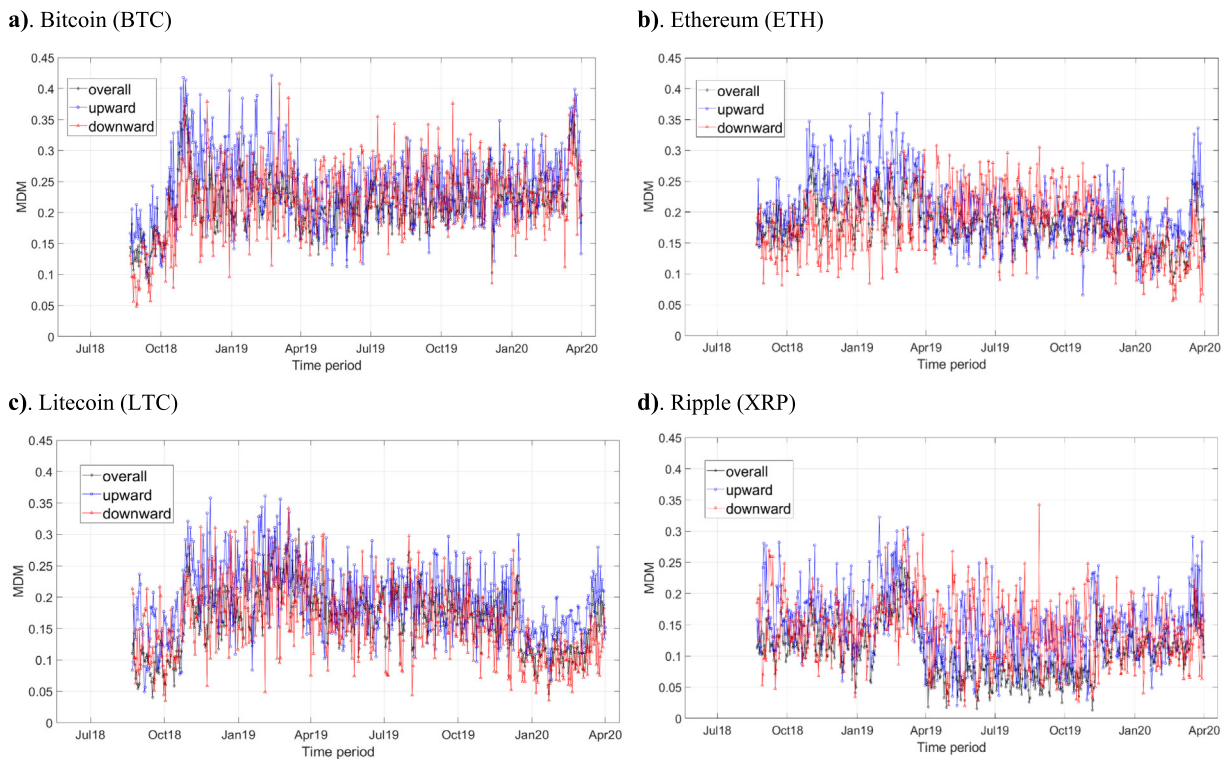
Fig. 6. Time-varying dynamics of market efficiency using *MDM* with $H(-4)$ and $H(4)$.

The results of multifractal spectra $f(\alpha)$ show that upward trends exhibit stronger multifractality than downward trends. Furthermore, Ripple (XRP) exhibits the strongest asymmetric multifractality compared with Bitcoin (BTC), Ethereum (ETH), and Litecoin (ETH). We also find that the source of the asymmetric multifractality is not the same for all the cryptocurrencies under study. The asymmetric multifractality of Bitcoin (BTC) cannot be explained by long-range correlations or fat-tail distribution. The asymmetric multifractality of Ethereum (ETH) and Ripple (XRP) comes from both long-range correlations and fat-tail distributions. For Litecoin (LTC), the asymmetric multifractality of small fluctuations comes from both long-range correlations and fat-tail distributions, but that of large fluctuations is more likely to come from fat-tail distributions.

This study extends our limited understanding of the adverse effects of the COVID-19 on cryptocurrency market efficiency. The findings show that important amounts of market inefficiency can emerge in periods of a global health crisis. Our findings are of concern to market participants who always chase abnormal returns in the immature, unstable, and unregulated cryptocurrency markets. The presence of multifractality indicates that cryptocurrency prices do not reflect all available information. The lack of efficiency implies exploitable trading opportunities and, thus, the possibility of earning abnormal profits. In other words, evidence of asymmetric multifractality may be useful to portfolio management and hedging strategists [14]. Such evidence may also shed light on cryptocurrency volatility and market crash forecast.

Our findings are also of interest to governments and regulatory bodies that have been monitoring the development of the cryptocurrency markets for financial stability. The future development of the cryptocurrency markets remains an appealing topic for future research. The cryptocurrency markets have evolved around anonymous and pseudonymous fundamentals. This market characteristic makes them less constrained by the regulatory criteria imposed on traditional financial markets. Will the market efficiency of leading cryptocurrencies improve in the post-COVID-19 period? Whether the implementation of some regulations will make cryptocurrencies more efficient? We leave these topics for future research.

CRediT authorship contribution statement

Muhammad Abubakr Naeem: Conceptualization, Data curation, Methodology, Writing - original draft. **Elie Bouri:** Methodology, Writing - review & editing. **Zhe Peng:** Methodology, Writing - original draft. **Syed Jawad Hussain Shahzad:** Formal analysis, Investigation, Methodology, Software, Supervision, Writing - review & editing. **Xuan Vinh Vo:** Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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