Journal of Systems Science and Information
Apr., 2023, Vol. 11, No. 2, pp. 139–159
DOI: 10.21078/JSSI-2023-139-21

An Event Analysis of Bitcoin Based on a Novel DRE Methods

Yao YUE
School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, *China*
E-mail: yueyao19@mails.ucas.ac.cn

Yuying SUN
Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, *China; Center for Forecasting Science, Chinese Academy of Sciences, Beijing* 100190, *China*
E-mail: sunyuying@amss.ac.cn

Kuo YANG
Minsheng Financial Leasing Co., Ltd., Shanghai 210000, *China*
E-mail: yangkuo96@hotmail.com

Shouyang WANG
School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, *China; Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing* 100190, *China; Center for Forecasting Science, Chinese Academy of Sciences, Beijing* 100190, *China*
E-mail: sywang@amss.ac.cn

Abstract Since Bitcoin came into the world, modelling and analyzing the underlying characteristics of Bitcoin has attracted increasing attention. This paper uses a framework including decomposition, reconstruction and extraction method (DRE) to analyze price fluctuations based on ultra-high-frequency data from Dec.1, 2019, to Nov.30, 2021. First, the ensemble mode decomposition (EMD) is employed to decompose the Bitcoin hourly spot price into 13 intrinsic mode functions (IMF) plus a residual. Second, the IMFs are reconstructed into high-frequency components, low-frequency components and a trend based on fine-to-coarse reconstruction. Furthermore, the intraday volatility analysis based on LM test is applied on 15-minutes frequency data to detect discontinuous jump arrivals and extract jump from realized quadratic variation. Empirical results show that three components of reconstruction can be identified as short term fluctuations process caused by microstructure noise, the shocks affected by major events, and a long-term trend based on inelastic supply and rigid demand. We find that approximately 40% of jumps can be matched with the news from the public news database (Factiva), and the jump sizes are larger than that of stock markets. This finding indicates that the Bitcoin market has more irregularly noise and unforeseen shocks from unscheduled events.

Keywords Bitcoin; EMD; jump; realized variation

Received April 12, 2022, accepted December 5, 2022
Supported by the National Natural Science Foundation of China (72073126, 71988101, 72091212) and Young Elite Scientists Sponsorship Program by CAST (YESS20200072)

1 Introduction

Bitcoin, established by Nakamoto[1], has become the most popular virtual currency since 2013[2]. Unlike the e-cash system which is based on the traditional tripartite model of "bank-individual-merchant" developed by Chaum[3], Bitcoin uses a decentralized framework based on blockchain technology to provide a public distributed ledger and record transactions without any central authority. Bitcoin is the first cryptocurrency that does not rely on the central bank for transactions, each Bitcoin can be treated as a divisible unit and transferred between the pseudonymous addresses in the cryptographical network. Unlike fiat money, Bitcoin can purchase the commodity and transfer money through a peer-to-peer network without the central bank. Except for recording transactions, blockchain can also verify the security of traders. Another characteristic of Bitcoin is the fixed amount of Bitcoin, which leads to the scarcity of Bitcoin.

The Bitcoin price fluctuated greatly due to the major events. For example, in 2021, the Bitcoin price firstly peaked at around \$64000 in April. However, concerned the energy consumption of mining[4–6] and financial risk, China has banned all mining activities and Bitcoin transactions since May 2021, some countries and international organizations limitations are also on the schedule. In addition, the launch of central bank digital currency also has dealt a blow to Bitcoin advocates committed to establishing a decentralized financial system. These limitation rules and bad news reduced the price of bitcoin to nearly \$29000 on July.19, 2021, but to our surprise, the price reversed to the new peak at more than \$68000 on Nov.09, 2021. Overall, consecutive information seems detrimental to the Bitcoin market in the past two years, but the price is not always decreasing. Thus, it is highly desirable to analyze events impacts on the Bitcoin market.

Except for supply and demand, Bitcoin price is affected by many factors. Unlike traditional financial assets, nearly 25% of users and half of the Bitcoin transactions are involved in illegal activities, mostly in the darknet marketplaces[7]. Money laundering through Bitcoin also caused a lot of concerns[8–10]. Bitcoin price is not only affected by supply and demand but also by regulations, speculative activities, underlying technologies[11], participants' behaviors and other factors. These factors can affect short fluctuations and the long term trend of Bitcoin price. A notable feature of the bitcoin market is high volatility[12, 13], low liquidity[2], nonlinear and nonstationary[11]. The previous literature mainly studies the single feature above, which does not reflect the whole characteristics of Bitcoin price. Thus, this paper concerns multivariate features which affect Bitcoin price.

This paper proposes a decomposition-reconstruction-extraction (DRE) method to analyze the underlying characteristics of the Bitcoin market. First, the empirical mode decomposition (EMD) is employed on the Bitcoin hourly spot price from Dec.1, 2019, to Nov.30, 2021, for decomposition. EMD, developed by Huang, et al.[14], is suitable for interpreting the price formation mechanism. The core of EMD is decomposing observed time series data into several independent intrinsic modes plus a residual. These sub-series are simpler and can identify influencing factors better than observed data[15]. Prior literature has studied the daily price of Bitcoin[16–18] based on EMD and its extensions. However, these studies neglect the fact that the fundamental value of Bitcoin is also controversial compared with other financial assets[19–21], so analysis by daily data may miss much intraday information. Therefore, we apply the EMD method to Bitcoin's hourly spot price to understand the underlying characteristics of Bitcoin firstly. The observed data is decomposed into several intrinsic modes from high to low-frequency with a residual by EMD.

Besides, we follow the spirit of Yang, et al.[11] and reconstruct the decomposition results by the Wilcoxon-signed rank test, which will avoid the misspecified assumptions of normal distribution for the sum of IMFs. Thus, the EMD based IMFs can be constructed into high-frequency compositions, low-frequency compositions, and long-term trends. These three components can be explained as follows: 1) Short term fluctuations caused by market microstructure noise; 2) the impacts of major events; and 3) rigid demand and inelastic supply. These findings reveal that the Bitcoin market has different reactions to major events. The duration of major events' effects is less than that of financial assets, and the Bitcoin price maintains trends upward for the long term.

Furthermore, this paper attempts to analyze the news effect on the Bitcoin market by using jump tests. As we mentioned earlier, the EMD method can explain the low-frequency part combined with major events. However, Bitcoin has unique characteristics. For example, lacking official market makers makes Bitcoin more fragile when facing large trading volumes[2] and rumors. Thus, we focus on the jumps in the Bitcoin market. Jumps are significant discontinuities caused by coincidence. Detecting irregular jumps is helpful to analyze sporadic events' effects. One popular approach is the jump test, which was firstly proposed by Press[22] and further studied by Merton[23] to construct type jump-diffusion model. Subsequently, a class of stochastic volatility plus jump models and GARCH-type models are developed to detect jumps[24]. After the realized variation was proposed by Andersen and Bollerslev[25], studies on jumps shifted away from model-based inference on low-frequency data to model-free inference based on intraday data. Barndorff-Nielsen and Shephard[26, 27] developed a new measure called bipower variation to detect the jumps from intraday data. However, this method only identifies whether the jump exists on a given day. To address this issue, Lee and Mykland[28] conducted a new statistic including the bipower variation to identify the jump arrival time, which is further suitable for nonlinear and nonstationary pricing processes.

