Vulnerability of Cryptocurrency Markets: A Study of the Relationship Between High-Impact Users and Bitcoin Market Price Volatility

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Abstract. While the blockchain cryptocurrency market is becoming increasingly sought after, the vulnerability of the crypto market has also been brought to the attention of some academics. Based on cryptocurrency price data in TradingView database, this paper studies the effect of high-impact users' comments on bitcoin price volatility in social media. The results show that when the Bitcoin market is in the listing channel, high-impact user speech does not bring significant abnormal returns. When Bitcoin market is in a downward channel, High-Impact community leaders' empty talk produces significant negative returns.

Keywords: Blockchain · Cryptocurrency · Vulnerability of the Crypto Market · Bitcoin

1 Introduction

In recent years, Wall Street investment institutions and individuals have deployed the field of cryptocurrency, pushing Bitcoin — a financial investment product to a historical peak of $64,000 in mid-April. However, with market speculation reaching its peak, Tesla, which previously publicly supported Bitcoin payment, announced that it would no longer accept Bitcoin as a payment method. Its founder Elon Musk frequently tweeted accusing Bitcoin of excessive energy consumption. This has caused extreme fluctuations in the cryptocurrency market, and the price of the currency has suddenly fallen sharply, seriously jeopardizing the self-interest of investors. As a financial investment product, the influence mechanism of price fluctuation behind cryptocurrency is a hot issue in academic circles at home and abroad in recent years. Based on the event study method, this study takes Musk as an example to investigate the impact of high-influential users of social media on the market price of Bitcoin. By constructing an abnormal return model for Bitcoin, this study provides more direct evidence that the posting of information by high-influential users triggers more noisy trading behaviour under social media.

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2 Literature Review

2.1 Research Related to Factors Affecting the Price of Cryptocurrencies

Cryptocurrencies emerged after the global financial crisis in 2008 [11] and Satoshi Nakamoto (2008) proposed Bitcoin in his article as a digital currency using an open-source payment system. Cryptocurrencies are mainly new electronic currencies that take a distributed book-keeping approach to mining, creating, issuing and circulating based on blockchain technology. It is divided into private digital currencies and legal digital currencies by sovereign endorsement [13]. Private digital currencies are issued by non-state entities, also known as virtual currencies, and are digital currencies that are issued and controlled by developers, are not regulated by governments, and circulate among members of a virtual community [5], such as Bitcoin and Ethereum.

With the advent of Bitcoin, hundreds of cryptocurrencies have been invented and the market capitalisation of cryptocurrencies as a whole has grown significantly. As an asset class [2], cryptocurrencies, represented by Bitcoin, have attracted widespread attention from investors, regulatory authorities, policy makers, technicians, entrepreneurs and academics [8].

At present, there are two research perspectives on the influencing factors of Bitcoin price fluctuation: the traditional financial theory under the assumption of rational man and the behavioural finance theory which is more explanatory to practical problems. In the study of traditional financial theory [6], Bitcoin, as a new financial asset, has a pricing theory based first on traditional theories such as the mean-variance model, option pricing theory and efficient market theory. In addition, one study used supply and demand equilibrium analysis in economics to construct a model of the operating mechanism of bitcoin price formation [1].

However, traditional financial theoretical research often relies on many assumptions and has inherent flaws. In the study of behavioural finance, investors' cognitive bias, choice preference, and will control will all cause abnormal fluctuations in the securities market. Chen uses the noise trading theory of behavioural finance to explain the phenomenon of abnormal fluctuations in financial asset prices [12]. Liu established an evolutionary game model of the trading behaviour of noise traders and rational investors in the financial market, which proved that noise trading strategies may exist for a long time in the financial market [15]. The high-traffic head users in the financial sector have a high reputation and a wide range of influence. They are a key node to promote noise trading and contribute to abnormal market fluctuations. Zhang believes that investor sentiment can be regarded as a "vane" of market trends [4]. Wang believes that the social network relationship of social media user interaction is an important factor influencing stock price fluctuations [14].

2.2 Research Related to the Influence of Opinion Leaders on Cryptocurrencies

Social media is becoming an important source of information for investors, containing effective information that can assist them in their investment decisions [3]. As hubs of social networks, opinion leaders control the flow of information between different

groups. They have relatively strong appeal and realisation power among their fan base and can influence asset price movements in financial markets.

Garcia and Schweitzer investigate the correlation between opinion signals such as voice indexes, sentiment scores, opinion polarisation and cryptocurrency prices by crawling social media for bitcoin-related tweets. The study demonstrates that trading strategies based on social media sentiment may yield positive investment returns in the cryptocurrency market [7]. Linden collects raw data such as text, user information and timestamps from an active cryptocurrency community. Based on these data, the research uses techniques such as dynamic topic modelling, text mining and unsupervised machine learning to investigate the correlation between the evolution of social media opinions and cryptocurrency prices [10].

