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Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: An asymmetric multifractal analysis approach

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ABSTRACT

This study investigates asymmetric multifractality and market efficiency of the major cryptocurrencies during the COVID-19 pandemic while accounting for different investment horizons. By applying the asymmetric multifractal detrended fluctuation analysis, we show that the outbreak affected the efficiency property of price behaviors differently between short- and long-term horizons. After the outbreak, the markets exhibited stronger multifractality in the short-term but weaker multifractality in the long-term. We also analyze asymmetric market patterns between upward and downward trends and between small and large price fluctuations and confirm that the outbreak has greatly changed the level of asymmetry in cryptocurrency markets.

1. Introduction

The spread of coronavirus (COVID-19) was officially declared as a pandemic in March 2020 and has become a threat to people's daily lives on a global scale. The on-going prevalence has triggered many channels relevant to the global economy such as stock markets (Topcu and Gulal, 2020; Zhang et al., 2020; Zaremba et al., 2020; Baker et al., 2020) and labor markets (Groshen, 2020), making investors and financial researchers increasingly concerned and nervous.

Since cryptocurrencies often show different features from conventional assets due to their unique block-chain technology, there is growing interest in the impact of COVID-19 on cryptocurrency markets. Conlon et al. (2020) and Ji et al. (2020) examine the performance of cryptocurrencies as a safe haven during the COVID-19 pandemic. Drożdż et al. (2020) show the impact of the outbreak on the internal structure of the market. More importantly, a number of studies focus on the major research subject of the efficient market hypothesis (EMH) for understanding cryptocurrency market characteristics. The EMH suggests that market prices of assets immediately reflect all available information including past data and its relevant data, so that price fluctuations can be best described as a random walk movement and thus it is impracticable to predict market prices or earn profits from returns.[1] It has been recognized in the finance literature that financial markets often exhibit anomalies, and hence informational efficiency is not always achieved. Although Bitcoin returns show the efficiency for certain periods, they do not follow a random walk behavior in general (Urquhart, 2016; Tiwari et al., 2018). The (in)efficiency of financial markets can also be time-varying (Jiang et al., 2018; Frezza et al., 2021). Wang and Wang (2021) finds that during the COVID-19 pandemic, the Bitcoin market became less inefficient than stock markets using an entropy-based analysis.

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[1] There are three forms of market efficiency. The weak form requires that current stock prices reflect all the data of past prices. The semi-strong form suggests that prices reflect all publicly available information including new public information. The strong form states that prices reflect all private and public information, so that no information that can be used to enjoy an advantage on the market.

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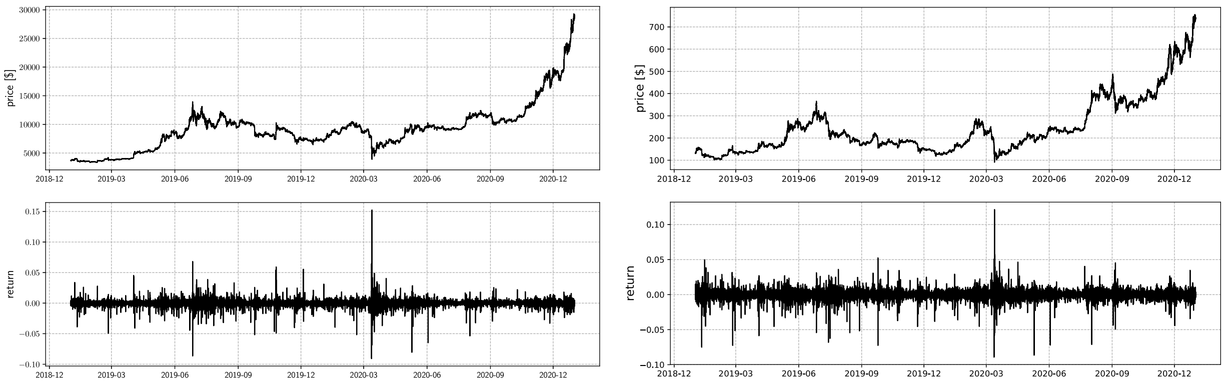

Fig. 1. Price and 1-hour return series of Bitcoin (left) and Ethereum (right) for the investigated period (2019/01/01 to 2020/12/31).

Extreme conditions of crisis and epidemic diseases often formulate behavioral biases of herding (Chang et al., 2000; Chiang and Zheng, 2010; Economou et al., 2011), and the presence of multifractality is a consequence of the presence of herding behavior (Cajueiro and Tabak, 2009). The concept of multifractality regards complexity and provides an explanation of market patterns and correlations in terms of self-similarity, long-memory, and scaling patterns, all of which the EMH fails to capture (Fernández-Martínez et al., 2019). According to the alternative fractal markets hypothesis (FMH) initiated by Peters (1994), short- and long-term investors have different investment horizons and different valuations for information flows. Market stability is achieved when the numbers of long-term investors balance those of short-term ones. However, once they start focusing on the current interim market fluctuations, the market equilibrium breaks down (Weron and Weron, 2000). The predominance of short-term investors leads to crashes in reaction to bad news. Moreover, herding behavior exhibits asymmetric characteristics between upward and downward trends (Tan et al., 2008; Chiang and Zheng, 2010), so the asymmetric herding behavior of cryptocurrency markets have also attracted attention (Stavroyiannis and Babalos, 2019; Mensi et al., 2019; Kristjanpoller et al., 2020).