Therefore, we follow Lee and Mykland[28] to detect jumps in the Bitcoin market. We find interesting findings by applying the LM test on 15-minute frequency data to extract jump components from the price process. First, we detect 266 jumps in 220 days, with approximately two detection days or three jumps per week. The frequency of jumps in our study is larger than prior researches on stock markets[27–29], which is aligned with Scaillet, et al.[2], indicating some unique characteristics of the Bitcoin market such as decentralization, particular actors, and inelastic supply affect the density of jumps. Second, we employ a runs test on jump occurrence dates and can reject the null hypothesis that the jump arrivals are random. The result is aligned with the assumption of the jump process proposed by Merton[23], Barndorff-Nielsen and Shephard[27], Lee and Mykland[28, 29], Christensen, et al.[24] and Bajgrowicz, et al.[30]. Moreover, the absolute sizes of the jumps in Bitcoin market are larger than that in stock market studied by Barndorff-Nielsen and Shephard[27] and Lee and Mykland[28].

After identifying jump arrivals, we search financial news around jump arrival times from the Factiva database and find that only approximately 40% of detected jumps could match the news released from Factiva. The matched top five news types are industries, regulations, central bank digital currency (CBDC), illegal transactions and commentators. The development of the cryptocurrency industry and related companies, regulations by the government, CBDC which undermine the probable monetary function of Bitcoin, illegal transactions, and commentators' attitudes are mainly taken into account by the participants of the Bitcoin market. Therefore, we conclude that the acceptance by officials and financial markets is the main factor in matched jumps. Other unmatched jumps we have detected may be induced by microstructure noise such as bid-ask spread and transaction mechanism.

Compared with the existing literature, we make several contributions. First, this paper is the first attempt to use the EMD method on ultra-high-frequency financial data, which broadens the application frontiers. To the best of our knowledge, previous studies mostly employ the EMD method and its extensions on low-frequency financial data, including monthly crude oil prices[31, 32], daily oil prices and gasoline prices[33], daily Bitcoin prices[16]. Second, we propose a new framework based on decomposition and integration to analyze the events impact on Bitcoin price and jumps in markets. The framework study the major events' effects by EMD methods and also consider the high frequency events' (i.e., news events) effects on Bitcoin price by matching news with jumps. Unlike the existing findings in stock markets, the jump characteristic of the Bitcoin market is different from the stock market. The jump size of Bitcoin is bigger, and jump matched news is less than that of stock markets. A possible explanation is that the stock exchange requires listed firms to disclose information timely and accurately, while the bitcoin market has no rules for information disclosure. Third, our research explores a new perspective on abnormal fluctuations of Bitcoin prices, approximately 60% of which cannot be explained by public information completely. Thus, we conjecture that some nonpublic information caused the jumps and high-frequency component in prices. Furthermore, our findings help the government put forward reasonable and precise regulations for maintaining healthy financial markets and help investors adjust their portfolios timely.

The remainder of this study is organized as follows: Section 2 presents the DRE framework, including EMD, reconstruction and intraday jump test; Section 3 shows the empirical results of EMD-based decomposition and reconstruction; Section 4 extracts the jump components based on the LM test and analyses events' impacts on jumps; Section 5 concludes this study.

2 Methodology

2.1 Empirical Mode Decomposition

EMD is proposed by Huang, et al.[14] as a decomposition method for nonlinear and nonstationary data series. It assumes that the real-time series consists of different oscillation modes. EMD can decompose the original data series into intrinsic mode functions (IMFs) based on the local characteristic scale of the data series. Each IMF represents a simple harmonic-like function and has to meet the following two prerequisites to ensure the function is an approximate periodic function with zero mean:

1) The number of extremum points is the same as that of zero-crossing points or differ at the most by 1.

2) The function should be symmetric with respect to the local zero mean.

According to the above definitions, the IMFs can be decomposed based on the following sifting process:

① Identify all the local extremum of time series $x(t)$;

② Connect all the local maxima points by cubic spline interpolation to generate the upper envelopes $e_u(t)$ and repeat the procedure for all the local minima points to generate the lower envelopes $e_l(t)$;

③ Calculate the mean $(m(t))$ of upper envelopes and lower envelopes point-by-point:

$$m(t) = (e_u(t) + e_l(t))/2. \tag{1}$$

④ Define $a(t)$ as the difference between $x(t)$ and $m(t)$:

$$a(t) = x(t) - m(t). \tag{2}$$

⑤ If $a(t)$ meets the two prerequisites, the $a(t)$ is derived as ith IMF and $m(t)$ is replaced by residual,

$$r(t) = x(t) - a(t). \tag{3}$$

Otherwise, replace $x(t)$ with $a(t)$.

Repeat 1) to 5) until the stop criterion is met. When the residual $r(t)$ is a monotonic function and no IMF can be extracted, the iterating can be stopped. The IMF number is limited to $\log_2 N$, where N is the amount of observed data[34]. Finally, the data series can be expressed as

$$x(t) = \sum_{i=1}^{N} a_i(t) + r_n(t). \tag{4}$$

where N is the total number of IMFs, $a_i(t)$ is the IMFs and $r_n(t)$ is the last residual.

2.2 Fine-to-Coarse Reconstruction Method

EMD extracts the components from observed data series from high-frequency to low-frequency modes (see Figure 2). Zhang, et al.[31] have developed the fine-to-coarse reconstruction method to categorize IMFs by adding high frequency components (IMFs with smaller index) up to low (IMFs with larger index) to a high-pass filter. Different from Zhang, et al.[31], this paper uses the Wilcoxon signed-rank test instead of a t-test to examine whether the medians of the two samples are different. Therefore, the components can be divided into high-frequency components and low-frequency components, the algorithm is as follows:

1) Calculate the sum of a_i from 1 to i for every component besides residual;

2) Use Jarque-Bera test to judge whether the sum of a_i follow the normal distributions;

3) Identify which i median is significant from zero by Wilcoxon signed-rank test;

4) Once i is identified as the change point, the partial reconstruction from the first IMF to IMF_{i-1} is identified as high-frequency components, and the other IMFs are reconstructed as low-frequency components.

2.3 Extracting Intraday Jump Components with LM Test

A common asset pricing model under the assumption that the asset price follows a continuous process is proposed by Black and Scholes[35]. However, the unexpected information will cause the discontinuous price volatility instantaneously[23], the volatility consists of a continuous component and a discontinuous component (jump)[27, 28, 36–38]. This paper follows Lee and Mykland[28] and Scaillet, et al.[2] to test jumps in bitcoin markets. We define a one-dimensional asset return process with a fixed complete probability space $(\Omega, \mathcal{F}_t, \mathcal{P})$, where Ω is a collection of bitcoin market events, $\{\mathcal{F}_t, t \in [0, T]\}$ is a right-continuous information filtration for market participants, and $\mathcal{P}$ is the physical probability measure. We denote the continuously compounded return as $\mathrm{d}\ln S(t)$ $(t \geqslant 0)$, where $S(t)$ is Bitcoin price at time t under $\mathcal{P}$. If the market is not slashed by unexpected information, there is no jump in the market, the price $S(t)$ is following:

$$\mathrm{d}\ln S(t) = \mu(t)\mathrm{d}t + \sigma(t)\mathrm{d}W(t), \tag{5}$$

where $W(t)$ is a standard Brownian motion. The drift $\mu(t)$ and spot volatility $\sigma(t)$ follow an Itô process. When the unexpected information breaks the balance of the market, the jumps occur, and $S(t)$ is represented as:

$$\mathrm{d}\ln S(t) = \mu(t)\mathrm{d}t + \sigma(t)\mathrm{d}W(t) + Y(t)\mathrm{d}J(t), \tag{6}$$

where $J(t)$ is the jump counting process which is independent with $W(t)$, $Y(t)$ is the jump size, σ is the constant volatility in a given time interval. $Y(t)$, the mean and volatility of $Y(t)$, that is, $\mu_y(t)$ and $\sigma_y(t)$, are also $\mathcal{F}_t$-predictable processes. Following Lee and Mykland[28] and Scaillet, et al.[2], we suppose that jump size $Y(t)$ is independent identically distributed, which is also independent of $W(t)$ and $J(t)$. $J(t)$ is also assumed as a Poisson-jump process[27, 28, 30]. The observed price of Bitcoin $S(t)$, or $\ln S(t)$, is observed at discrete times $0 = t_0 < t_1 < t_2 < \cdots < t_n = T$. This paper suppose that observation times are equispaced, which can be generally to be non-equidistance by letting $\max_i(t_i - t_{i-1}) \to 0$.

