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A Comparative Analysis of the Price Explosiveness in Bitcoin and Forked Coins

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Highlights

- This study uses the PSY method to track Bitcoin and its forked coins ' price bubbles.
- Bitcoin price bubbles are more common and last longer, while some forked coins do not have bubbles.
- The correlation between the price bubble of Bitcoin and several forked coins is significant.
- BCH and BTC are the closest, while BSV is the farthest from BTC.

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Abstract

This study employs the PSY method to detect the price bubble of Bitcoin (BTC) and its forked coins. The statistical relationship between BTC and its forked coins is then calculated using Pearson correlation coefficients and six distance measurement methods. The findings indicate that (1) BTC has more bubbles with longer periods. In contrast, certain forked coins do not have bubbles; (2) The correlation between the price bubble of BTC and several forked coins is significant; (3) From the distance of binary time series, Bitcoin Cash and BTC are the closest, while Bitcoin SV is the

farthest from BTC.

Keywords

Bitcoin; Forked coins; Price bubbles; Explosiveness; PSY test

1. Introduction

Since Nakamoto (2008) introduced the notion of Bitcoin (BTC), an increasing number of cryptocurrencies have surfaced and garnered extensive interest (Ghabri et al., 2021; Elsayed et al., 2022; Bonaparte and Bernile, 2023). As of 2023, the website coinmarketcap estimates that there will be over a thousand distinct types of cryptocurrencies, with a market valuation of $1.39T. Bitcoin is widely recognized as one of the most prominent cryptocurrencies. However, Bitcoin forked coins, such Bitcoin Cash (BCH), are also gaining prominence as significant cryptocurrencies. BCH's market capitalization has surpassed $4.2 billion.[1] As its market value has skyrocketed in recent years, Bitcoin is gaining more scrutiny as a market in the process of developing a bubble (Arnosti and Weinberg, 2022; Hinzen et al., 2022; Li et al., 2023), and extensive research has demonstrated the existence of the Bitcoin price bubble (Corbet et al., 2018; Geuder et al., 2019; Bazán-Palomino, 2022; Pagnotta, 2022). To follow the Bitcoin price bubble, the majority of research assesses the gap between the price and actual value of Bitcoin (Griffin and Shams, 2020; Wei and Dukes, 2021).

Existing besides Bitcoin are numerous other cryptocurrencies (Liu et al., 2022). The speculative nature of the cryptocurrency market (Sockin and Xiong, 2023), with forked coins making up a sizable category (Hu et al., 2019; Mensi et al., 2023), has a

[1]Data Sources: The website is https://coinmarketcap.com/, Access time November 28, 2023 (Beijing time)

significant impact on portfolio variety, market efficiency, and financial stability (Lucey et al., 2022; Wang et al., 2022b). There are now 74 active Bitcoin forked coins, of which 45 have their own networks[2]. All initiatives that inherit the status of the BTC ledger and then issue coins can be included in the study scope of forked coins, according to the definition of forked coin information website forkdrop.io[3].

Due to the close relationship between BTC and BTC forked coins, the increased popularity of BTC is expected to attract more attention to BTC forked coins. Nevertheless, there is a dearth of study about the nature of price bubbles involving forked coins. The stability of the financial market will be called into question if a price bubble develops in the forked coins that is connected to the price explosion of BTC. This would result in an increase in the volatility of the cryptocurrency market.

For multiple reasons, this study concentrates on BTC and its forked coins. To begin with, forked coins are progressively gaining prevalence. Hard forks imply the original blockchain community's governance has failed, dividing cryptocurrency users into two groups, which may undermine cryptocurrency value and confidence as a payment method (Trump et al., 2018). Concurrently, forked coin-related research, including that of Bazán-Palomino (2021), and Ahmed et al. (2023), continues to expand. Furthermore, in light of the meteoric rise in the price of BTC (Bouri et al., 2019; Shahzad et al., 2022), the inquiry into whether forked coins also experience price explosions has gained significance. Similarities and distinctions exist between Bitcoin and forked coins. Forking behavior is a consequence of irreconcilable differences that exist within the Bitcoin network (Bazán-Palomino, 2020). However,

[2] data source: https://forkdrop.io/

[3] According to this website's introduction to forked coins, forked coins can be divided into four categories: Straight fork (a forked coin directly or indirectly derived from the BTC blockchain); Passive Airdrop (an airdrop to Bitcoin holders); Registered Airdrop (an airdrop issued to Bitcoin holders who participate in the registration process separately); Blend (a forked coin that blends the three features above).

upon the completion of the fork, the forked coin acquires all the records that existed before to the fork in Bitcoin. Hence, a parallel may be drawn between BTC and forked coins. Additional examination is required in order to ascertain whether there is a similarity between the price explosiveness of forked coins and BTC. Third, academics are apprehensive about the behavior of price explosiveness due to the cryptocurrency market's notable degree of speculation (Baur et al., 2018; Kyriazis et al., 2020). Moreover, abrupt fluctuations in asset market prices would have substantial societal repercussions, including the exacerbation and proliferation of economic inequalities (Kyriazis et al., 2020). Consequently, if the price-explosive behavior of these forked coins resembles that of BTC is a vital study topic. A cryptocurrency price bubble has the potential to propagate to other cryptocurrencies (Bouri et al., 2019). Failing to recognize the co-explosive characteristics of cryptocurrencies may lead investors to overlook lucrative investment prospects. As a result, we monitor the closing prices of BTC and the thirteen forked coins in order to investigate the correlation between BTC bubbles and forked coins.

