COVID-19, bitcoin market efficiency, herd behaviour

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Abstract

Purpose – Unlike previous crisis where investors tend to put their assets in safe havens like gold, the recent coronavirus pandemic is characterised by an increase in the Bitcoin purchasing described as risk heaven. This paper aims to analyse the Bitcoin dynamics and the investor response by focusing on herd biases. Therefore, the main objective of this work is to study the degree of efficiency through multifractal analysis in order to detect herd behaviour leading to build the best predictions and strategies.

Design/methodology/approach – This paper develops a novel methodology that detects the presence of herding biases and assesses the inefficiency of Bitcoin through an inefficiency index (MLM) by using statistical indicators defined by measures of persistence. This study, also, investigates the nonlinear dynamical properties of Bitcoin by estimating the Multifractal Detrended Fluctuation Analysis (MFDFA) leading to deduce the effect of COVID-19 on the Bitcoin performance. Besides, this work performs an event study to capture abnormal changes created by COVID-19 related events capable to analyse the Bitcoin market response.

Findings – The empirical results of the generalized Hurst exponent GHE estimation indicates that Bitcoin is multifractal before this pandemic and becomes less fractal after the outbreak. Using an efficiency index (MLM), Bitcoin is found to be more efficient after the pandemic. Based on the Hausdorff topology, the authors showed that this pandemic has reduced the herd bias.

Research limitations/implications – The uncertainty of COVID-19 disease and the lasting of its duration make it difficult to make the best prediction.

Practical implications – The main contribution of this study is the evaluation of the Bitcoin value after the COVID19 outbreak. This work has practical implications as it provides new insights on trading opportunities and social reactions.

Originality/value – To the authors' knowledge, this work represents the first study that analyses the Bitcoin response to different events related to COVID-19 and detects the presence of herding behaviour in such a crisis.

Keywords Bitcoin, Herding bias, Efficiency index, Generalised Hurst exponent, COVID19

Paper type Research paper

1. Introduction

In December 2019, a new respiratory illness known as COVID-19, caused by a novel coronavirus was first detected in the central Chinese city of Wuhan. Within the first five weeks of the outbreak, tens of thousands of people were infected and more than a thousand died. The outbreak has been categorized by the world health organization as a public health emergency. The virus is having economic impacts throughout the world. Major companies and airlines around the world have cancelled flights to and from the region. On January 31, 2020, the Dow dropped more than 2% during the day on coronavirus fears, wiping out all the gains of January. COVID-19 is devastating economics around the world. As declared by the United Nations, the global economic impact of the coronavirus could reach 2 trillion dollars. The Federal Reserve estimates a cost of 47 million in American jobs. On the other side, the Bitcoin cryptocurrency presents different behaviour during the coronavirus outbreak as shown in Figure 1. Some studies consider Bitcoin as a hedge safe heaven (Dyhrberg, 2016) while others found that it is a poor hedge and it is suitable for diversification matters (Bouri *et al.*, 2017). Studying the impact of epidemic diseases has renewed the attention of academics in crypto studies. The main purpose of this paper is to

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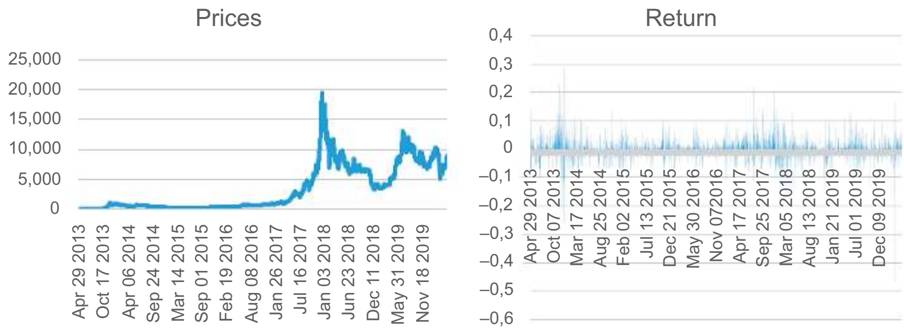

Figure 1.
Bitcoin prices and returns

assess the level of herding behaviour in Bitcoin market and to deduce its degree of resilience and efficiency.

Recently, multiple academic research has explored the concept of market efficiency to predict the market and determine suitable strategies (Dotsika and Watkins, 2017). Market efficiency suggests that prices reflect certain information related to asset pricing and that it is not possible to earn abnormally high average returns using said information. As new information randomly arrives, prices will change randomly. Major studies classified efficiency into weak form efficiency based on technical analysis reflecting all past prices with trading volume information (Gupta and Basu, 2011), semi-strong efficiency based on fundamental analysis indicating all public information (Vidal-Tomás and Ibañez, 2018), and the strong form of efficiency integrating all private information based on both technical and fundamental analysis (Chau and Vayanos, 2008). Several models based on multifactor have been explored to judge the level of market efficiencies such as the three-factor model (Daniel *et al.*, 2020), the q-factor model (Hou *et al.*, 2015), the four-factor model (Stambaugh and Yuan, 2017), and the q^5-factor model (Hou *et al.*, 2019). Even though, recent studies have introduced the disaster risk in their predictive analysis (Bai *et al.*, 2019; Tsai and Wachter, 2016). Besides, several academic researchers have focused on the presence of herding behaviour during periods of crisis.