The main idea of the LM test is to use instantaneous volatility to standardize realized return. The Bitcoin price changes continuously over time, letting the jump occurs at time t_i, the realized return and spot volatility would be much higher than usual continuous innovation. However, the observed price is discrete actually, if there is no jump at t_i in the market, the spot volatility may be high enough with the realized return as high as the return owed to an actually jump. To separate these two situations, the instantaneous volatility (σ_i), explaining the local variation only from the continuous process, is used to standardize the return. The realized quadratic variation (RQV) established by Andersen and Bollerslev[25] is widely used as a nonparametric estimator for instantaneous volatility[39–41].

$$p\lim_{n\to\infty}\sum_{i=2}^{n}\left(\ln\frac{S(t_i)}{S(t_{i-1})}\right)^2. \tag{7}$$

The variation estimator obtained by the above method in a given period is inconsistent in the appearance of jumps in a return process. Barndorff-Nielsen and Shephard[26] modified this version and proposed the realized bipower variation (RBPV), RBPV is the sum of products of consecutive absolute realized returns and given by:

$$p\lim_{n\to\infty}\sum_{i=3}^{n}\left|\ln\frac{S(t_i)}{S(t_{i-1})}\right|\left|\ln\frac{S(t_{i-1})}{S(t_{i-2})}\right|. \tag{8}$$

The RBPV is a consistent estimator for the integrated volatility whether the jump occurs or not (see proof in Barndorff-Nielsen and Shephard[26]). LM test incorporate the estimator to make the jump detection process is independent of the appearance of jumps, especially those jumps for volatility estimation. Another advantage is that the LM test can detect the jumps even if rarely Poisson jumps accurately in a high volatility market by using high-frequency observations[28], which is also suitable for the Bitcoin market. Considering the instantaneous volatility, the LM test statistic is defined as:

Definition 1 The statistic $\mathcal{L}(i)$, which tests whether there was a jump from t_{i-1} to t_i at time t_i,

$$\mathcal{L}(i) \equiv \frac{\ln \frac{S(t_i)}{S(t_{i-1})}}{\widehat{\sigma(t_i)}}, \tag{9}$$

where

$$\widehat{\sigma(t_i)}^2 \equiv \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} \left| \ln \frac{S(t_j)}{S(t_{j-1})} \right| \left| \ln \frac{S(t_{j-1})}{S(t_{j-2})} \right|. \tag{10}$$

If there is no jump at testing time t_i, the test statistic $\mathcal{L}(i)$ approximately obey the normal distribution with mean 0 and variance $\frac{2}{\pi}$. If the jump exists at testing time t_i, $\mathcal{L}(i)$ will be very large. A jump point is detected when the testing statistic is larger than the threshold. In this paper, the significance level is set as 5%, Lee and Mykland[28] demonstrate that the test statistic follows Gumbel distribution. If $\frac{\mathcal{L}(i)-C_n}{S_n} > 2.9702$, the hypothesis of no jump at t_i is rejected at the significance level of 5%, where

$$C_n = \frac{(2\ln n)^{\frac{1}{2}}}{c} - \frac{\ln \pi + \ln(\ln n)}{2c(2\ln n)^{\frac{1}{2}}}, \tag{11}$$

$$S_n = \frac{1}{c(2\ln n)^{\frac{1}{2}}}, \tag{12}$$

and $c = \frac{\sqrt{2}}{\sqrt{\pi}}$, n is the number of observations (see Lee and Mykland[28]).

Assuming that asset price can be observed continually, the realized quadratic variation (RQV) is stochastic volatility plus drift model[27, 42], so

$$\mathrm{RQV} = \int_0^t \sigma_s{}^2 \mathrm{d}s + \sum_0^t Y^2(i), \tag{13}$$

where $\int_0^t \sigma_s{}^2 \mathrm{d}s$ represents the continuous component and $\sum_0^t Y^2(i)$ is the jump component in instantaneous volatility. The RQV is calculated as Equation (7). The realized bipower variation (RBPV), defined as Equation (8), is shown as a consistent estimator for the whole volatility[26–28, 38]. Finally, the jump size detected by the LM test in a given interval of time of length $\delta > 0$, $Y(\delta)$ is calculated as follows:

$$Y(\delta) = \mathrm{RQV}(\delta) - \mathrm{RBPV}(\delta), \tag{14}$$

In this study, we first use the LM test to detect the presence of intraday jump by high-frequency observations. If the jumps exist, we calculate the jump size by Equation (14). Finally, we search the news related to Bitcoin or cryptocurrency from the Factiva database to judge whether the jumps are related to the news.

3 EMD-Based Event Analysis

3.1 Data

The data of Bitcoin hourly closed price is obtained from https://www.cryptodatadownload.com/data/gemini/. Figure 1 depicts the Bitcoin hourly price series from Dec.1, 2019, to Nov.30, 2021, consisting of 17543 hourly data. The unit of Bitcoin prices is reported in US dollars.

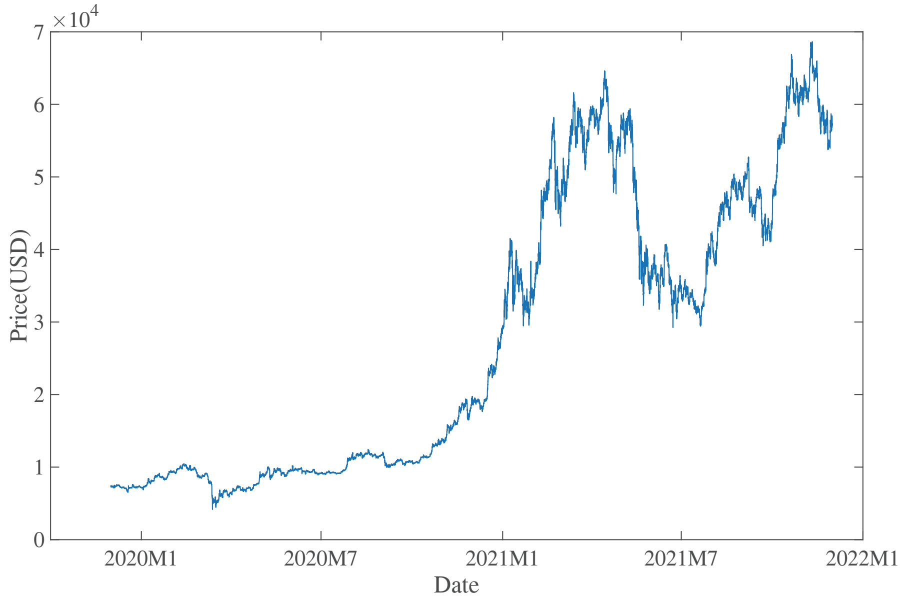

Figure 1 The hourly Bitcoin price from Dec. 1, 2019 to Nov.30, 2021

3.2 Emperical Results and Statistics

EMD is used to decompose Bitcoin hourly prices, with a total of 17543 data points. Finally, the data series are decomposed into thirteen IMFs plus one residue. Figure 2 shows the results. The first row in Figure 2 is observed data. IMF1 to IMF13 are listed in order of high-frequency to low-frequency. The last row is residual. The frequency and amplitudes of each IMF are changing with time. The residue is a pattern that changes slowly around the long-term average[14, 31].