The study has made several contributions, which are outlined below. (1) This is the first study that we are aware of that has monitored the price bubble of several Bitcoin forked coins. Our ongoing investigation remains centered on the matter of cryptocurrency asset price bubbles, in line with previous scholarly investigations. In contrast, our attention is directed towards a distinct category of cryptocurrencies known as forked coins. (2) As a result of the shift in research subjects, we find that some forked coins, for instance, do exhibit price bubbles. The price explosion behavior exhibited by forked coins is comparatively less frequent and of shorter length than that of BTC. (3) To conduct empirical investigation on the price co-explosion of Bitcoin and forked coins, we utilized a range of ways to quantify binary sequence distance as opposed to the conventional approach of constructing a regression model, which increases the robustness of our research.

The paper proceeds as follows. Section 2 introduces data and methodologies. Section 3 highlights the empirical findings, and Section 4 presents the conclusion.

2. Data and methodology

2.1 Data

The period of data used in this paper is from the observed closing price of each BTC forked coin to February 6, 2021. Meanwhile, to coincide with the time interval of BTC forked coins, the Bitcoin closing price ranges from January 1, 2017 to February 6, 2021. This study collects BTC and BTC forked coin closing price data from the Coimarketcap website[4]. A sample list of forked coin is compiled in accordance with the information provided on the website forkdrop.io. In light of the quantity of observation and the availability of data, thirteen forked coins are ultimately chosen. Relevant information is presented in Table 1. In summary, there are significant differences in the statistical characteristics of the closing prices of these cryptocurrencies. Firstly, the closing price of Bitcoin is much higher than its forked coins, with an average closing price of $8204.67, while the highest closing price, Bitcoin Cash (BCH), has an average closing price of only $518.39. A large number of forked coins, such as Bitcoin Interest (BCI), BitcoinX (BCX), and Bitcoin File (BIFI), close at less than $1. Secondly, the price distribution of cryptocurrencies exhibits a right-skewed distribution feature, as the median of the closing price is lower than the average, which indicates that there is a maximum value in the closing price of cryptocurrencies, thereby increasing the average price. It means that there may exist

[4] https://coinmarketcap.com/.

price explosiveness in the sample forked coins. The skewness coefficient also proves our judgment because they are all greater than 0. Among all the samples, the cryptocurrency with the most obvious right-skew distribution is Bitcoin Atom (BCA), whose skewness coefficient is 12.30. Thirdly, the kurtosis of some forked coins is very different from the normal distribution, because the kurtosis is much higher than 3, indicating that there are extreme values that increase the sample variance. For example, the kurtosis of BCA is 169.49 and the kurtosis of BCI is 40.26. These are much higher than 3, the existence of extreme values makes it more necessary for us to monitor price bubble behavior. Fourthly, there is also a difference in the degree of variation of the closing prices of cryptocurrencies in the sample, as the coefficient of variation (CV) we calculated varies greatly. The highest degree of variation is achieved with BCA reaching 8.91, indicating that the standard deviation of the sample is 8.91 times the mean. The lowest degree of variation is BSV, with a coefficient of variation of 0.42. Finally, the forking of cryptocurrencies in the sample does not occur simultaneously. Most cryptocurrency forks occur at a Bitcoin block height of around 490000. The earliest forking in the sample is BCH and BSV, while the latest forking is Micro Bitcoin (MBC). In summary, the heterogeneity of cryptocurrencies in the sample is a prerequisite for our empirical analysis, as high price variability and the presence of extreme values suggest that price explosive behavior may occur.

Insert Table 1 here

2.2 Method

Sornette et al. (1996) and Johansen et al. (2000) introduced the Log Periodic Power Law Singularity (LPPLS) model, which is frequently used to identify asset price bubbles. However, Gustavsson et al. (2016) contend that the effectiveness of LPPLS detection is time dependent. Phillips et al. (2011) introduced the PWY algorithm for bubble identification, which exhibits inadequate asymptotic qualities when confronted with sequences comprising numerous bubble periods (Phillips et al., 2015b). The PSY method (Phillips et al., 2015a, b) is used to detect bubbles in cryptocurrency markets (Bouri et al., 2019; Wang et al., 2022a). Phillips et al. (2015b) proved that the PSY moving window detector is more reliable than the PWY method. As a result, the PSY test is employed initially to identify bubbles in BTC and forked coins, and subsequently the bootstrap approach proposed by Phillips and Shi (2020) is utilized to obtain the recursive solution. Following this, the correlation and distance between BTC and the series of forked coin bubbles are computed using Pearson correlation and many other calculating methods.