Several studies have examined cryptocurrency markets during the COVID-19 pandemic in a framework of fractal analysis, but the results seem rather mixed. Mnif et al. (2020) and Yarovaya et al. (2020) investigate the long-term properties of cryptocurrencies and find that the market became more efficient after the outbreak, thus concluding that COVID-19 does not significantly increase herding. Naeem et al. (2021), on the other hand, finds traces of temporarily increased inefficiency during the COVID-19 pandemic by using a time-varying approach to detect self-similarity and its asymmetric properties. One missing point is that past studies discuss the efficiency without explicitly incorporating possible differences between short and long investment horizons. To fill the gap, this study extends our limited understandings of short- and long-term behaviors of cryptocurrency markets during the COVID-19 pandemic.

For this purpose, we analyze market efficiency of cryptocurrency markets during the pre- and post-COVID-19 periods, accounting for short and long investment horizons with different scaling regimes, by applying the asymmetric multifractal detrended fluctuation analysis (A-MFDFA) proposed by Cao et al. (2013). This method allows us to detect the asymmetric efficiency level of cryptocurrency markets. For a given range of scales, the A-MFDFA method well quantifies the generalized Hurst exponents for uptrend and downtrend price movements under different magnitudes of price fluctuations. The main finding suggests that after the outbreak, major cryptocurrency markets became more efficient in the long-run, but in the short-run, the markets exhibit an increase in the degree of inefficiency, which implies the presence of herding. We also confirm that the outbreak has changed asymmetric patterns in cryptocurrency markets. Our results are crucial for financial regulators and investment managers to mitigate cryptocurrency market distortion and conduct effective risk controls during extreme conditions, like the COVID-19 pandemic.

2. Data

Several studies suggest using such high-frequency data because inefficiency and asymmetric behaviors are more likely to be highlighted than intra-day data (Zargar and Kumar, 2019; Stavroyiannis et al., 2019; Naeem et al., 2021). We use hourly-based Bitcoin (BTC) and Ethereum (ETH) prices traded on https://poloniex.com/ against the cryptocurrency Tether (USDT), which is designed to maintain the same value as the US dollar, during the period from 2019/01/01 to 2020/12/31. Given that the first case of COVID-19 cluster was reported to the WHO China Country Office on December 31, 2019, we split the whole sample into two subperiods: the year 2019 (before outbreak) and the year 2020 (after outbreak).[2]

The return series are calculated as $r_t = \ln p_t - \ln p_{t-1}$ where p_t denotes the price at time t. We show in Fig. 1 the price and return series of BTC and ETH for the investigated period and we report in Table 1 the descriptive statistics of returns for each sample period. Both major cryptocurrencies have a more significant level of deviation, kurtosis and non-gaussianity after the outbreak. Significant

[2] Other relevant studies such as Mnif et al. (2020) and Aslam et al. (2020) also employ this date to divide the period for analyzing financial markets before and after the COVID-19 outbreak.

Table 1
Descriptive statistics for 1-hour Bitcoin and Ethereum return series for the periods before and after the COVID-19 outbreak. For the Jarque–Bera test, *** denotes statistical significance at 1% level.

	BTC		ETH	
	Before outbreak	After outbreak	Before outbreak	After outbreak
Mean (%)	0.0076	0.0159	−0.0003	0.0198
Median (%)	0.0083	0.0133	−0.0003	0.0153
Std. Dev. (%)	0.7043	0.7935	0.8528	0.9702
Max. (%)	9.0774	16.122	9.7788	13.892
Min. (%)	−9.1708	−19.200	−14.191	−23.273
Skewness	0.0800	−2.5899	−1.0883	−1.9389
Kurtosis	26.754	119.30	27.807	62.920
Jarque–Bera	261243***	5218673***	283917***	1454321***
ADF	−93.436***	−19.080***	−95.628***	−98.403***
KPSS	0.096	0.073	0.059	0.056

statistics of Augmented Dickey–Fuller (ADF) tests and insignificant statistics of Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests show that the return series are stationary for all cases.

3. Methodology

The algorithm of the A-MFDFA method (Cao et al., 2013) starts by calculating the profile, which is defined as $X(t) = \sum_{j=1}^{t}(x_j - \bar{x})$ for $t = 1, \dots, N$, where $\bar{x}$ is the average over the entire return series $\{x_t : t = 1, \dots, N\}$. Next, we divide the profile $X(t)$ and the original series x_t into $N_s = \lfloor N/s \rfloor$ non-overlapping segments of length s. If N is not a multiple of s, a short part of the profile may remain. To consider all the profile, the division is repeated starting from the other end of the data set, making $2N_s$ segments for both series.

Let $S_v = \{s_{v,i},\ i = 1, \dots, s\}$ be the vth segment series of length s. For each segment $v = 1, \dots, 2N_s$, the local trend of the profile is calculated by fitting a least-square degree-2 polynomial y_v. In the same manner, the local least-square linear fit of the series $\hat{x}_{S_v}(i) = a_{S_v} + b_{S_v} i$ is estimated for each segment. The polynomial fit y_v is used to detrend the profile, and $\hat{x}_{S_v}$ is used to determine the direction of the original series. Positive (upward) or negative (downward) trends depend on the sign of the slope b_{S_v}.