Herding behaviour is defined by Banerjee (1992) as the fact of doing what others are doing without using their own information. This behaviour bias leads to excessive volatility in financial markets with short term trends (Humayun Kabir and Shakur, 2018). Consequently, speculative bubbles and crashes are created from repeated behavioural scenarios. The herding bias in finance can be caused by unintentional behaviour triggered by an event making traders and investors sell and buy simultaneously the same asset (Lakonishok *et al.*, 1992). In the same way, this bias can be linked to intentional factors such as informational cascades (Avery and Zemsky, 1998) and reputational concerns (Scharfstein and Stein, 1990). Forbes and Rigobon (2002) found that the investor biases generated by herding behaviour, the lack of confidence, and the great uncertainty provides excessive co-movement. Herding behaviour is classified as rational (Orléan, 1992) and non-rational, market-wide (Henker, Henker and Mitsios, 2012) and group-wide (Lillo *et al.*, 2008). The previous studies captured the market-wide herding via the relation between the cross-sectional dispersion and stock returns (Christie and Huang, 1995). Hereafter, Hwang and Salmon (2004) proposed a novel approach based on the cross-sectional dispersion of the betas. Lakshman *et al.* (2013) and Chen *et al.* (2007) estimated the herding behaviour using the dispersion of betas and they found that herding behaviour is a result of the sentimental and psychological components rather than macro factors. Consequently, they showed this behaviour is less widespread during periods of market stress. Several previous studies pay particular attention to stock markets (Chiang and Zheng, 2010) and commodity markets (Demirer *et al.*, 2015) to examine the presence of this bias. Some recent empirical works studied this behaviour in cryptocurrency markets (Ballis and Drakos, 2019). Motivated by the lack of studies on exploring the herding behaviour through multifractal detrended fluctuation analysis and considering the importance of COVID-19 pandemic on cryptocurrency markets, we examine the presence of herding behaviour and the Bitcoin efficiency during this coronavirus crisis using the MFDFA approach and event study methodology. This paper contributes to the existing literature in various novel ways.

First, this paper uses epidemic virus events instead of including disasters related to macroeconomic factors such as productivity and consumption. The COVID-19 coronavirus infected the entire world; therefore, we study an international asset widely spread in all territories. Second, this study employs both technical and fundamental tools to assess the efficiency level and the resilience of Bitcoin in such a crisis. In other words, we use the multifractal detrended fluctuation analysis to determine the complexity and the weak form efficiency of Bitcoin. Besides, we employ the event study approach to present the effect of the pandemic crisis on the Bitcoin value by focusing on the abnormal returns capable to interpret the semi-strong form of efficiency. Third, we analyse the multifractality states before and during the COVID19 pandemic. Therefore, our analysis covers the entire period and provides a full picture on the price dynamics of Bitcoin. The fourth contribution is illustrated in the use of Bitcoin assets as it plays an essential role in both financial markets and technological instruments.

Finally, the last contribution of this work is that it tries to explain the drivers of these results by using search volume queries from "Google Trends".

The empirical results show that Bitcoin behaves in a multifractal process before the COVID 19 event afterward it becomes less fractal indicating more efficiency after the epidemic outbreak. Besides, the results highlight significant abnormal returns during the selected event dates. Furthermore, COVID-19 events have a significant negative and positive effect during the selected event window. In summary, the efficiency of the Bitcoin market is sensitive to scales, to the COVID 19 outbreak, and to market trends highlighting the investor sentiment effect and the level of herding behaviour. Consequently, these findings have several implications for traders, investors and policymakers.

The rest of this paper is planned along these lines: In the second section, a summarized literature review is gathered. Data are described in the third section and methodology is presented in the fourth section. The empirical results were discussed in the fifth section. The conclusion is drawn in the last section.

2. State of the art

The financial stability in markets is essential for investment security and safety. The excessive volatility can be the genesis of an unstable market for a certain period (Demirer *et al.*, 2015). Therefore, stability conditions might be spelled by financial innovation tools such as mathematics-based models. Previous theories based on Gaussian distribution are insufficient to predict the future of capital markets (Fry and Cheah, 2016). Multifractal models are more accurate patterns in forecasting matters with different market risks. Mandelbrot (1975) is the leader of the first study on fractal theory and he defined fractals as complex geometrical bodies with one feature of scaling embed in them. These fractals are employed in finance to detect crashes and crises. In 1997, Benoit B. Mandelbrot created a multifractal model to identify the price variation of financial assets. In 2009, the Multifractal Detrended Fluctuation was proposed by Kantelhardt to determine the statistical characteristics of the stochastic series over different time scales (Winsor, 1995).Recent studies have focused on the weak-form efficiency by employing market fractal theory (Han *et al.*, 2019). This theory was, also, applied to Bitcoin to assess the semi-strong and weak form efficiency (Nan and Kaizoji, 2019). Furthermore, this approach was investigated to determine the dynamic efficiency during catastrophic events (Sensoy and Tabak, 2016).