2.2.1 PSY test

According to Phillips et al.(2015a), assume that the equation below describes the data-generating process:

$$\begin{gathered} Price_t = dT^{-\eta} + \theta Price_{t-1} + \varepsilon_t \\ \theta = 1 \\ \varepsilon_t \overset{iid}{\sim} \left(0, \sigma^2\right) \end{gathered} \tag{1}$$

where $Price_t$ represents the logarithmic price of Bitcoin and Bitcoin forked coins in period *t*, *d* is a constant. In addition, *T* is the sample size, $\eta > \frac{1}{2}$The model used for hypothesis testing is denoted as

$$\Delta\, Price_t = \alpha_{r_1, r_2} + \beta_{r_1, r_2} Price_{t-1} + \sum_{i=1}^{k} \varphi^i_{r_1, r_2} \Delta\, Price_{t-i} + \varepsilon_t \tag{2}$$

where *k* represents the lag order. $r_1$represents the first r_1 part of the sample size □, and $r_2$represents the last r_2 part of the sample size □. The test statistic is recorded as $ADF_{r_1}^{r_2}$. In addition, the test statistic is documented as follows, r_0 represents the smallest sample window width fraction.

$$SADF(r_0) = \sup_{r_2 \in [r_0,1]} \{ADF_0^{r_2}\} \tag{3}$$

Then, for the rolling window, the generalized sup ADF (GSADF) test statistic is:

$$GSADF(r_0) = \sup_{\substack{r_1 \in [0, r_2 - r_0] \\ r_2 \in [r_0, 1]}} \{ADF_{r_1}^{r_2}\} \tag{4}$$

In contrast, the backward SADF (BSADF) value is specified as:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \{ADF_{r_1}^{r_2}\} \tag{5}$$

The starting time $\hat{r}_{i,b}$ and ending time $\hat{r}_{i,e}$ of each bubble period are recorded as:

$$\hat{r}_{i,b} = \inf_{r_2 \in [r_0,1]} \{r_2 : BSADF_{r_2}(r_0) > scv_{r_2}^{\alpha_T}\} \tag{6}$$

$$\hat{r}_{i,e} = \inf_{r_2 \in [\hat{r}_{i,b} + \frac{\gamma \log(T)}{T}, 1]} \{r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\alpha_T}\} \tag{7}$$

According to Phillips et al.(2015a), $scv_{r_2}^{\alpha_T}$ is the $100(1-\alpha_T)\%$ critical value of the sup ADF statistic based on $\lfloor Tr_2 \rfloor$ observations.

2.2.2 Distance measurement

We use binary variables to depict the price explosive behavior, when cryptocurrency is in the non-explosive period, the variable value is 0; when it is in the explosive period, the variable value is 1. Therefore, several binary data series will be generated that depict the price explosive behavior of BTC and its forked coins. The following algorithms are frequently used to calculate the distance between binary data series.

Suppose the two binary data series *x* and *y*. n_{11}represents the number of times the observation value is taken as 0 simultaneously, n_{10}represents the number of times the observation value of series *x* is taken as 1, and the number of times the observation value of series y is taken as 0 simultaneously; n_{01} indicates the number of times the observation value of series x is taken as 0 and the observation value of sequence y is taken as 1 during the same period; n_{00} represents the number of times two series simultaneously take 0. Therefore, $n_{11} = a$, $n_{10} = b$, $n_{01} = c$, $n_{00} = d$. We chose six calculation methods from Gower and Legendre (1986) and Chessel et al. (2009). We choose these methods in part because they are standard distance computation methods and in part, because we attempt to analyze various ways, such as those that account for simultaneous nonoccurrence and those that do not. Most importantly, the findings obtained by different methods can be used to assess the robustness of each other.

(1) Jaccard index (Jaccard, 1901):

$$S_1 = \frac{a}{a+b+c} \tag{8}$$

(2) Simple matching coefficient (Sokal and Michener, 1958):

$$S_2 = \frac{a+d}{a+b+c+d} \tag{9}$$

(3) Distance measurement proposed by Rogers and Tanimoto (1960):

$$S_3 = \frac{a+d}{a+2(b+c)+d} \tag{10}$$

(4) Distance measurement proposed by Dice (1945) and Sorensen (1948):

$$S_4 = \frac{2a}{2a+b+c} \tag{11}$$

(5) Distance measurement proposed by Ochiai (1957):

$$S_5 = \frac{a}{\sqrt{(a+b)(a+c)}} \tag{12}$$

(6) Phi of Pearson (Gower and Legendre, 1986):