The residual variance for each segment is calculated as:

$$F^2(s, v) := \frac{1}{s}\sum_{i=1}^{s}\left\{X[(v-1)s + i] - y_v(i)\right\}^2 \quad \text{for} \quad v = 1, \dots, N_s, \tag{1}$$

$$F^2(s, v) := \frac{1}{s}\sum_{i=1}^{s}\left\{X[N - (v - N_s)s + i] - y_v(i)\right\}^2 \quad \text{for} \quad v = N_s + 1, \dots, 2N_s. \tag{2}$$

The upward and downward qth order fluctuation functions are calculated by taking the average over all segments as:

$$F_q^+(s) = \left\{\frac{1}{M^+}\sum_{v=1}^{2N_s}\frac{1 + \mathrm{sgn}(b_{S_v})}{2}\left[F^2(s, v)\right]^{q/2}\right\}^{1/q}, \tag{3}$$

$$F_q^-(s) = \left\{\frac{1}{M^-}\sum_{v=1}^{2N_s}\frac{1 - \mathrm{sgn}(b_{S_v})}{2}\left[F^2(s, v)\right]^{q/2}\right\}^{1/q}, \tag{4}$$

for any real value $q \neq 0$, and

$$F_0^+(s) = \exp\left\{\frac{1}{2M^+}\sum_{v=1}^{2N_s}\frac{1 + \mathrm{sgn}(b_{S_v})}{2}\ln\left[F^2(s, v)\right]\right\}, \tag{5}$$

$$F_0^-(s) = \exp\left\{\frac{1}{2M^-}\sum_{v=1}^{2N_s}\frac{1 - \mathrm{sgn}(b_{S_v})}{2}\ln\left[F^2(s, v)\right]\right\}, \tag{6}$$

for $q = 0$. $M^+ = \sum_{v=1}^{2N_s}\frac{1+\mathrm{sgn}(b_{S_v})}{2}$ and $M^- = \sum_{v=1}^{2N_s}\frac{1-\mathrm{sgn}(b_{S_v})}{2}$ respectively represent the numbers of segments with positive and negative trends under the assumption of $b_{S_v} \neq 0$ for all $v = 1, \dots, 2N_s$, such that $M^+ + M^- = 2N_s$. Note that

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}\left[F^2(s, v)\right]^{q/2}\right\}^{1/q} \quad \text{and} \quad F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s}\ln\left[F^2(s, v)\right]\right\} \tag{7}$$

correspond to the MFDFA method, which is equivalent to the case of overall trend in this study.

If the series x_k is long-range power-law correlated, then the power-law relationship $F_q^+(s) \sim s^{h^+(q)}$, $F_q^-(s) \sim s^{h^-(q)}$, and $F_q(s) \sim s^{h(q)}$ are satisfied, where the generalized Hurst exponents are calculated by performing a log–log linear regression against time scale s.

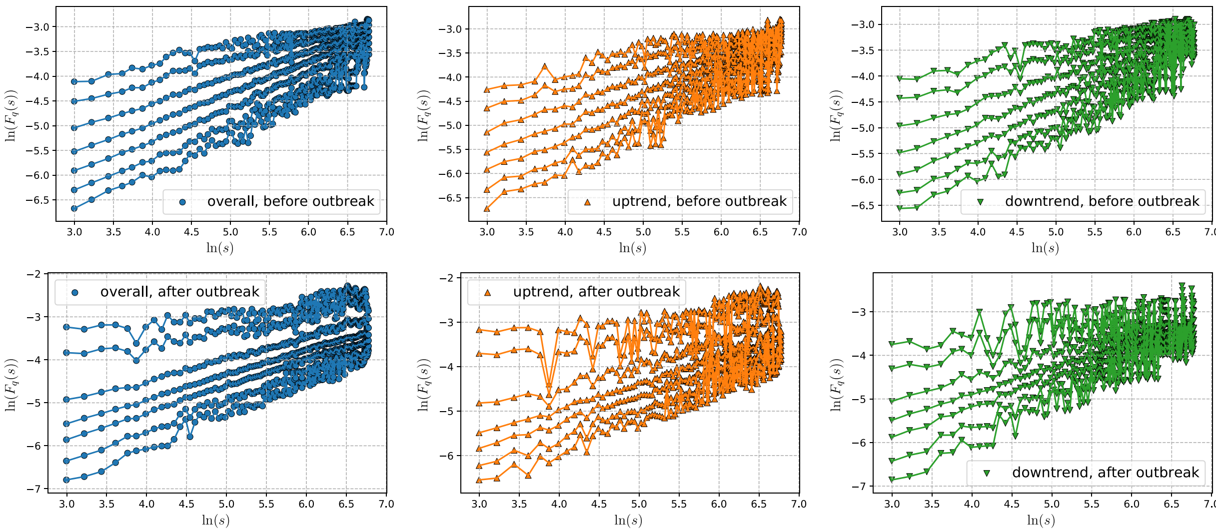

Fig. 2. The case of Bitcoin. Log–log plot of $F_q(s)$ versus time scale s for different market trends and before and after the outbreak where q take the values of -10, -5, -2, 0, 2, 5, and 10.