Event study methods were employed especially in stock markets to assess the impact of certain events on the performance of the market index and firms (Lyon *et al.*, 1999). It was also employed in the health care domain (Baril *et al.*, 2016), tourism business (Kaplanski and Levy, 2010), and cryptocurrency trade studies (Ante, 2019). Particularly, this approach was investigated to analyse the effect of some epidemic disease on stock markets (Chen *et al.*, 2007). The influence of infectious disease studies was explored by many research such as Malaria (Cervellati *et al.*, 2018) and SARS epidemic disease (Kostoff, 2011). Furthermore, their impact on financial and economic dimensions was investigated by Bennett *et al.* (2015) and Claessens *et al.* (2010). Recent studies have studied the effect of the geographic proximity of Ebola information on stock markets in the United States of America using search volumes intensity and event study methods (Ichev and Marinč, 2018). Their findings indicate that the Ebola disease has broken out in African companies with a greater effect. However, the recent epidemic disease COVID-19 was not widely developed because of its uncertainty. This study employed the event study approach to explore the effect of COVID-19 coronavirus outbreaks on Bitcoin value. The event study method has been widely used in financial markets and strategy studies (Ederington *et al.*, 2015; Civitarese, 2018).

This work contributes to the literature by exploring the effect of the recent epidemic coronavirus on the cryptocurrency value. The implications of this analysis are essential for cryptocurrency traders and strategy-makers in analysing and forecasting the behaviour of financial market outcomes during the coronavirus epidemic period.

3. Data

The sample consists of financial and search volume data. Financial data includes Bitcoin cryptocurrency during the period between1 19 April 2013 to 5 May 2020, extracted in daily frequency according to their availability from www.coinmarketcap.com. The search volume data retrieved from "Google Trends" for the term "FED Bitcoin" during the period between February and May 2020 in daily frequencies.

The daily returns of Bitcoin are defined as:

$$r_t = \log\left(\frac{p_t}{p_{t-1}}\right) \quad (1)$$

where r_t is the cryptocurrency return at date t, and P_t is the cryptocurrency price at date t.

Figure 1 depicts the evolution of daily cryptocurrencies' prices and returns.

4. Methodology

In the first part of our methodology, we begin by applying the fractal theory to detect the efficiency level of Bitcoin market.

4.1 Market multifractality

4.1.1 The MFDFA approach. The *Multifractal detrended fluctuation analysis (MFDFA) method mainly contains 5 steps as detailed by* Kantelhardt *et al.* (2002). The MDFA approach can be expressed as follow: x_i is a time series of length N, i ranges from 1 to N.

In step 1, we identify the profile or cumulative sum $Y(i)$:

$$Y(i) = \sum_{k=1}^{i} |x(k) - \bar{x}|, \tag{2}$$

$\bar{x}$ denotes the mean value of the whole series $\left(\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i\right)$.

Step 2 consists of dividing the profile Y_t into $N_s \equiv \frac{N}{s}$ segments of equal length s. To ensure that the complete information is included, the same process is run starting from the opposite of the series Y_v. Therefore, $2N_s$ segments are constructed.

The local trend is estimated, in the next step, by least-square fitting polynomial $\widetilde{Y_v}$ for any segment of length v.

$$F_S^2(v) = \frac{1}{s}\sum_{k=1}^{s} \left(Y_v(k) - \widetilde{Y_v}(k)\right)^2 \tag{3}$$

This detrending process is repeated over a range of various window sizes s.

In the fourth step, we average the segments to draw the qth order fluctuation function F_q:

$$F_q(S) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s} \left[F_s^2(v)\right]^{\frac{q}{2}}\right\}^{\frac{1}{q}} \tag{4}$$

In the last step, the scaling behaviour of the fluctuation functions is identified by plotting the log-log plots of $F_q(s)$ for each value of q versus s:

$$F_q(S) \propto S^{H(q)} \tag{5}$$

The series is monofractal when $H(q)$ is constant for all q. Otherwise, the series becomes multifractal.

In this paper, we estimate the multifractal spectrum with various m values ($m = 1, m = 2$, and $m = 3$). Accordingly, we chose to set the order at $m = 1$ to avoid over fitting as detailed in the work of Lashermes *et al.* (2004).

4.1.2 Generalized Hurst exponent (GHE). Hurst exponent (Hurst, 1951) is used as a metric of bubble detection. In other words, when $H < 0.5$, the series are antipersistent with no shape and lesser fractal quotient. Therefore, we are in the case of no herd behaviour.

$H = 0.5$ implies that the series follows a theoretical random walk and they are entirely stochastic in nature.

Finally, when $H > 0.5$, the series is evidently persistent with clear shape, higher fractal quotient, and a trace of herd behaviour.