$$S_6 = \frac{ad-bc}{(a+b)(a+c)(d+b)(d+c)} \tag{13}$$

The distance between binary data series is recorded as

$$d = \sqrt{1 - S} \tag{14}$$

3. Empirical findings

This study detects bubbles in Bitcoin and its forked coins using the PSY monitoring algorithm. Table 2 displays the results, and we can see that: (1) From the frequency of price explosive behavior, the number of BTC price bubbles is much more than that of its forked coins. During the sample time, there are a total of 22 price explosiveness in BTC, while the total number of price bubbles for all selected forked coins is 24. Additionally, Geuder et al. (2019), Cretarola and Figà-Talamanca (2021), Yao and Li (2021), Shahzad et al. (2022) validated the presence of a Bitcoin price bubble. Not all forked coins have price explosiveness, such as Bitcoin Gold (BTG), BitcoinX (BCX) and other forked coins have no bubbles throughout the period. This indicates that the price explosive behavior of Bitcoin is more frequent, with a stronger impact on the cryptocurrency market than its forked coins. (2) From the perspective of bubble duration, the price bubble of Bitcoin lasted for a long time, and there are 3 price bubbles lasting more than 10 days. They are from June 2nd to June 11th, 2017, November 25th to December 20th, 2017, and December 24th, 2020 to January 20th, 2021. The maximum duration can reach 28 days. In a similar vein, Bazán-Palomino (2022) discovered that the peak concentration of Bitcoin's price bubbles occurred in 2017 and 2021. The forked coins are relatively short, with only BitCore (BTX) experiencing 2 price bubbles lasting more than 5 days, from November 14, 2017 to November 22, 2017, and from November 24, 2017 to November 28, 2017. This indicates that the persistence of Bitcoin's price explosive behavior is longer than its forked coins. (3) Initially, the majority of bubbles appeared in the BTC price series.

For example, in the first half of 2017, only Bitcoin experienced price explosiveness, while among forked coins, the price bubble of BCH appeared as early as November 2017.

Numerous scholars theorized on the causes of the cryptocurrencies' price explosiveness, particularly Bitcoin. The global monetary environment (Geuder et al., 2019), Bitcoin-based online transactions (Geuder et al., 2019), and market sentiment (Cretarola and Figà-Talamanca, 2021) are among the most influential factors. Moreover, Yao and Li (2021) found that the price bubble at the end of 2017 is associated with the rapid expansion of Initial Coin Offering (ICO), but the price bubble in June 2019 is strongly associated with the emergence of Libra. Figure 1 plots the changing trend of the closing prices of Bitcoin and forked coins. The shaded part indicates that cryptocurrency is in the price-explosive period.

Insert Table 2 here

Insert Figure 1 here

The relationship between the bubble series is then analyzed. Table 3 displays the Pearson correlation coefficients and significance levels for binary variables. A weak correlation exists between the bubbles. Specifically, the positive correlation between Bitcoin and the price bubble series of most forked coins is significant, such as BCH, BTX, BCD, and GOD. However, the relationship between the price bubble series of the forked coin is almost insignificant, and only BCH and BCD BTX have a significant positive correlation.

Insert Figure 2 here

To analyze the time distribution characteristics of the price explosiveness of Bitcoin and forked coins, we also draw the timeline of the bubbles (see Figure 2). We have three findings. Firstly, the occurrence of cryptocurrency bubbles is not uniform, but concentrated over a period of time. For example, in late 2017, mid-2019, and early 2021. This indicates that the impact of cryptocurrency price explosiveness has a certain period. Secondly, when Bitcoin experiences a price explosive behavior, its forked coins also generate bubbles one after another, which means that the price bubbles of forked coins and Bitcoin may correlate. Thirdly, when there are no price bubbles in Bitcoin, it is rare for forked coins to experience price explosiveness alone during similar periods. The above findings also confirm the conclusion of correlation analysis that there is a correlation between the price bubble series of Bitcoin and forked coins, while the correlation between the bubble series of forked coins is weak.

Insert Table 3 here

Next, we measure the distance between Bitcoin and the 6 forked coin binary bubble series. Table 4 provides the results. First, the distances calculated by various methods vary. After sorting the forked coins according to the calculated distance, it is found that the sorting results are not the same. Second, BCH is the most similar to Bitcoin's bubble. The shortest distance between BCH and BTC is found in the six measuring methods. Specifically, BCH's price explosive behavior occurred three days and coincided with BTC's price bubble period, so their binary bubble series have a high similarity. Third, the distance between the binary bubble sequence of BSV and the binary bubble sequence of BTC is the farthest, which can be consistent among the six calculation methods. Only on May 29, 2019, BSV and BTC show characteristics of co-explosion Therefore, when the time of explosive behavior is inconsistent, there is the greatest difference between BSV and BTC.