There might exist crossover scales s^* separating regimes with different scaling exponents due to different regulation mechanisms on fast and slow time scales.

The order q decides which magnitude the fluctuation should be evaluated. Generalized Hurst exponents for $q > 0$, which are dominated by large fluctuations in the fluctuation function, reflect the behavior of larger fluctuations, while those for $q < 0$ reflect the behavior of smaller fluctuations. If $h(q)$ is independent of q, then the series is monofractal since the scaling behavior of the residual variance is identical for all segments. On the other hand, if the value differs depending on q, the series is multifractal where small and large fluctuations are described by different scaling exponents. It should be noticed that when $q = 2$, $h(q)$ corresponds to the Hurst exponent.

4. Results and discussions

Figs. 2 and 3 depict the log–log plots of the fluctuation functions ($F_q(s)$, $F_q^+(s)$, and $F_q^-(s)$) versus the time scale s during the periods before and after the COVID-19 outbreak for Bitcoin and Ethereum. As mentioned in Thompson and Wilson (2016), we consider the scale ranges from 20 to $N/10$ to avoid biases and assure the validity of the scaling exponent estimates. We find a crossover point s^* of each fit at $\ln(s^*) \simeq 5.5$ ($s^* \simeq 10$ days) for both markets, where short- and long-term component dynamics are described by different scaling regimes.[3] Moreover, the location of this point seems to be consistent over different market trends and periods. The presence of the crossover uncovers that investors' behaviors differ depending on horizons, and their strategies have distinctive features in terms of herding and multifractal behavior. The generalized Hurst exponents for the short-term components are calculated by using the log–log regression within the scale ranges $20 \le s \le s^*$, and those for the long-term components are calculated within the scale ranges $s^* < s \le N/10$.

Figs. 4 and 5 show the results of $h(q)$, $h^+(q)$, and $h^-(q)$ for Bitcoin and Ethereum, respectively. Both short- and long-term components show signs of multifractality since the values of the generalized Hurst exponents decrease as q becomes large. When focused on the Hurst exponent $H = h(q = 2)$, the values are nearby 0.5, meaning that the series may show signs of weak persistence or anti-persistence.[4] For smaller fluctuations ($q < 0$), the markets are more persistent in the short-term after the outbreak (left-side panels in Figs. 4 and 5), but the opposite is observed in the long-term (right-side panels in Figs. 4 and 5). Asymmetric properties of persistence are also detected. Throughout our investigated period, we find the tendency of less asymmetry in the short-term where uptrend and downtrend markets show similar scaling properties (left-side panels), but the markets are more likely to exhibit asymmetry in the long-term (right-side panels). This is consistent with the findings of Naeem et al. (2021) which suggests that asymmetry results from the tendency of investors paying more attention to persistence in the longer term. Moreover, to some extent, both multifractality and asymmetry vary after the outbreak.

3 See Wang et al. (2009) and Tiwari et al. (2017) for detailed discussions about crossover points.

4 We analyze the autocorrelation functions (ACF) and the partial ACF (PACF) of the return series at various lags to examine the persistence and anti-persistence phases. Although ACF and PACF show several significant spikes (both negative and positive spikes) at different lags, the correlation functions die down quickly, and no obvious pattern of serial dependence is confirmed (see Appendix).

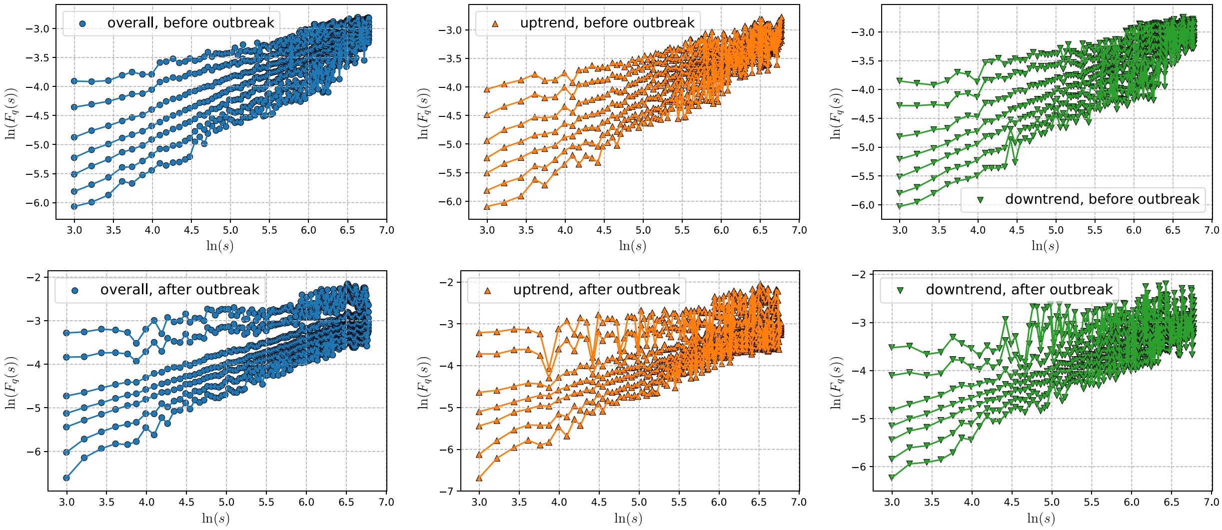

Fig. 3. The case of Ethereum. Log–log plot of $F_q(s)$ versus time scale s for different market trends and before and after the outbreak.