In Table 1, six measures are taken to describe the characteristics of each component: Mean periods of each IMF, correlations between each IMF and observed data series (Pearson's correlation and Kendall's correlation), the variance, each component's variance divided by observed data series' variance, each component's variance divided by total variance. Following Zhang, et al.[31], the mean period is calculated as the number of peaks of each IMF divided by the total number of data points to simplify the changing periods of each IMF caused by various frequencies and amplitudes.

From the results of decompositions, the dominant mode of observed data is determined by residuals. Both Pearson's and Kendall's correlation between residual and observed data are more than 0.7 at the significance level of 1%. Meanwhile, the residual accounts for 77.18% of the total variance, suggesting that the Bitcoin price are determined by long-term trend.

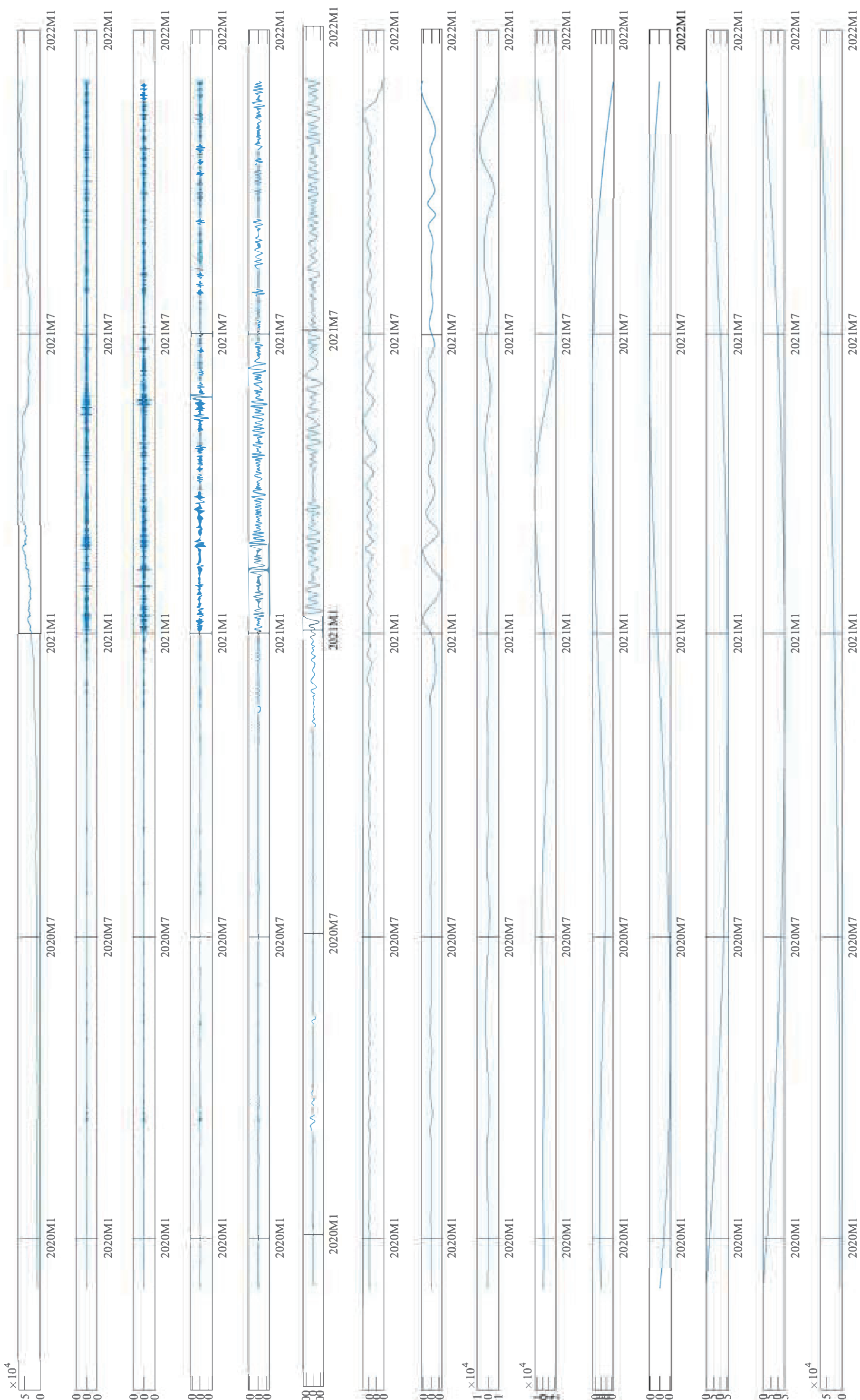

Figure 2 The IMFs and residue for Bitcoin daily price from Dec.1, 2019 to Nov.30, 2021 derived through EMD

Table 1 Measures of IMFs and the residue for the Bitcoin hourly price Dec.1, 2019 to Nov.30, 2021 derived through EMD

	Mean period (hours)	Pearson correlation	Kendall correlation	Variance	Variance as % of observed	Variance as % of ($\sum$IMFs+residual)
observed				386293729.10		
IMF1	3.15	0.01	0.01	24494.17	0.01	0.01
IMF2	7.57	0.02^{**}	0.01^{*}	35821.83	0.01	0.01
IMF3	17.58	0.01	0.01	90931.33	0.02	0.02
IMF4	41.77	0.03^{***}	0.02^{***}	185222.83	0.05	0.04
IMF5	94.32	0.02^{***}	0.02^{***}	438948.19	0.11	0.10
IMF6	233.91	-0.04^{***}	0.02^{***}	2065775.00	0.53	0.47
IMF7	548.22	0.16^{***}	0.04^{***}	2849341.38	0.74	0.65
IMF8	1449.46	0.12^{***}	0.08^{***}	4535869.72	1.17	1.04
IMF9	5847.67	0.08^{***}	0.01	68870488.61	17.83	15.83
IMF10	8771.50	0.39^{***}	0.31^{***}	19511988.24	5.05	4.49
IMF11	17543	0.84^{***}	0.55^{***}	645792.21	0.17	0.15
IMF12	17543	0.10^{***}	-0.07^{***}	20.68	0.00	0.00
IMF13	17543	0.10^{***}	-0.07^{***}	20.64	0.00	0.00
Residual		0.88^{***}	0.75^{***}	335770332.47	86.92	77.18
Sum					112.62	100

Note: ***, **, and * present the significance level of 1%, 5%, and 10%, respectively (2-tailed).

The second important mode is IMF9 which has a mean period of nearly eight months. It has the same directions of two correlations and accounts for 15.83% of the total variance. A strange phenomenon is that the two correlations have great differences in IMF6, IMF12, and IMF13, especially in directions. The observed data has high volatility, but the movement of the low-frequency part will last for a long time before the direction changes. The residual remains an upward trend along with most observed data points.