In addition to the data characteristics of the fork price bubble series, the historical background of the fork also explains why BCH and BTC are the closest and BSV and BTC are the furthest. From the perspective of the network structure of the blockchain that cryptocurrencies rely on, Javarone and Wright (2018) analyzed the network structure of BCH and BTC and found that the network structure of the two cryptocurrencies is very similar except for the scale of nodes. From the history of BTC fork behavior, BCH was directly forked from the original Bitcoin blockchain, and the fork was due to the failure to reach an agreement when solving the problem of BTC blockchain expansion. BSV is not directly forked from BTC, it was separated from the Bitcoin Cash blockchain in 2018 and belongs to the secondary fork of Bitcoin (Yi et al.,2021).

Insert Table 4 here

4. Conclusion

This study employs the PSY method to track the price bubbles of BTC and its forked coins, calculating their connection and bubble series distance. We find that: Firstly, BTC price bubbles occur more frequently and last longer. Secondly, the correlation between BTC and its forked coins is significant, but the correlation between forked coins is mostly not significant. Thirdly, BCH is the forked coin closest to BTC, while BSV is far away. For cryptocurrency investors, they must not only pay attention to the possible losses caused by Bitcoin price bubble, but also cannot ignore the potential price bubbles of forked coins. When the price bubbles of BTC and forked coins appear at the similar time, it will bring greater risks to investors. For regulatory authorities, they need to pay close attention to the abnormal fluctuations in the price of BTC and forked coins, regulate the daily operations of cryptocurrency exchanges, improve the cryptocurrency transaction management mechanism, and pay more attention to forked coins, especially those with price bubbles closet to BTC.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Tables

Table 1 Descriptive statistics of the closing price of Bitcoin and its fork projects

Cryptocurrency	Abbreviation	Mean	Medium	Standard Deviation	Kurtosis	Skewness	Min	Max	CV	Observations	Fork block height	Start time
Bitcoin	BTC	8204.67	7486.82	6026.20	8.70	2.45	777.76	40797.61	0.73	1498	None	2017/01/01
Bitcoin Atom	BCA	8.62	0.13	76.80	169.49	12.30	0.02	1377.98	8.91	1120	505888	2018/1/14
Bitcoin Diamond	BCD	3.69	0.83	9.57	20.49	4.26	0.30	94.22	2.59	1170	495866	2017/11/25
Bitcoin Cash	BCH	518.39	318.33	499.90	8.47	2.66	77.37	3923.07	0.96	1294	478558	2017/7/24
Bitcoin Interest	BCI	0.58	0.05	1.60	40.26	5.55	0.00	17.45	2.76	1010	505083	2018/5/4
BitcoinX	BCX	0.01	0.00	0.01	23.94	4.57	0.00	0.10	1.00	1149	498888	2017/12/16
Bitcoin File	BIFI	0.00	0.00	0.00	7.37	2.39	0.00	0.02	None	924	501225	2018/7/29
Bitcoin SV	BSV	149.44	159.38	62.67	0.50	0.57	42.75	422.74	0.42	820	478558	2018/11/10
Bitcoin 2	BTC2	1.13	0.99	0.57	3.50	1.08	0.31	4.97	0.50	620	507850	2019/5/29
Bitcoin Gold	BTG	39.70	13.03	68.75	9.58	3.11	4.93	453.45	1.73	1202	491407	2017/10/24
BitCore	BTX	3.19	0.42	6.60	7.63	2.88	0.11	39.42	2.07	1381	492820	2017/4/28
Bitcoin God	GOD	10.11	6.61	14.51	17.37	3.41	0.07	137.80	1.44	1121	501225	2018/1/13
MicroBitcoin	MBC	0.00	0.00	0.00	23.92	4.48	0.00	0.00	None	834	525000	2018/10/27
Super Bitcoin	SBTC	10.02	2.15	33.92	39.96	6.09	0.20	323.73	3.39	1149	498888	2017/12/16

Note: (1) Missing value processing method: We calculated the average value of the data corresponding to adjacent dates to fill in for missing data. (2) Calculation of CV: CV is equal to the variable's standard deviation divided by the corresponding mean. (3) We keep the calculation results of descriptive statistics to two decimal places.