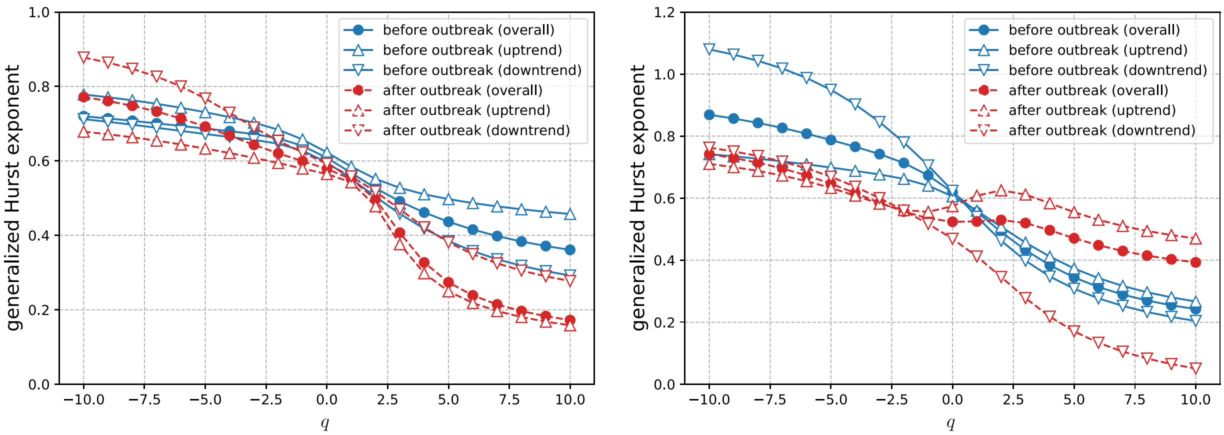

Fig. 4. The case of Bitcoin. q dependencies of generalized Hurst exponents with different trends in the short-term $s < s^*$ (left) and in the long-term $s > s^*$ (right), where $\ln(s^*) = 5.5$. The blue solid lines present the results for the period of before the outbreak, and the red lines after the outbreak.

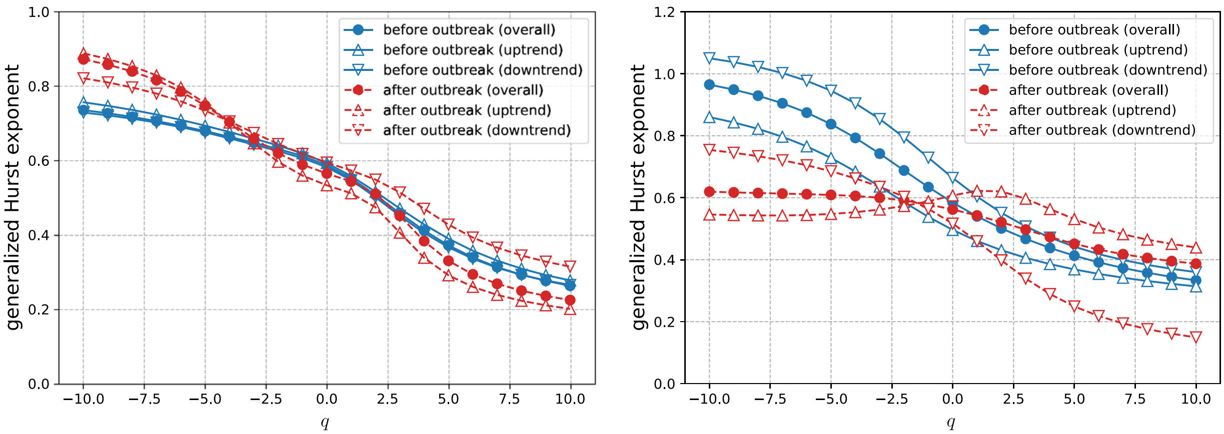

Fig. 5. The case of Ethereum. q dependences of generalized Hurst exponents with different trends in the short-term $s < s^*$ (left) and in the long-term $s > s^*$ (right), where $\ln(s^*) = 5.5$.

Table 2
Values of the MDM for short-term and long-term under different market trends. The larger values between before and after the outbreak are shown in bold.

		Short-term ($s < s^*$)		Long-term ($s > s^*$)	
		Before outbreak	After outbreak	Before outbreak	After outbreak
BTC	overall	0.179	**0.300**	**0.313**	0.174
	uptrend	0.160	**0.260**	**0.238**	0.120
	downtrend	0.210	**0.300**	**0.438**	0.356
ETH	overall	0.236	**0.324**	**0.316**	0.116
	uptrend	0.240	**0.344**	**0.273**	0.053
	downtrend	0.232	**0.253**	**0.345**	0.302