3.3 Compositions

In this part, a fine-to-coarse reconstruction algorithm is used to analyze decomposition results. First, the Jarque-Bera test is used to examine whether each IMF follows the normal distribution. In Table 2, Column (2) shows that all IMFs of decomposition don't follow the normal distribution. Therefore, the Wilcoxon signed-rank test is used to find the index K of fine-to-coarse reconstruction to compose the IMFs to high-frequency components and low-frequency components. Column (3) presents that the median of fine-to-coarse reconstruction departs from zero significantly at IMF2 firstly. The result means that IMF1 construct the high-frequency components, the partial reconstruction of IMF2 to IMF13 represent low-frequency components, and the residual is also regarded as the trend of Bitcoin price. Figure 3 shows the observed data, high-frequency components, low-frequency components and trend. Table 3 reports the statistical results.

Table 2 Fine to coarse reconstruction

	Jarque-Bera test	Wilcoxon signed rank test
1	46123.95***	77512769
2	60596.87***	78731360***
3	101629.56***	78868027***
4	20791.31***	78448528**
5	4638.64***	77726081
6	109812.18***	75243027**
7	12558.92***	74122018***
8	12842.42***	83848283***
9	440.81***	63296773***
10	342.41***	57195847***
11	1714.20***	53878907***
12	1730.43***	53824829***
13	1730.43***	53770641***

Note: ***, **, and * present the significance level of 1%, 5%, and 10%, respectively (2-tailed).

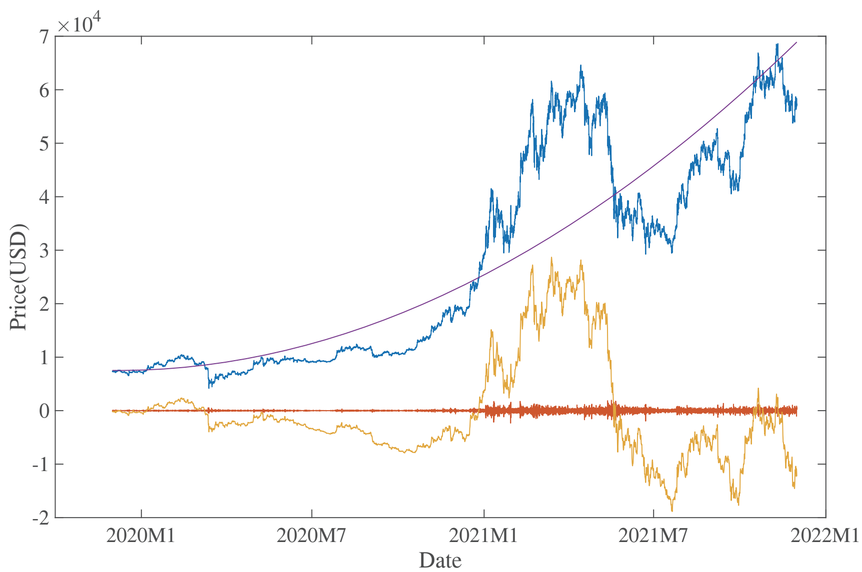

Figure 3 The compositions of Bitcoin hourly price from Dec.1, 2019 to Nov.30, 2021

3.3.1 Trend

In Table 3, the trend is highly correlated to the Bitcoin price, the Pearson's and Kendall's correlations are 0.88 and 0.75 at 1% significance. The trend accounts for more than 78.95% of the variance and holds a high coefficient with observed data, indicating that the trend is a decisive factor for Bitcoin price in the long run. The continued increasing trend is attributed to the limited supplication of Bitcoin and the particular necessity such as illegal transactions

Table 3 The correlation and the variance of the components for the Bitcoin hourly data series from Dec.1 2019 to Nov.30 2021

	Mean period	Pearson correlation	Kendall correlation	Variance	Variance as % of observed	Variance as % of ($\sum$IMFs+residual)
Observed				386293729.10		
high-frequency components	3.59	0.02^{**}	0.02^{***}	59937.54	0.02	0.01
low-frequency components	20.38	0.38^{***}	0.03^{***}	89487205.91	23.17	21.04
Trend		0.88^{***}	0.75^{***}	335770332.47	86.92	78.95
Sum					110.10	100

Note: ***, **, and * present the significance level of 1%, 5%, and 10%, respectively (2-tailed).

by Bitcoin[7, 43], safe-havens for the economic downturn[44, 45], which may imply that the long term trend of Bitcoin price is determined by the demand with the expected established supply. Specially, we define this demand as rigid demand which is decided by Bitcoin's characteristics such as trust framework and pseudoanonymity.

Compared with the trend and observed data, the Bitcoin price is fluctuated substantially due to the major events. However, the price would reverse to the trend when the event is over. For example, Coinbase, the world largest digital currency exchange, was listed on NASDAQ on April 14,2021, and the Bitcoin price raised at the new peak of \$64,630. However, with some gainers selling out their Bitcoin, the regulations by the government of Turkey, India, the US, China in succession, the price fell to \$29,240 on June 22, 2021, Still, the price rose slowly after that and finally reversed to the trending price of \$69,640 on Nov.10, 2021.

3.3.2 Effects of Major Events

The effects of major events are mainly described by IMF2 to IMF13. In Table 3, the low-frequency components account for 23.17% of the total variance. The Pearson's and Kendall's correlations are 0.38 and 0.03, significantly at the 1%. The mean periods of these IMFs range from 17.58 hours to 17543 hours, indicating that the market could eliminate some major event effects soon by itself. However, some impacts last nearly two years, suggesting that the impacts caused by some major events can't be eliminated by the market soon. For example, the change rates of some data points are more than 15% which means that some major events affect Bitcoin price seriously. The trend is rising smoothly, and the market fluctuations are frequent but with small ranges. Therefore, the large waves can only arise from major events, which is consistent with Zhang, et al.[31, 32].

Figure 3 shows that the low-frequency components can measure the impacts of the major event on the Bitcoin price. For example, the outbreak of COVID-19 all over the world and the loosened monetary issued by the Federal Reserve caused the biggest black swan on Mar.12, 2021, the low-frequency components of Bitcoin dramatically decreased from -721.86 at 01:00 to -2435.30 at 18:00 on Mar.12, 2020, which last 17 hours. In addition, the regulation of governments and the public concerns about energy consumption in Bitcoin minings caused a series of negative impacts on Bitcoin prices. For instance, the Chinese government proposed to crack down on Bitcoin mining and trading behaviors on May.21, 2021. A series of clearance measures for mining has been carried out in several provinces with abundant electricity. The thorny topic of the regulation of cryptocurrencies will also be on the agenda at the G7 meeting on June 4, 2021. However, most of these major events last less than 48 hours, and the negative effects of these major events on Bitcoin price could not match the positive effects of the long trend. These findings are consistent with Ciaian, et al.[46] that the macroeconomic factors only affect Bitcoin price in short durations and have few effects on long term trends.

3.3.3 Short-term Fluctuations

From Table 3, the Pearson and Kendall correlation of high-frequency components both are 0.02 at the significance of 5% level at least, which are smallest among those of components. The high-frequency components only account for 0.01% of the total variance, supporting the evidence that high volatility but low correlation with high-frequency component in Bitcoin price. The mean period of the high-frequency component is 3.59 hours, suggesting that the impacts of high-frequency components last shortly. The high-frequency component can be regarded as an index of short term fluctuations.