The roughness of financial markets was firstly introduced by Mandelbrot (1963). In the case of fractional Brownian, the roughness of the series was evaluated by estimating the Holder exponent (H) (Mandelbrot and Van Ness, 1968). The fractal dimension (d) is then defined as:

$$d = 2 - H \text{ when } 0 < \mathrm{H} < 1 \tag{6}$$

$$\text{and } d = 1.5 - \alpha \text{ when } -0.5 < \alpha < 0.5 \tag{7}$$

The scaling function of the multifractal process $\tau(q)$ is concave for the multifractal and linear for the monofractal process. $\tau(q)$ can be formulated from either the generalized Hurst exponent:

$$H(q) = \frac{1 + \tau(q)}{q} \tag{8}$$

Or from the generalized fractal dimension:

$$d(q) = \frac{\tau(q)}{q - 1} \tag{9}$$

The following relations in Eqn 10 are obtained from a Legendre transform:

$$\alpha = H(q) + q.H^{'}(q) \tag{10}$$

Therefore, the singularity spectrum $f(\alpha)$ is defined as

$$f(\alpha) = q\alpha - q.H(q) + 1 \tag{11}$$

In this study, we fix the scaling range at $s_{\min} = 10$ and $s_{\max} = (T/4)$ for MF-DFA as suggested by (Rizvi *et al.*, 2014), where T is the series' length of the used cryptocurrency.

4.1.3 Magnitude of long-memory or the inefficiency index (MLM). In this section, we define a measure of long memory magnitude related to the generalized Hurst exponent to quantify the market efficiency level.

The inefficiency index based on the multifractal dimension indicates that the fluctuations comprising smaller $H(-5)$ and larger $H(5)$ follow the random walk process.

In other words, when MLM = 0 the volatility of Bitcoin returns is absolutely efficient with no long memory.

Accordingly, a higher (lower) value of MLM indicates a higher (lower) level in long memory and a higher level in herding behaviour in Bitcoin market. Ultimately, this work evaluate the efficiency level by the inefficiency index (MLM) suggested by (Khuntia and Pattanayak, 2020), denoted as:

$$\text{Magnitude of Long} - \text{memory (MLM)} = \frac{1}{2}\left(|h(-5) - 0.5| + |h(5) - 0.5|\right) \tag{12}$$

4.2 COVID-19 impact on the financial market

After studying the market efficiency, we lead an event study to see how the Bitcoin prices react to the return of a special event.

Event studies are helpful in evaluating how the previous events affected the value of the asset. Prices are used in this approach rather than returns because accounting measures (return) cannot differentiate between the event's impact and business trends (MacKinlay, 1997). According to this theory, the investors estimate the impact of an event based on the changes in the trading activities (Nicolau, 2002). When the market is efficient, the event study method can capture abnormal changes in the market value of an asset created by an event. Cryptocurrencies present distinct characteristics than the stock markets and commodities. They are more complex and nontrivial for event conceptualisation. Nevertheless, recent studies underlined the importance of using event studies to generate abnormal returns and to detect the crypto-market response (Civitarese, 2018). MacKinlay (1997) fixed the length of the estimation window at 250 days because the frequency of the trading dates in stock markets during one year is equal to 250. That is why we chose to set the estimation window at 365 because Bitcoin is traded every day. The event dates correspond to, respectively, 31 December 2019, 23 March 2020, and 06 April 2020. The abnormal returns and cumulative abnormal returns of Bitcoin affected by the COVID-19 disease are estimated by using the mean-adjusted return market. The CAPM model is not employed because of two major reasons. First, Bitcoin represents more than half of the total cryptocurrency market capitalisation. Therefore, it corresponds to a descent value-weighted market proxy. Second, there is not an evident risk-free for the cryptocurrency market. In this part, we follow Kim *et al.* (2020) in setting the event window at five days before the event day and ten days after the event date as it is suitable for epidemic diseases cases. The abnormal return AR of Bitcoin on day t belonging to the event window is defined as:

$$AR_t = R_t - E(R_t) \tag{13}$$

where R_t is the return of the Bitcoin on day t and $E(R_t)$ is average of the returns R_t. The cumulative average residuals are summarized as:

$$CAR_t = \sum_{t}^{j} \mathrm{AR}_t \tag{14}$$

In a final step of this methodology, this work tends to explain the drivers of the Bitcoin behaviour by using the search volume engine "Google Trends". The searched volumes can capture the attention of people towards Bitcoin during this outbreak.

5. Empirical results

The qth-order Hurst exponent in Figure 2 has been expressed as "h_q" for Bitcoin and it has been found to have various traces. The scaling function $\tau(q)$ of the multifractal process plots in Figure 3 before the outbreak is concave implying that Bitcoin is multifractal processes, however, it becomes almost linear after the outbreak implying that Bitcoin returns become less fractal after the outbreak. In Figure 4, the spectrum is left-skewed before the outbreak and it becomes slightly right-skewed after the COVID-19 outbreak showing the relative dominance of certain fluctuations in the time dynamics of the Bitcoin series.