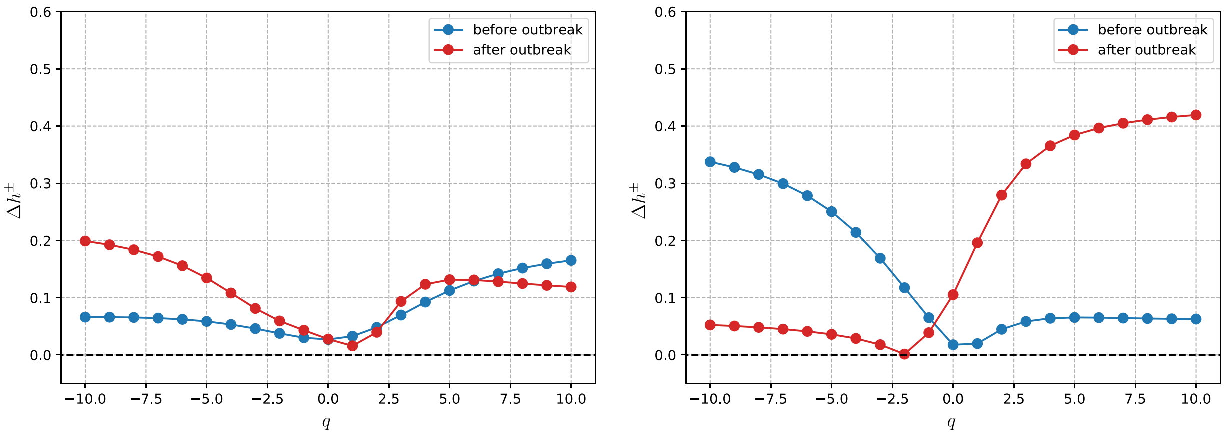

Fig. 6. The case of Bitcoin. Asymmetric degree of multifractality between uptrend and downtrend for the short-term horizon (left) and long-term horizon (right), respectively. We represent the results for the period before the outbreak in blue and after the outbreak in red.

To quantify the degree of multifractality and inefficiency, we use the market efficiency measure (MDM) defined in Wang et al. (2009):

$$D = \frac{1}{2}(|h(-10) - 0.5| + |h(10) - 0.5|). \tag{8}$$

This measure illustrates the discrepancy from an efficient market by evaluating the deviation from a random walk process in terms of both large ($q = 10$) and small ($q = -10$) fluctuations. Zero value of the MDM implies market efficiency with monofractal structure satisfying $h(q) = 0.5$ for any q. Large values of the MDM indicate strong inefficiency. We find that regardless of market trends, the values decrease after the outbreak in the long-term ($s > s^*$) (Table 2). This result is consistent with Mnif et al. (2020) and Naeem et al. (2021) which find that in the long-term, multifractality is reduced and thus the pandemic has a positive impact on cryptocurrency market efficiency. However, when focusing on short-term horizon ($s < s^*$), we find the opposite result where the MDM values significantly increase after the outbreak, and thus the markets become inefficient. These results imply that after the outbreak, cryptocurrency investors shift their strategy towards shorter horizons, which means that strong herding behavior is present in the short-term.

We further examine the asymmetric herding behaviors between upward and downward market trends for each of the different periods and horizons. Figs. 6 and 7 show the degree of asymmetry for the two investigated cryptocurrencies:

$$\Delta h^{\pm}(q) = |h^{+}(q) - h^{-}(q)|, \tag{9}$$

which corresponds to various fluctuation magnitudes. Larger values of $\Delta h^{\pm}(q)$ indicate higher asymmetry of multifractality between upward trends and downward trends. It is evident that asymmetric features are not constant over time. The results show that the degree of asymmetry increases only slightly in the short-term (left-side panels in Figs. 6 and 7).

However, asymmetric properties in the long-term horizon (left-side panels) is different from those observed in the short-term horizon. For relatively smaller fluctuations ($q < 0$), the degree of asymmetry, particularly for Bitcoin, greatly decreases during the pandemic so that the market persistence becomes close to symmetry. On the contrary, for relatively larger fluctuations ($q \geq 0$), the degree significantly increases and the persistence is no longer symmetric. In line with the long-term study of Bitcoin, Ethereum also shows evidence of weaker degree of asymmetry for small fluctuations but stronger degree of asymmetry for large fluctuations. Our results imply that the pandemic urged long-term cryptocurrency investors to switch their attention from smaller toward larger fluctuations, which results in the presence of asymmetric multifractality for larger q under different signs of market returns (Chiang and Zheng, 2010). The pandemic did not inspire short-term investors to focus on certain fluctuation magnitudes, because the asymmetry level was not raised significantly for any q.