According to previous studies, speculation is an important factor of Bitcoin price formation[19, 46]. The short-term fluctuations may be caused by investors' emotions, hackers attacks, short-term imbalances, etc. Therefore, those events are regarded as high-frequency events and their effects are included in high-frequency components. Usually, these effects are of short duration. It should be noted that the data in our study is hourly data, so the short term is less than 12 hours generally.

Unlike other assets such as stocks and commodities, Bitcoin has an amount limitation with its own mechanism, so the high-frequency components account for minor effects on total volatility. Investors emotions, miners' behaviors, speculative behaviors, illegal trades are significant for short-term predictions.

In this section, our study uses EMD and fine-to-coarse reconstruction to decompose and compose Bitcoin price into high-frequency component, low-frequency component and trend. For Bitcoin, the high-frequency component can be treated as market fluctuations, and some events only have several hours effects on Bitcoin price. The low-frequency component reflects the effects of major events. The residual shows the long term trend of Bitcoin price. For example, the Bitcoin price at 16:00, Mar.12, 2020 can be decomposed into: 1) high-frequency component (\$23.20); 2) low-frequency component (\$−2548.76); 3) Trend (\$8613.24).

4 Intraday Jump Analysis

Section 3 mainly analyzes the major events' effects on Bitcoin price, however, the high frequency events' effects can't be captured well by EMD method. To find the news' or small events' effects on Bitcoin markets, this section applies the LM test on Bitcoin returns to study the jump arrivals and jump size. We aim to evaluate the presence of jumps and analyze which events caused these jumps.

4.1 Data

The data of Bitcoin minute's closed price is obtained from https://www.cryptodatadownload.com/data/gemini/. The Bitcoin minute's price series from 00:00, Dec.1, 2019, to 23:59, Nov.30, 2021. Based on the algorithm of the LM test, we delete the data of one hour with more than ten consecutive missing data firstly, then the remaining missing data is filled with the recently realized minute's price. Finally, 1,022,400 data are in our sample. The unit of Bitcoin prices is also reported in US dollars. Then we calculate the realized returns as the difference of natural logarithm prices. Lee and Mykland[28] have examined that a 15-minute frequency is high enough for the LM test to detect jumps by Monte Carlo Simulation, so we follow them to choose 15-minute frequency observations in our test. We also suppose that the jump size dominate returns once the jump occurs, but we can't assume the number of jumps in one day.

4.2 Results of LM Test

We apply the LM test at a significance of 5% and find 266 jumps in 220 days in the period 00:00, Dec.1, 2019, to 23:59, Nov.30, 2021, nearly three jump dates per week. Table 4 presents the descriptive statistics for the jumps detected from 15-minute intervals. There are 214 positive jumps and 52 negative jumps. The average size of positive jump is 34.97%, and that of negative jump is −13.66%. We also find that the absolute size of 37.61% jumps is more than 40%, with only one negative jump included. Based on the LM test results, we infer that the unexpected information, which seems like good news, caused bigger jumps than bad news.

The intraday jump test assumes that the jump arrival time follows the Poisson process, or the duration between successive jumps are independent and follow exponential distributions[24, 27, 28]. LM test only reports whether a jump exists in a given time interval, so we can't test the null hypothesis of exponential inter jump durations. We follow Bajgrowicz, et al.[30] and Scaillet, et al.[2] to apply runs test to examine the randomness of jump detections by comparing the sequence of consecutive time intervals with jumps and no jumps with their sampling distribution in the case of random arrival. We employ the runs test on the whole sample and two subsamples with the period of one year, Table 5 presents the results. The p-value of each sample is bigger than the given alpha (0.05), so we can't reject the null hypothesis. That is to say, there is no significant clustering in jump durations.

Table 4 Descriptive statistics of jumps

	Total jumps	Positive jumps	Negative jumps
Numbers	266	214	52
Mean	25.46%	34.97%	−13.66%
Sd.	30.10%	25.39%	8.68%
Max	100.00%	100.00%	−1.82%
Min	−41.25%	0.70%	−41.25%
Std.Dev	30.10%	25.39%	8.68%
Skewness	0.35	0.58	−0.72
Kurtosis	2.40	2.34	3.48

Table 5 Results of runs test

Sample period	p-value	Numbers of jumps	Days
Dec.1, 2019–Nov.30, 2020	0.60	168	347
Dec.1, 2020–Nov.30, 2021	0.13	98	363
The whole sample	0.89	266	710

Note: The days is less than 365 of each year because we delete the days with more than 20 missing minutes-frequency data.

4.3 High-Frequency Events' Impacts on Jumps

In this part, we search for real-time news and events around jump arrival times from Factiva database based on detected jumps by LM test. News and event sources searched from the Factiva include the Financial Times, the Wall Street Journal, Dow Jones Newswire, Reuters Newswire, Xinhua Agency and Agence France-Presse. Unlike the stock market, some jumps don't match the news or events.

The empirical results don't happen at regular intervals. Different from the stock market[27, 28], not all jumps are caused by financial news. Table 6 summarizes the matching results of jumps and news. More than 60% of jumps can't match the public information. The Bitcoin market is not effective based on the effective market hypothesis. The driving factors may refer to market microstructure noise and investors' motions, which are not induced by public news or events.

We identify the relations between information and jumps into ten groups. There are 33 jumps classified into industries. In this group, seven jumps are about accepting Bitcoin as payment, including large payment institutions such as Paypal, Visa and Mastercard; Six jumps are related to accepting bitcoin derivatives by exchange. These derivatives include options, futures, index funds and ETFs. Five jumps of this group match the news of the mining tax, other digital assets and fit into the portfolio by the hedge fund company. Fifteen jumps are matched with information from related companies. In this subgroup, nine jumps are related to corporate merging, investment in mining and company listing; Three are related to mining performance; Five are about technologies innovations on security and hash rates; One jump matches the news of an exchange's violations. Some jumps are also caused by several pieces of news. For example, the negative jump in 13:45, Dec.12, 2020 matches three items of news related to investment and technologies.

The second group is affected by information about regulations by the government. There are 28 jumps matching news about regulations. Seventeen jumps are affected by policy restrictions, while some policies have not been implemented. China and EU states have shown negative attitudes to cryptocurrency. Considering the Bitcoin risk and carbon emissions, China has taken the strictest limitations for Bitcoin minings, transactions, settlements, and electricity supply. There are seven jumps related to news about Chinese ban rules. Although nine pieces of news are only about regulation advice or partially constraints, they also caused nine jumps. Regulators sometimes show goodwill to cryptocurrency. For example, regulators have approved some cryptocurrency exchanges, including Canada, Singapore, the UK, and Ukraine. Combining with other good news, such as no regulations on the agenda, permissions for transactions, these good news match twelve jumps. As regulations, only China has taken the ban rules in

Table 6 Jumps and news

News' types	Jumps	Jumps(+)	Jumps(−)	News example
Industry	33	24	9	Mastercard accelerates crypto card partner program, making it easier for consumers to hold and activate cryptocurrencies.
Regulations	28	22	6	China's central bank warned companies on Tuesday against assisting cryptocurrency-related businesses as it shut down a software firm over suspected involvement in digital currency transactions.
CBDC	12	10	2	The BoE said that if it introduced its own digital currency, it would be denominated in sterling and would not replace banknotes or commercial bank deposits, and need not be based on the blockchain technology that underpins cryptocurrencies.
Illegal transaction	12	8	4	Latin American crime cartels turn to cryptocurrencies for money laundering.
Commentator	8	6	2	BOEs Bailey says hard to see that Bitcoin has intrinsic value.
Social Media	6	4	2	See Table 7.
Fiat Money	3	2	1	Central American Bank for economic integration says will give technical assistance to El salvador to implement bitcoin's legal tender.
Economics	3	2	1	The FED slashed interest rates to zero and announced it would be carrying out an additional $700bn-worth of asset purchases, along with deploying a whole host of other tools that it has not used since the global financial crisis.
Forks	1	1	0	TAAL is pleased to announce that it has successfully completed the upgrade to its Bitcoin_V Node mining software to support the Genesis network upgrade code-named Genesis that activated on Feb.4, 2020.
Unmatched	160	135	25	
Sum	266	214	52	

our sample period, other countries-most notably the US-are more friendly to cryptocurrency (including Bitcoin).