In Figure 2, we set $H(q = \pm 5)$ because of the soft change in the slope for $q > 5$. The estimation results of the GHE are drawn in Table 1 where q ranging between -5 and 5. In Table 1, we use negative q for explaining the effects of small price variations and positive q for large variations. The original return series is fractional Gaussian Motion (fGN) because *Hq* () ranges from 0 to 1 for both periods. Table 1 shows that the Hurst estimate of Bitcoin (*Hq*) is about 0.5221 before the COVID19 outbreak when $q = 2$. After the outbreak, *Hq* value becomes less than 0.5 denoting antipersistent behaviour and therefore no herding behaviour. The generalised Hurst exponent *Hq*() varies moderately when q change for both periods.

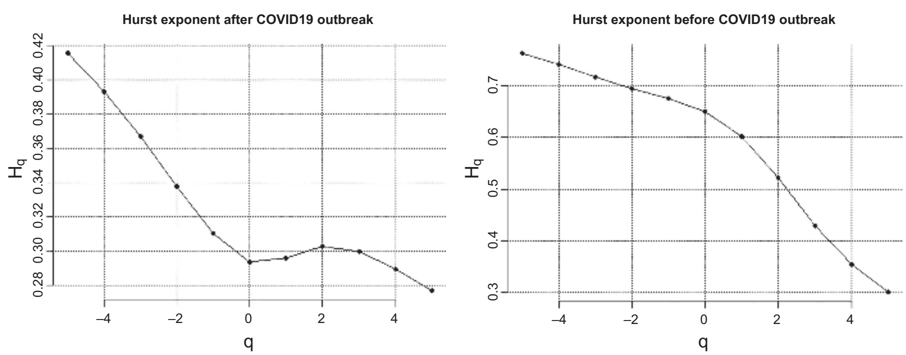

Figure 2.
Hurst exponent

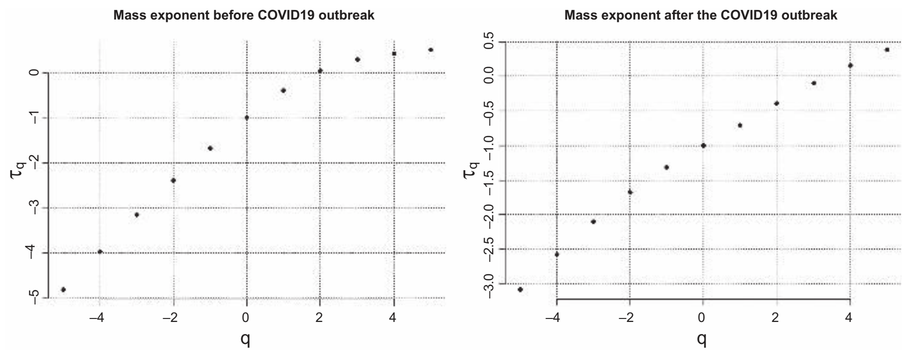

Figure 3.
Mass exponent

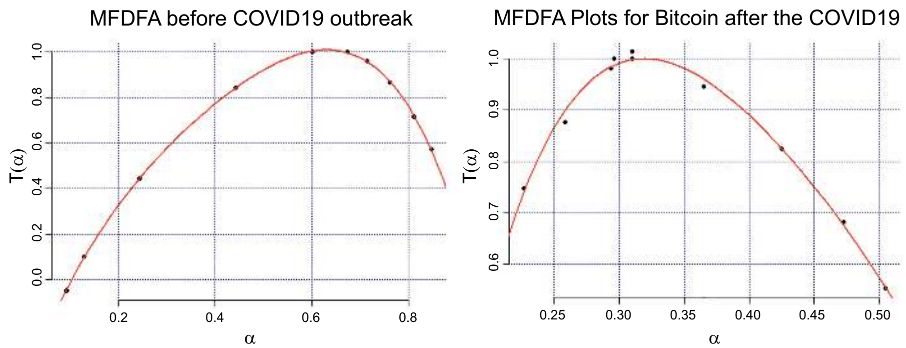

Figure 4.
MFDFA plots

Table 1.
Generalised Hurst exponent

	Before the COVID-19 outbreak				After the COVID-19 outbreak			
	Tau-*q*	*Hq*	α	$f(\alpha)$	Tau-*q*	*Hq*	α	$f(\alpha)$
−5	−4.8085	0.7617	0.8473	0.5720	−3.0775	0.4155	0.5047	0.5540
−4	−3.9612	0.7403	0.8473	0.5720	−2.5728	0.3932	0.5047	0.5540
−3	−3.1498	0.7166	0.8114	0.7156	−2.1001	0.3667	0.4727	0.6820
−2	−2.3880	0.6940	0.7618	0.8644	−1.6750	0.3375	0.4251	0.8248
−1	−1.6742	0.6742	0.7138	0.9604	−1.3101	0.3101	0.3649	0.9452
0	−1.0000	0.6491	0.6742	1.0000	−1.0000	0.2936	0.3101	1.0000
1	−0.3981	0.6019	0.6019	1.0000	−0.7041	0.2959	0.2959	1.0000
2	*0.0442*	*0.5221*	*0.4423*	*0.8404*	*−0.3944*	*0.3028*	*0.3097*	*1.0138*
3	0.2870	0.4290	0.2428	0.4414	−0.1009	0.2997	0.2935	0.9814
4	0.4164	0.3541	0.1294	0.1012	0.1576	0.2894	0.2585	0.8764
5	0.5085	0.3017	0.0921	−0.048	0.3840	0.2768	0.2264	0.7480
Efficiency index	*0.23*				*0.15*			