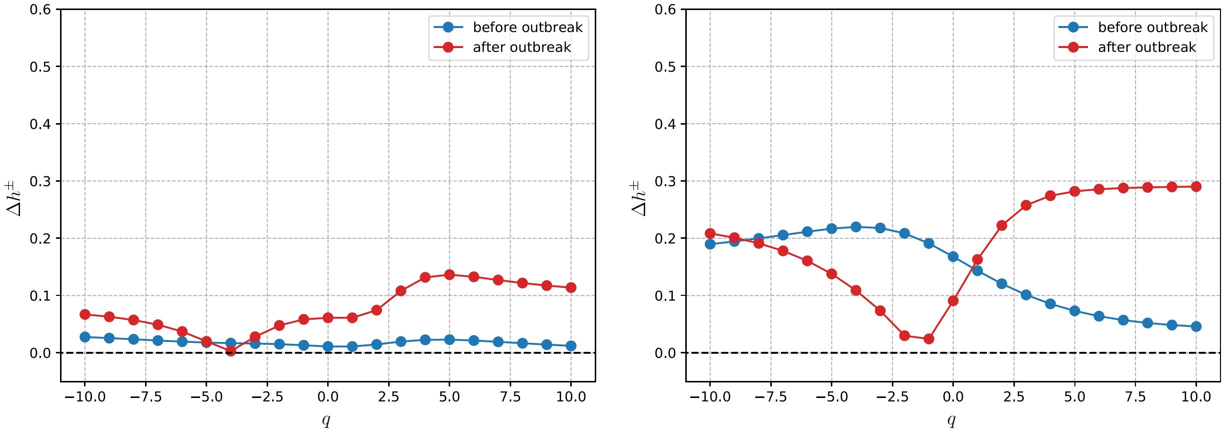

Fig. 7. The case of Ethereum. Asymmetric degree of multifractality between upward trends and downward trends for the short-term horizon (left) and long-term horizon (right), respectively.

Table 3
The level of multifractality Δh for the shuffled and surrogated series with respect to short-term horizons. The smaller values between shuffled and surrogated series are shown in bold.

Short-term ($s < s^*$)		Before outbreak			After outbreak		
		Original	Shuffled	Surrogated	Original	Shuffled	Surrogated
BTC	overall	0.359	0.459	**0.086**	0.599	0.568	**0.255**
	uptrend	0.321	0.464	**0.161**	0.520	0.565	**0.244**
	downtrend	0.420	0.450	**0.037**	0.600	0.578	**0.206**
ETH	overall	0.473	0.446	**0.154**	0.647	0.528	**0.251**
	uptrend	0.479	0.423	**0.193**	0.687	0.502	**0.273**
	downtrend	0.464	0.440	**0.151**	0.506	0.520	**0.213**

Table 4
The level of multifractality Δh for the shuffled and surrogated series with respect to the long-term horizon. The smaller values between shuffled and surrogated series are shown in bold.

Long-term ($s > s^*$)		Before outbreak			After outbreak		
		Original	Shuffled	Surrogated	Original	Shuffled	Surrogated
BTC	overall	0.627	0.174	**0.093**	0.349	0.274	**0.162**
	uptrend	0.475	0.194	**0.018**	0.240	0.271	**0.122**
	downtrend	0.875	**0.199**	0.275	0.712	**0.308**	0.332
ETH	overall	0.632	**0.174**	0.278	0.232	**0.207**	0.242
	uptrend	0.546	0.187	**0.162**	0.183	0.226	**0.157**
	downtrend	0.690	**0.193**	0.346	0.605	**0.220**	0.415

Although the empirical findings uncover properties of asymmetric multifractality and how they have changed during the pandemic, further implications of multifractality need to be addressed to advance the discussions of EMH. Therefore, we explore the sources of multifractality. It is well known that the multifractality of financial time series is mainly a consequence of the two major phenomenon: the broad probability density function and long-range correlations between elements of time series. To understand the contribution of long-range correlations, we compare the level of multifractality between the original series and random shuffled series. The shuffling procedure can destroy all correlations of returns, while the distribution remains unchanged. To understand the contribution of broad probability density function, we surrogate the returns with Gaussian distribution, while maintaining the same rank ordering by sorting the generated returns, and compare its multifractality with the original one. This procedure eliminates the fat-tails but the linear correlations are preserved (Cao et al., 2013). To quantify the level of multifractality, we employ the following measure (Cao et al., 2013):

$$\Delta h = \max_q(h(q)) - \min_q(h(q)). \tag{10}$$

Greater values indicate stronger multifractality.

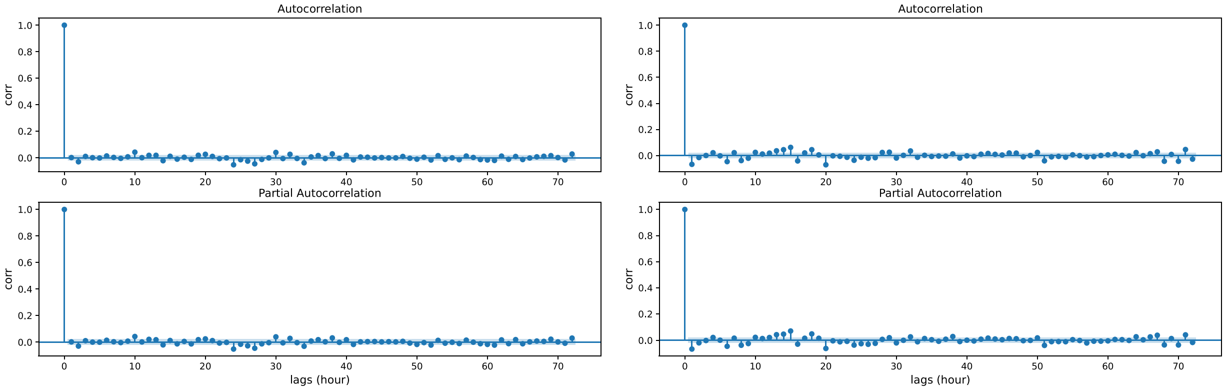

Fig. A.8. ACF and PACF functions for the case of Bitcoin return series before the outbreak (left) and after the outbreak (right).