Table 2 The period of cryptocurrency bubbles

Cryptocurrency	Start	End	Days	Cryptocurrency	Start	End	Days
BTC	2017/5/11	2017/5/11	1	BCH	2017/11/17	2017/11/17	1
BTC	2017/5/19	2017/5/25	7	BCH	2017/12/20	2017/12/20	1
BTC	2017/5/29	2017/5/29	1	BCH	2017/12/23	2017/12/23	1
BTC	2017/6/2	2017/6/11	10	BCH	2019/4/3	2019/4/3	1
BTC	2017/11/4	2017/11/5	2	BCH	2019/4/7	2019/4/7	1
BTC	2017/11/8	2017/11/8	1	BCH	2021/1/9	2021/1/11	3
BTC	2017/11/25	2017/12/20	26	BCH	2021/1/14	2021/1/14	1
BTC	2018/11/24	2018/11/24	1	BTX	2017/9/12	2017/9/13	2
BTC	2018/11/26	2018/11/26	1	BTX	2017/11/14	2017/11/22	9
BTC	2019/5/11	2019/5/16	6	BTX	2017/11/24	2017/11/28	5
BTC	2019/5/19	2019/5/20	2	BTX	2017/11/30	2017/12/1	2
BTC	2019/5/26	2019/5/29	4	BTX	2019/5/11	2019/5/11	1
BTC	2019/6/23	2019/6/26	4	BTX	2020/2/12	2020/2/12	1
BTC	2019/6/28	2019/6/29	2	BTX	2020/2/14	2020/2/14	1
BTC	2020/11/17	2020/11/25	9	BTX	2020/2/16	2020/2/19	4
BTC	2020/11/30	2020/11/30	1	BCD	2019/4/5	2019/4/5	1
BTC	2020/12/3	2020/12/3	1	BCD	2021/1/10	2021/1/10	1
BTC	2020/12/17	2020/12/22	6	GOD	2020/11/28	2020/11/30	3
BTC	2020/12/24	2021/1/20	28	GOD	2021/1/4	2021/1/4	1
BTC	2021/1/22	2021/1/22	1	MBC	2019/9/14	2019/9/14	1
BTC	2021/1/29	2021/1/30	2	MBC	2021/1/22	2021/1/25	4
BTC	2021/2/1	2021/2/6	6	BSV	2019/5/29	2019/5/31	3
				BSV	2019/6/2	2019/6/4	3
				BSV	2020/1/14	2020/1/17	4

Note: Start represents the starting date of the price explosive behavior of Bitcoin and forked coins, End represents the date on which the price explosive behavior ended. Days represents the duration of the price explosion of Bitcoin and forked coins.

Table 3 Correlation analysis of price bubbles

Coins	BTC	BCH	BTX	BCD	GOD	MBC	BSV
BTC	1.000						
BCH	0.1472*	1.000					
	(0.000)						
BTX	0.0924*	0.0558*	1.000				
	(0.001)	(0.045)					
BCD	0.0614*	0.2476*	-0.004	1.000			
	(0.036)	(0.000)	(0.881)				
GOD	0.1046*	-0.004	-0.005	-0.003	1.000		
	(0.001)	(0.883)	(0.874)	(0.933)			
MBC	0.030	-0.007	-0.007	-0.004	-0.005	1.000	
	(0.381)	(0.849)	(0.837)	(0.913)	(0.877)		
BSV	0.004	-0.010	-0.010	-0.006	-0.008	-0.009	1.000
	(0.914)	(0.785)	(0.768)	(0.875)	(0.824)	(0.804)	

Note：* represents p<0.05, the values in parentheses correspond to the P-value.

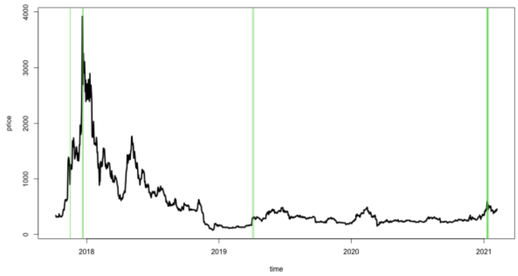
Table 4 The distance between binary bubble series

Forked Coins	Jaccard index	Simple matching coefficient	Rogers and Tanimoto (1960)	Dice (1945)	Ochiai (1957)	Phi of Pearson
BCD	0.993 (3)	0.300 (2)	0.407 (2)	0.987 (3)	0.958 (3)	0.964 (3)
BCH	0.973 (1)	0.296 (1)	0.402 (1)	0.949 (1)	0.900 (1)	0.910 (1)
BSV	0.994 (4)	0.316 (6)	0.426 (6)	0.988 (5)	0.981 (6)	0.998 (6)
BTX	0.994 (4)	0.310 (5)	0.419 (5)	0.988 (5)	0.978 (5)	0.991 (5)
GOD	0.987 (2)	0.300 (2)	0.407 (2)	0.974 (2)	0.940 (2)	0.949 (2)
MBC	0.994 (4)	0.306 (4)	0.414 (4)	0.987 (3)	0.974 (4)	0.985 (4)

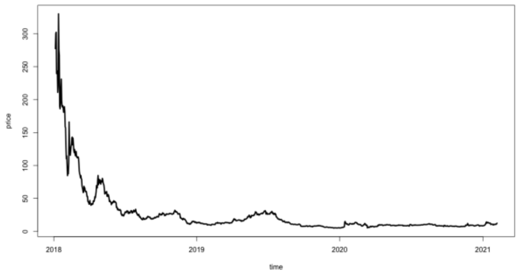
Note: (1) Before calculating the distance of binary data series, we only reserve the time period in which the observed values of BTC and six forked coins with price explosive behavior exist, that is, from November 10, 2018 to February 6, 2021. (2) We sort the distances calculated using each method from smallest to largest, and label the sorted results in parentheses after each distance.