These results of *Hq* () change show that the Bitcoin market becomes less fractal. This result is consistent with the findings of Mnif *et al.* (2020) where they found that cryptocurrency markets demonstrate different regimes with various characteristics of multifractality before the COVID 19 outbreak and become less fractal after the outbreak. Figure 4 displays the multifractal spectrum before and during the COVID19 pandemic. The results in Figure 4 show that the multifractal spectrum has a larger width before the outbreak than the spectrum after the outbreak.

In addition, Table 1 summarizes the results of the efficiency index for Bitcoin before and after the outbreak. This measure is about 0.23 before the outbreak and it is reduced to 0.15385 after the outbreak showing that the Bitcoin market becomes more efficient after the outbreak. These results are consistent with those of Demirer *et al.* (2015).

Based on the Hausdorff topology (Hausdorff, 1918) the level of herding bias increases when the fractal dimension (d) decease (Ghosh and Kozarevic, 2019). In the case of $q = 2$, $d = 1.4779$ before the COVID-19 outbreak and becomes 1.6972 after the outbreak showing that this pandemic has reduced the herding bias. These findings are in line with those of Soofi *et al.* (2020) who demonstrated that the COVID 19 pandemic can stimulate several behavioural biases such as herding behaviour, status quo bias, optimism effect, heuristics bias, and framing effects.

All of these results are in line with previous studies on Bitcoin efficiency (Nadarajah and Chu, 2017;Tiwari *et al.*, 2018). However, these studies lack a quantification study on the efficiency and herding levels over time in moments of epidemic diseases. Furthermore, the impact of diseases and disasters has not been explicitly measured in previous research.

This paper develops these issues by firstly quantifying the level of efficiency and multifractality with the efficiency index and the singularity spectrum which is measured by the singularity spectra $f(\alpha)$ for Bitcoin series against the Holder exponent α. Secondly, we employ the event study methodology to assess the influence of COVID19 events on Bitcoin returns. We select three major events that happen during the COVID19 outbreak. These events are summarized in Table 2 and classified into positive and negative events. By examining the returns after an event, profitable rules can be retrieved when abnormal returns are generated denoting inconsistence with the market efficiency. Therefore, the cumulative average residual approach (CAR) is used to test market efficiency hypothesis and providing the overall influence of an event on the Bitcoin market as depicted in Figures 5 and 6.

Table 3 provides abnormal returns and their statistical significance. Accordingly, the COVID 19 event does not generate significant abnormal returns because corresponding t-statistics are less than 1.96 during the period between 5 days before and 10 days after the event. However, the quantitative easing policy announced by the FED provides positive significant abnormal returns before 4 days, after 7 days, and on the day of the announcement of this policy. However, Treasury's Payment Protection Program event announced by the FED does not stimulate significant abnormal returns.

Table 4 estimates the impact of the cited events on Bitcoin efficiency. Accordingly, the COVID 19 event has a significant negative effect on the same date of the event announcement, after one day, and for 2 days because the corresponding t-statistics are less than 1.96. It has also a significant positive effect during 6, 7, 8, 9, and 10 days after the event occurrence. Besides, it has a significant positive impact when we strengthen the window between 5 days

Event date	Event designation	Event	Positive/Negative
31/12/2019	COVID19	In Wuhan City, a cluster of 27 pneumonia cases is reported by Wuhan Municipal Health Commission including seven severe cases and linked it to the Wuhan market	Negative
23 March 2020	FED QE	Federal Reserve announced the quantitative easing with no upper limit	Positive
06 April 2020	FED	The FED will provide support to Treasury's Payment Protection Program	Negative