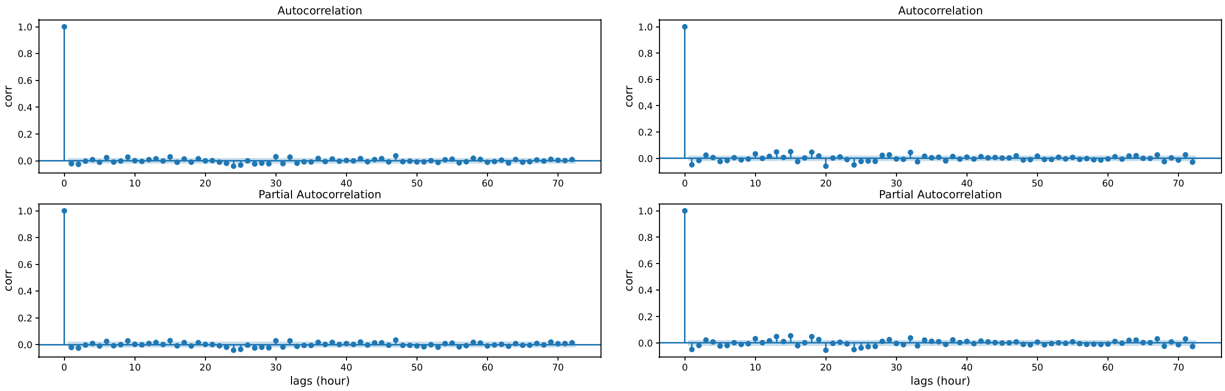

Fig. A.9. ACF and PACF functions for the case of Ethereum return series before the outbreak (left) and after the outbreak (right).

We show in Tables 3 and 4 the level of multifractality for the shuffled and surrogated series of Bitcoin and Ethereum returns before and after the outbreak with respect to different investment horizons.[5] When focused on the short-term horizon (Table 3), the multifractality levels of the shuffled series are hardly weaker than those of the original series, but the surrogated ones are obviously weaker during both periods. This indicates that fat-tailed distribution is the main cause of multifractality and correlations of large and small fluctuations is not an essential factor. We note that this nature does not change before and after the outbreak. In the long-term horizon (Table 4), we can see that both sources have significant impacts on multifractality, especially before the outbreak. The impact of both sources become smaller after the outbreak, which highlights the positive effect on EMH in the long-run. Nevertheless, the surrogated results suggest that fat-tailed distribution contributes to multifractality in the long-run as well, meaning that local behaviors caused by fat-tails are likely to be reflected in the global behaviors. Interestingly, the levels of multifractality are weaker for the surrogated series in uptrend markets, while they are weaker for the shuffled series in downtrend markets. This implies that fat-tails contribute more to multifractality than autocorrelations when the market value goes up, while autocorrelations contribute more than fat-tails when the market value goes down. Therefore, substantial asymmetric properties of Bitcoin and Ethereum in the long-term horizon, shown in the right panels of Figs. 6 and 7, can be due to the presence of different predominant sources of multifractality between bull and bear markets.

5. Conclusion

This study evaluated market efficiency and asymmetric multifractality of the two major cryptocurrencies (Bitcoin and Ethereum) during the periods before and after the COVID-19 outbreak, accounting for the different scaling regimes on fast and slow time scales. By using the A-MFDFA method, we found that the markets have asymmetric multifractality with crossovers of approximately 10 days, indicating that scaling behaviors are dependent of investment horizons. Our results provided empirical evidence of increasing inefficiency for the short-term, while the markets show traces of efficiency for the long-term. In other words, COVID-19 significantly

[5] For the level of multifractality, we employ the average of 100 synthetic Δh calculated from the shuffled/surrogated series to avoid strong biases due to sample size.

increased herding in the short-run but not in the long-run. This study also discussed the features of asymmetric properties between upward and downward trends. For the short-term, there was only a subtle change of asymmetry after the outbreak, but for the long-term, there was a substantial shift in the degree of asymmetry where investors have focused more on larger fluctuations. Although fat-tailed distribution of returns generally causes the multifractal behavior, the contribution of autocorrelations to multifractality becomes substantial in the long-term when the market is in a downtrend (bear market). The presence of different predominant sources of multifractality between bull and bear markets could be a driver to the substantial asymmetric properties of Bitcoin and Ethereum observed in the long-term. Our findings argue that analyzing different scales of horizons can be a key to reveal complex behaviors during crisis periods, although the relationship between multifractality and asymmetric efficiency of the on-going COVID-19 pandemic is still debatable. These results offer opportunities for investors and portfolio managers to understand cryptocurrency market efficiency that plays a crucial role in their decision-making.

CRediT authorship contribution statement

Shinji Kakinaka: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing, Visualization. **Ken Umeno:** Validation, Writing – review & editing, Supervision.

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.

Appendix. ACF/PACF functions

We show in this section the ACF and PACF functions for the cases of Bitcoin and Ethereum return series before and after the outbreak. Note that for stationarity stochastic process, the Hurst exponent ranges from 0 to 1, and the ACF takes the form $\rho(\tau) \sim H(2H-1)\tau^{2H-2}$ (Løvsletten, 2017). The correlation functions in Figs. A.8 and A.9 die down very quickly, which is consistent with our results of $H \simeq 0.5$.

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