The Bitcoin market also cares about central bank digital currency (CBDC), although it is treated as a financial asset by the public. There are ten jumps matching news about CBDC, and nine jumps are about issuing CBDC; one jump relates to news that the digital-Yen is not on the agenda in Japan. Compared to issuing CBDC, the acceptance of the underlying technology of Bitcoin has attracted more attention. The Bank of England has said that its own digital currency need not rely on blockchain technology. When this information was released, the price of Bitcoin fell by 14.50% in 15 minutes intervals, which is the biggest price fluctuation in all detected jumps. Even if the Bitcoin market is accustomed to the CBDC, the abandonment of Bitcoin's underlying technology still causes a bigger market panic. China is the first country to issue digital currency by the central bank, the news released by Reuters induced three jumps (see Figure 4) on Sep.21, 2020. Even if the public accepts Bitcoin as a financial asset, the CBDC don't accept the "decentralization praised by Bitcoin advocates, causing severe jumps and undermining the confidence of decentralized finance advocates. There are still small countries seeking to legalize Bitcoin, there are three jumps about the legalization of Bitcoin in El Salvador, but the news has little impact on Bitcoin price.

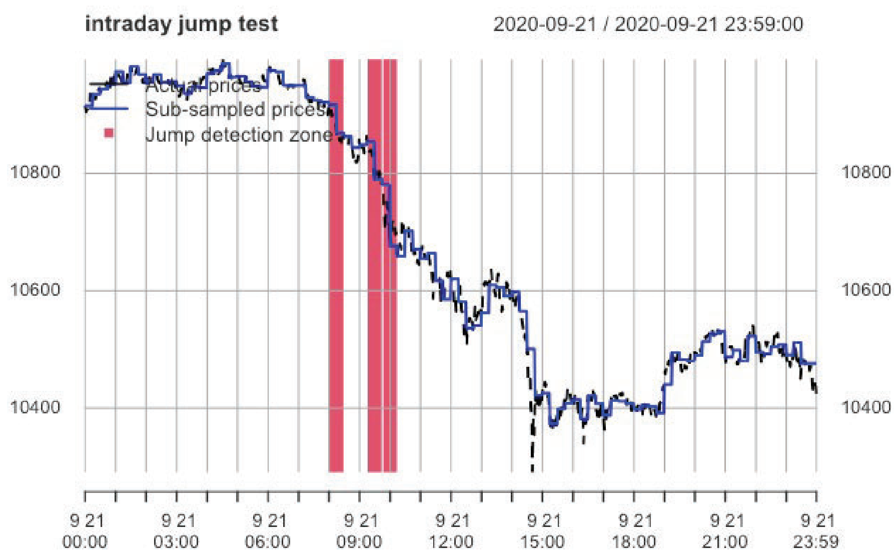

Figure 4 Jumps on Sep.21, 2020

Illegal transactions are not avoidable in the Bitcoin market[7], We find that twelve jumps match the news of defrauding, extortions and other illegal transactions. A global pandemic, economic fluctuations and economic policies also caused three jumps. Forks also account for one jump.

The attitudes of some influential people are also related to jumps. Eight jumps match the comment articles of famous news agencies, six comments are negative, one comment accepts the safe-haven property of Bitcoin, and one comment highly appraises the related firms work.

In 2021, social media's information matched six jumps. All these jumps are related to Musk's tweets. We collect all tweets referred to Bitcoin by Musk in Table 7, and find that the tweets which show Musk's clear stand will cause the jumps. These tweets were tweeted on Jan.29, Feb.8, Mar.24, May.12, May.19 and June.13 in 2021.

From the jumps review, we find that not all jumps are caused by news released publicly. Industry development, regulations, CBDC, and illegal transactions are the main driven factors of jumps. It is worth mentioning that "decentralization opposed by the central bank and undermining the status of blockchain in monetary systems are not favored by the Bitcoin market because the attitudes of central banks to underlying technologies shake the foundations of Bitcoin belief.

Table 7 Musk's Twitter or Public Information about Bitcoin

Time(UTC 0)	Tweets
08:21, Dec.20, 2020	Bitcoin is my safe word.
09:24, Dec.20, 2020	Bitcoin is almost as bs as fiat money.
08:22, Jan.29, 2021	changed twitter's bio as Bitcoin.
12:32, Feb.8, 2021	Tesla announces investing $1.5 billion Bitcoin in financial report.
09:08, Feb.11, 2021	Indicata that Bitcoin rules all cryptocurrencies.
Feb.20, 2021	Musk changes twitter avatar containing Bitcoin elements.
07:02, Mar.24, 2021	You can now buy a Tesla with Bitcoin.
07:09, Mar.24, 2021	Tesla is using only internal open source software operates Bitcoin nodes directly.Bitcoin paid to Tesla will be retained as Bitcoin, not converted to fiat currency.
07:10, Mar.24, 2021	Pay by Bitcoin capability available outside US later this year.
22:06, May.12, 2021	Tesla has suspended vehicle purchases using Bitcoin.
14:42, May.19, 2021	Tesla has diamonds hands.
1:07, June.4, 2021	Musk posted about the Bitcoin hashtag and the Broken Heartemoji, along with an image of a couple in conflict.
Jul.22, 2021	It appears that Bitcoin is turning more to renewable energy, with a trend of more than 50% of renewable energy. In this case, Tesla will resume accepting Bitcoin.

5 Conclusions

This paper uses EMD and intraday jump test to analyze Bitcoin price at high-frequency. Based on the EMD method, the hourly spot price of Bitcoin is decomposed into 13 IMFs plus a residual. The fine-to-coarse reconstruction composes the IMFs into high-frequency component, low-frequency component and long term trend. Besides, the Bitcoin price can be explained as a composition of a long-term trend, effects of major events, and short term fluctuations caused by market microstructure noise. In the long-term, Bitcoin price is determined by trend, which is upward due to inelastic supply and rigid demand. Unforeseen major events induce the drastic price changes, but the duration of impacts last less than two days, and the price will reverse to its trend. The correlation and the percentage variation of long-term trends show that the trend mainly determines the observed data. Furthermore, we identify jump arrivals and jump size based on the LM test. Only nearly 40% of jumps can match financial news; others may be driven by microstructure noise or private information. We also find that the jump size of the Bitcoin market is larger than stock markets compared to prior studies. Industry development, roles in the financial market and acceptance by officials are the driving factors of jump-matched news.

DRE framework provides some insights into analyzing characteristics of Bitcoin price. For the government, analyzing and forecasting Bitcoin prices can help put forward reasonable regulations to maintain a stable financial market and reduce illegal transactions. Particularly, analyzing high-frequency data help government propose more precise measures and help investors adjust the portfolio in time. The jump size and directions can also be considered in price prediction models. Still, the jump test can't identify the relationship between news attitude and jumps, which is highly desirable into investigated in future work. In addition, the high-frequency component of price and jumps unmatched news may be related to microstructure noise, which will be also studied in the future.