Table 2.
Major events

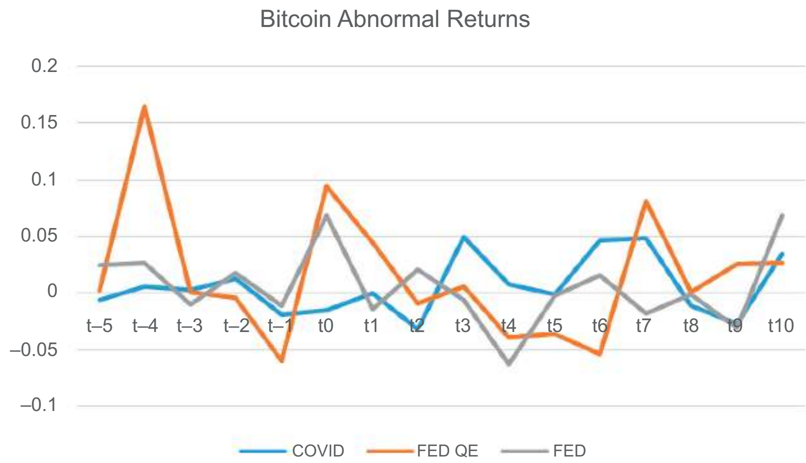

Figure 5.
Bitcoin abnormal return

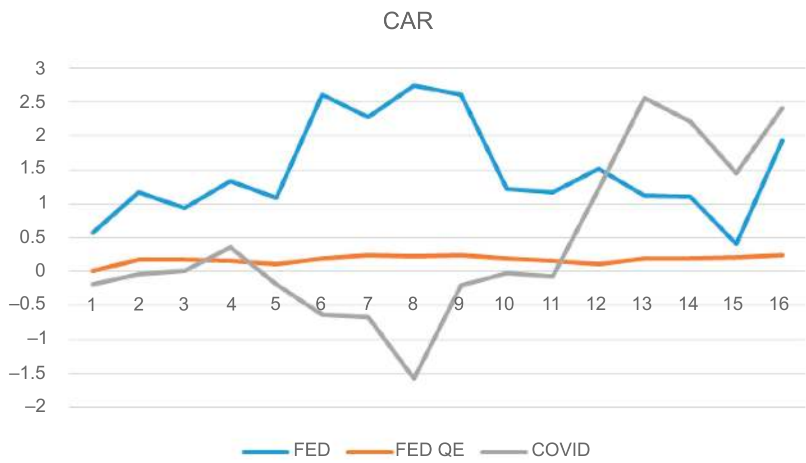

Figure 6.
CAR plots

before and 10 days after the event. However, the quantitative easing policy announced by the FED does not provide any significant effect during these periods.

Furthermore, Treasury's Payment Protection Program event announced by the FED has a significant positive effect on Bitcoin on the day of the FED announcement and in the period between 5 days before and 10 days after this event announcement.

Most government has announced the self-quarantine during this pandemic. This situation lets people working from home and leading to a bump in online searches. In particular, Bitcoin was the most searched term in the world. According to the Chinese BAIDU report, the searches for Bitcoin jumped to one hundred and eighty-three percent over the past three months. In addition, search volumes on "Google Trends" shows a significant interest of users towards "Bitcoin". Particularly, users are searching for the Federal Reserve regulation and Bitcoin as indicated by Figure 7.

The peak of this interest is reached on 16 March of 2020 after the notable decline in Bitcoin prices. If the FED is printing much money to face this crisis, people are wondering how they

Table 3. Abnormal returns

	COVID19		FED QE		FED	
	Abnormal return	t-statistic	Abnormal return	t-statistic	Abnormal return	t-statistic
t_{-5}	−0.00618562	−0.19387438	0.00113608	0.02522721	0.02517177	0.55979526
t_{-4}	0.00590339	0.14823609	0.16474288	3.65820738*	0.02707522	0.60212615
t_{-3}	0.00271699	0.05806319	0.00012176	0.00270385	−0.01027378	−0.22847864
t_{-2}	0.01299867	0.34902728	−0.00449115	−0.09972854	0.01817265	0.40414168
t_{-1}	−0.01854869	−0.54374047	−0.06018679	−1.33648112	−0.01127261	−0.25069168
t_0	−0.0151689	−0.44809485	0.0945621	2.09980411*	0.06802507	1.51281031
t_1	−0.00051465	−0.03338983	0.04425233	0.98264756	−0.01426992	−0.31734887
t_2	−0.03185108	−0.92018864	−0.00962246	−0.21367212	0.02052328	0.45641755
t_3	0.04907186	1.36987277	0.00513446	0.11401347	−0.00571395	−0.1270726
t_4	0.00759973	0.19624119	−0.0388813	−0.86338101	−0.06270241	−1.3944395
t_5	−0.00113084	−0.05082757	−0.03644902	−0.80937081	−0.0020304	−0.04515412
t_6	0.04603038	1.28380108	−0.05422856	−1.20417534	0.01553321	0.34544334
t_7	0.04834778	1.34938185	0.08064871	1.79084953*	−0.0182746	−0.4064099
t_8	−0.01135557	0.96273215	0.00021881	0.00485886	−0.00093654	−0.02082769
t_9	−0.02671484	−0.34018027	0.02495497	0.55413894	−0.0309829	0.68902918
t_{10}	0.0346849	−0.77483663	0.02685842	0.59640616	0.06846613	1.52261914

Table 4.
Cumulative average residual (CAR)