Figure

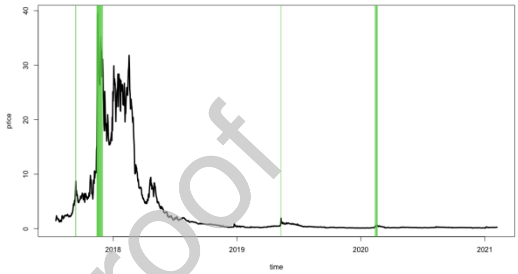
(1) Bitcoin



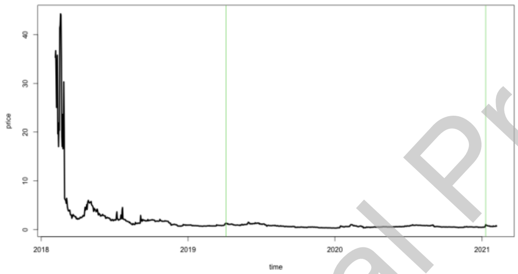
(2) BCH



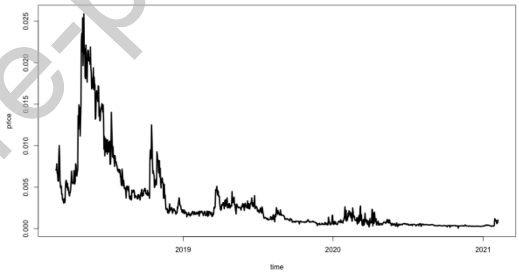
(3) BTG



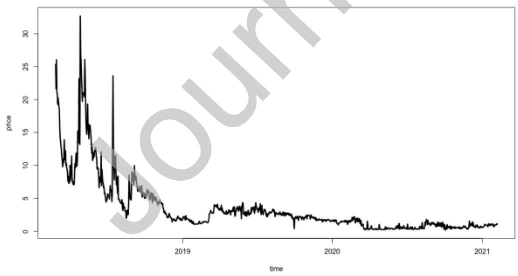
(4) BTX



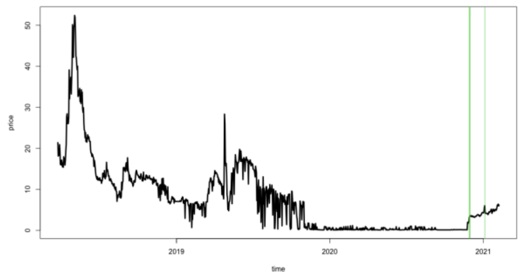
(5) BCD



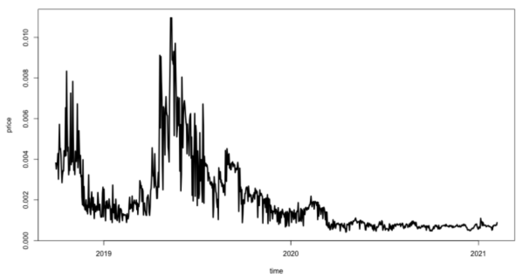
(6) BCX



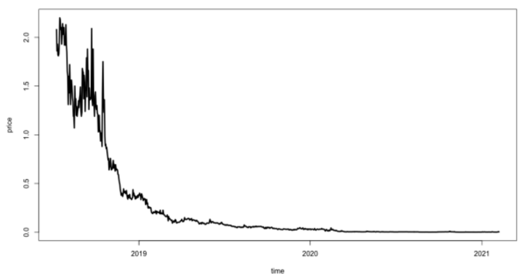
(7) SBTC



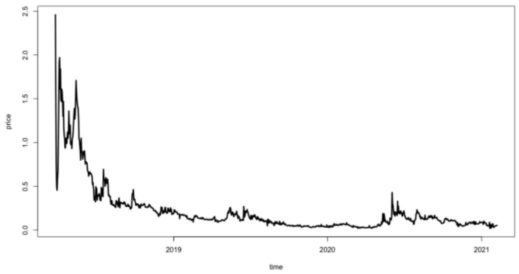