Acknowledgements The authors gratefully acknowledge the Editor and two anonymous referees for their insightful comments and helpful suggestions that led to a marked improvement of the article.

References

[1] Nakamoto S. Bitcoin: A peer-to-peer electronic cash system. Decentralized Business Review, 2008: 21260. doi: 10.2139/ssrn.3977007.

[2] Scaillet O, Treccani A, Trevisan C. High-frequency jump analysis of the bitcoin market. Journal of Financial Econometrics, 2020, 18(2): 209–232.

[3] Chaum D. Blind signatures for untraceable payments. Advances in cryptology. Springer, Boston, MA, 1983: 199–203.

[4] Mora C, Rollins R L, Taladay K, et al. Bitcoin emissions alone could push global warming above 2°C. Nature Climate Change, 2018, 8(11): 931–933.

[5] Jiang S, Li Y, Lu Q, et al. Policy assessments for the carbon emission flows and sustainability of Bitcoin blockchain operation in China. Nature Communications, 2021, 12(1): 1–10.

[6] Corbet S, Lucey B, Yarovaya L. Bitcoin-energy markets interrelationships — New evidence. Resources Policy, 2021, 70: 101916.

[7] Foley S, Karlsen J R, Putniņš T J. Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies?. The Review of Financial Studies, 2019, 32(5): 1798–1853.

[8] Stokes R. Virtual money laundering: The case of Bitcoin and the Linden dollar. Information & Communications Technology Law, 2012, 21(3): 221–236.

[9] Vandezande N. Virtual currencies under EU anti-money laundering law. Computer Law & Security Review, 2017, 33(3): 341–353.

[10] Whitford A B, Anderson D. Governance landscapes for emerging technologies: The case of cryptocurrencies. Regulation & Governance, 2021, 15(4): 1053–1070.

[11] Yang B, Sun Y, Wang S. A novel two-stage approach for cryptocurrency analysis. International Review of Financial Analysis, 2020, 72: 101567.

[12] Yi S, Xu Z, Wang G J. Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?. International Review of Financial Analysis, 2018, 60: 98–114.

[13] Baur D G, Dimpfl T. The volatility of Bitcoin and its role as a medium of exchange and a store of value. Empirical Economics, 2021, 61(5): 2663–2683.

[14] Huang N E, Shen Z, Long S R, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 1998, 454(1971): 903–995.

[15] He K, Tso G K F, Zou Y, et al. Crude oil risk forecasting: New evidence from multiscale analysis approach. Energy Economics, 2018, 76: 574–583.

[16] Jin X, Zhu K, Yang X, et al. Estimating the reaction of Bitcoin prices to the uncertainty of fiat currency. Research in International Business and Finance, 2021, 58: 101451.

[17] Bouoiyour J, Selmi R, Tiwari A K, et al. What drives Bitcoin price. Economics Bulletin, 2016, 36(2): 843–850.

[18] Bouoiyour J, Selmi R, Wohar M E. Safe havens in the face of presidential election uncertainty: A comparison between Bitcoin, oil and precious metals. Applied Economics, 2019, 51(57): 6076–6088.

[19] Cheah E T, Fry J. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Economics Letters, 2015, 130: 32–36.

[20] Hayes A S. Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. Telematics and Informatics, 2017, 34(7): 1308–1321.

[21] Symitsi E, Chalvatzis K J. The economic value of Bitcoin: A portfolio analysis of currencies, gold, oil and stocks. Research in International Business and Finance, 2019, 48: 97–110.

[22] Press S J. A compound events model for security prices. Journal of Business, 1967, 40(3): 317–335.

[23] Merton R C. Theory of rational option pricing. The Bell Journal of Economics and Management Science, 1973, 4(1): 141–183.

[24] Christensen K, Oomen R C A, Podolskij M. Fact or friction: Jumps at ultra high frequency. Journal of Financial Economics, 2014, 114(3): 576–599.

[25] Andersen T G, Bollerslev T. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. International Economic Review, 1998, 39(4): 885–905.

[26] Barndorff-Nielsen O E, Shephard N. Power and bipower variation with stochastic volatility and jumps. Journal of Financial Econometrics, 2004, 2(1): 1–37.

[27] Barndorff-Nielsen O E, Shephard N. Econometrics of testing for jumps in financial economics using bipower variation. Journal of Financial Econometrics, 2006, 4(1): 1–30.

[28] Lee S S, Mykland P A. Jumps in financial markets: A new nonparametric test and jump dynamics. The Review of Financial Studies, 2008, 21(6): 2535–2563.

[29] Lee S S, Mykland P A. Jumps in equilibrium prices and market microstructure noise. Journal of Econometrics, 2012, 168(2): 396–406.

[30] Bajgrowicz P, Scaillet O, Treccani A. Jumps in high-frequency data: Spurious detections, dynamics, and news. Management Science, 2016, 62(8): 2198–2217.

[31] Zhang X, Lai K K, Wang S Y. A new approach for crude oil price analysis based on empirical mode decomposition. Energy Economics, 2008, 30(3): 905–918.

[32] Zhang X, Yu L, Wang S, et al. Estimating the impact of extreme events on crude oil price: An EMD-based event analysis method. Energy Economics, 2009, 31(5): 768–778.

[33] Tang L, Wu Y, Yu L. A randomized-algorithm-based decomposition-ensemble learning methodology for energy price forecasting. Energy, 2018, 157: 526–538.

[34] Huang N E, Wu M L C, Long S R, et al. A confidence limit for the empirical mode decomposition and Hilbert spectral analysis. Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences, 2003, 459(2037): 2317–2345.

[35] Black F, Scholes M. The pricing of options and corporate. Management Science: An Anthology, 1995, 2: 309.

[36] Andersen T G, Benzoni L, Lund J. An empirical investigation of continuous? Time equity return models. The Journal of Finance, 2002, 57(3): 1239–1284.

[37] Eraker B, Johannes M, Polson N. The impact of jumps in volatility and returns. The Journal of Finance, 2003, 58(3): 1269–1300.

[38] Aıt-Sahalia Y. Disentangling diffusion from jumps. Journal of Financial Economics, 2004, 74(3): 487–528.

[39] Bouri E, Lucey B, Saeed T, et al. The realized volatility of commodity futures: Interconnectedness and determinants. International Review of Economics & Finance, 2021, 73: 139–151.

[40] Alam M S, Shahzad S J H, Ferrer R. Causal flows between oil and forex markets using high-frequency data: Asymmetries from good and bad volatility. Energy Economics, 2019, 84: 104513.

[41] Bubák V, Kočenda E, Žikeš F. Volatility transmission in emerging European foreign exchange markets. Journal of Banking & Finance, 2011, 35(11): 2829–2841.

[42] Ghysels E, Harvey A C, Renault E. 5 Stochastic volatility. Handbook of Statistics, 1996, 14: 119–191.

[43] Conti M, Gangwal A, Ruj S. On the economic significance of ransomware campaigns: A Bitcoin transactions perspective. Computers & Security, 2018, 79: 162–189.

[44] Hakim das Neves R. Bitcoin pricing: Impact of attractiveness variables. Financial Innovation, 2020, 6(1): 1–18.

[45] Corbet S, Hou Y G, Hu Y, et al. Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. Economics Letters, 2020, 194: 109377.

[46] Ciaian P, Rajcaniova M, Kancs A. The economics of BitCoin price formation. Applied Economics, 2016, 48(19): 1799–1815.