	COVID19 outbreak		FED QE		FED announcement	
	CAR	t-statistic	CAR	t-statistic	CAR	t-statistic
t_{-0}	−0.44809485	−2.38373346*	0.0945621	0.18149575	1.19546145	5.63758758*
$t_{-0}\sim t_1$	−0.48148468	−1.81115332*	0.13881442	0.24666672	1.65187899	5.50834279*
$t_{-0}\sim t_2$	−1.40167332	−4.30500759*	0.12919196	0.21474125	1.52480638	4.1515646*
$t_{-0}\sim t_3$	−0.03180055	−0.08458482	0.13432642	0.21050633	0.13036679	0.30739351
$t_{-0}\sim t_4$	0.16444064	0.39121175	0.09544512	0.14189879	0.08521266	0.17971191
$t_{-0}\sim t_5$	0.11361307	0.24674048	0.0589961	0.08362804	0.43065601	0.82911087
$t_{-0}\sim t_6$	1.39741415	2.80972528*	0.00476754	0.00647036	0.0242461	0.0432166
$t_{-0}\sim t_7$	2.746796	5.16617549*	0.08541625	0.11137656	0.00341841	0.0056995
$t_{-0}\sim t_8$	2.40661572	4.26749713*	0.08563506	0.10760007	−0.68561077	−1.07774026
$t_{-0}\sim t_9$	1.6317791	2.74504272*	0.11059003	0.51992528	0.83700837	1.24820962
$t_{-0}\sim t_{10}$	2.59451124	4.16147181*	0.13744844	0.6461968	0.83700837	1.19012118
$t_{-5}\sim t_0$	−0.63038312	−1.36904176	0.19588488	0.37596746	2.59970309	5.0050204*
$t_{-5}\sim t_{10}$	2.41222297	3.20808007*	0.23877122	1.12255327	1.92390114	9.07278208*

can protect their money value especially when stock markets and precious metals are suffering during this pandemic crisis. People are looking, therefore, to hold value in this time of turmoil. Consequently, people are more interested in buying cryptocurrencies offering, therefore, more security to their money.

In moments of crisis and uncertainty, people often follow the masses. This phenomenon can be explained by some psychological elements such as herd behaviour which can be caused by media or some reports or news. Consequently, bubbles will be created causing market crashes. In the case of the Bitcoin market, this bias is very weak before the COVID-19 outbreak and it is absent after the outbreak according to the reported results in Table 1 providing, therefore, more value to Bitcoin.

6. Conclusion

This paper studies the efficiency level and detects the existence of herding behaviour in the Bitcoin market using the generalized Hurst exponent (GHE) as an evaluation measurement of fractality through the multifractal fractal detrended fluctuation approach. In addition, this work focuses on the influence of the COVID19 on Bitcoin efficiency. The empirical results of the GHE estimation indicate the Bitcoin is multifractal before this pandemic and becomes less fractal after the outbreak. Using an efficiency index (MLM), we find that Bitcoin becomes more efficient after the outbreak. These findings are in line with other empirical findings (Cohen, 2020) and they are suitable for the general expectation about most cryptocurrency markets. The efficiency analysis may help cryptocurrency traders in making their trading strategies.

Unlike political and social events such as wars, the recent coronavirus COVID19 is a biological disaster that damages human health and the economic sphere leading to spillover and market reaction. Through an event study, we demonstrate that the COVID 19 event and the Treasury's Payment Protection Program event do not generate significant abnormal returns during the selected period. However, the quantitative easing policy announced by the FED provides positive significant abnormal returns in some periods. Furthermore, we find that the COVID 19 event has a significant negative effect on the same date of the event announcement, after one day, and for 2 days. It has also a significant positive effect during 6, 7, 8, 9, and 10 days after the event occurrence. In addition, it has a significant positive impact when we strengthen the window between 5 days before and 10 days after the event. However, the quantitative easing policy announced by the FED does not provide any significant effect during these periods. Furthermore, Treasury's Payment Protection Program event announced by the FED has a significant positive effect on Bitcoin on the day of the FED announcement and in the period between 5 days before and 10 days after this event announcement. Overall, we find that the efficiency of Bitcoin is sensitive to scales, COVID 19 outbreak, and related events highlighting investor sentiment effects. These findings provide valuable implications illustrated as follow:

First, Bitcoin prices display inefficient behaviour before and during the COVID-19 pandemic which brings the possibility to predict future pricing dynamics based on past

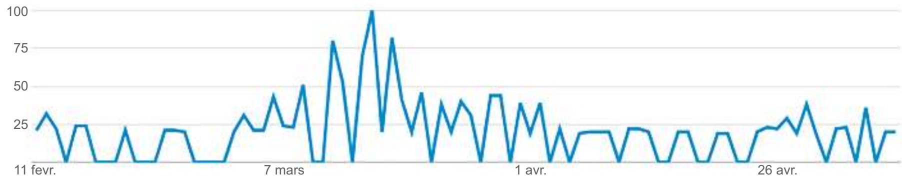

Figure 7.
"FED Bitcoin" search volumes by "Google Trends"

information. This situation generates exploitable patterns during the COVID 19 pandemic. Second, Bitcoin is found to be vulnerable to FED announcements and COVID 19 related events. This finding can be a key driver for traders, investors in the next FED announcement event. Third, studying the presence of herding behaviour during this pandemic is helpful in detecting market bubbles and explosive periods. This coronavirus pandemic event enhanced uncertainty and market volatility among cryptocurrency and commodity markets. We let future studies explore the contagion effect of the cryptocurrency and the other financial markets to make the best strategies and decisions.

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