(8) GOD



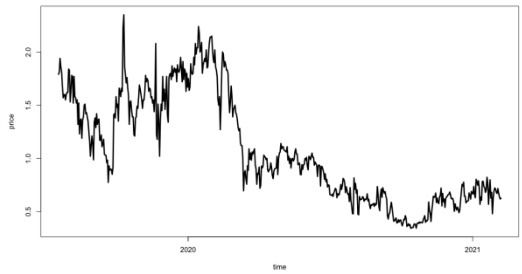
(9) BIFI



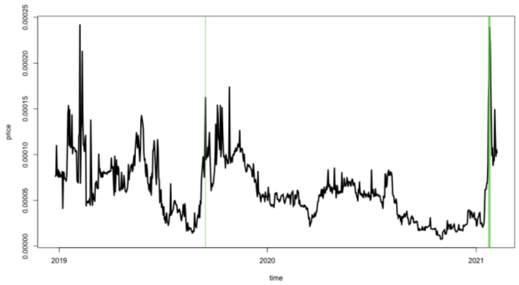
(10) BCI



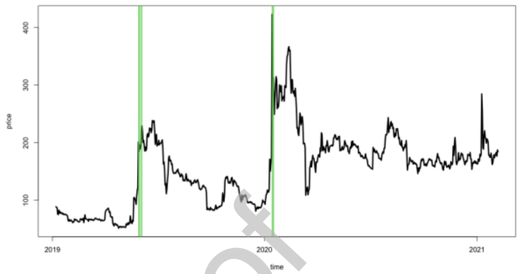
(11) BCA



(12) BTC2



(13) MBC



(14) BSV

Figure 1 The price trend and explosive behavior period

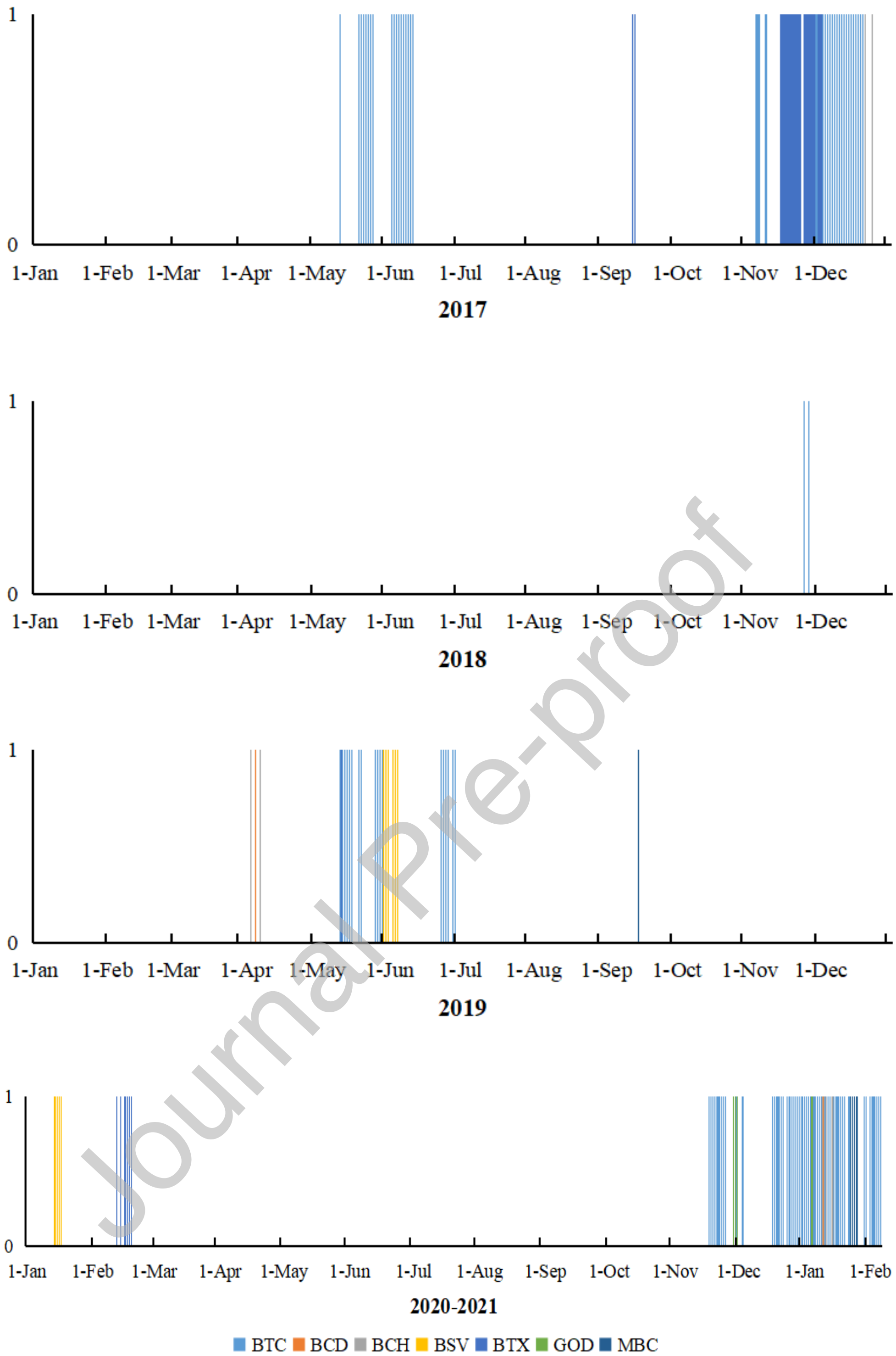


Figure 2 Timeline of Bitcoin and forked coins price explosiveness

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