3 Materials and Methods

3.1 Data Sources

In this paper, the daily data of Bitcoin price and Dogecoin price are from the TradingView database. Event one represents Tesla submitting documents to the Securities and Exchange Commission (SEC) to disclose the company's purchase of 1.5 billion dollars of bitcoin (event 1). Event two represents Musk's announcement that Tesla supports bitcoin payment (event 2). Event three indicates that Tesla no longer accepts bitcoin payment (event 3). In order to compare the impact of high-impact users of social media on different cryptocurrency markets, this study adds empirical study to study the impact of Musk's speech on the price of dog-dog coins. The selected events are Musk Twitter's release of "Dogecoin rise to the moon" (event 4) and Musk's drama of "Dogecoin is a fraud" in variety shows (event 5). Event days corresponding to each event and range settings for the estimation window, event window, and ex-post window can be found in Table 1.

3.2 Empirical Study

This study selects the market model of event analysis method to conduct specific research on Musk's comments on Bitcoin. The market model needs to select the market index with strong representativeness and high accuracy. In this study, the median filter-improved Pearson correlation model is used to explore the synchronization relationship between the two market indexes of "Total market value of cryptocurrency with bitcoin" and "Total market value of cryptocurrency without bitcoin". In addition, the relationship between the dynamic adjustment of the window range of the estimation window and the event window and the R^2 value of the regression model is studied. By observing the real-time trend of bitcoin prices before and after the event, we set appropriate parameters for the market model in the event study method and construct the abnormal rate of return model of bitcoin. In order to measure the impact of high-impact users on abnormal market volatility, this paper further explores the comments of the same high-impact user – Musk on Bitcoin and Dogecoin cryptocurrencies, analyses the differences between the abnormal market volatility of the two cryptocurrencies, and uses the prospect theory of behavioural finance to demonstrate the underlying reasons.

Table 1. Selection of Event Windows

	Experiment 1			Experiment 2	
	Event1	Event2	Event3	Event4	Event5
Event Day	2021.2.8	2021.3.24	2021.5.13	2021.1.28	2021.5.9
Estimated Window	[−30,−11]	[−30,−11]	[−30,−11]	[−90,−11]	[−90,−11]
(Time Period)	2021.1.9–2021.1.28	2021.2.22–2021.3.13	2021.4.13–2021.5.2	2020.10.30–2021.1.17	2021.2.8–2021.4.28
Event window	[−10,10]	[−10,10]	[−10,10]	[−10,10]	[−10,10]
(Time Period)	2021.1.29–2021.02.18	2021.3.14–2021.4.3	2021.5.3–2021.5.23	2021.1.18–2021.2.7	2021.4.29–2021.5.19
Post-event window	[11,30]	[11,30]	[11,30]	[11,30]	[11,30]
(Time Period)	2021.02.19–2021.3.10	2021.4.4–2021.4.23	2021.5.24–2021.6.12	2021.2.8–2021.2.27	2021.5.20–2021.6.8

3.2.1 Market Index Comparison in Market Model

Abnormal yield is the most critical index in the event analysis method, which refers to the difference between the actual yield and the normal yield. It is mainly used to determine whether the occurrence of a characteristic event in the capital market affects asset prices. Wang compares mean adjustment model, market adjustment model and market model to describe the use range of abnormal return model [9]. Previous studies on Bitcoin have mostly used constant mean return models for estimation. However, Wall Street institutions such as Goldman Sachs and Morgan Stanley have begun to embrace cryptocurrencies, the cryptocurrency space has created a financial market with a total market capitalisation of over US$2 trillion. Therefore, a market model can be used to derive a more accurate estimate of normal returns from the relationship between bitcoin returns and the cryptocurrency market. After comparing the three models, this study selects the market model for estimation, and the model is set as follows:

$$\mathrm{AR_{it}} = \mathrm{R_{it}} - (\alpha_\mathrm{i} + \beta_\mathrm{i}\mathrm{R_{mt}}) \tag{1}$$

Where AR_{it} represents the abnormal return of the Asset I in period t, R_{mt} represents t-period market index, corresponding to normal yield. Based on the characteristics of the cryptocurrency market, this study chooses a market model where the market index is estimated using the "total market value of cryptocurrencies containing bitcoin". The abnormal return is the difference between the actual return R_{it} and the normal return ER_{it} in the event window:

$$\mathrm{AR_{it}} = \mathrm{R_{it}} - \mathrm{ER_{it}} \tag{2}$$

3.2.2 Relationship Between Market Index and Regression Model Parameters

The market model is related to the R^2 value of the regression model. The larger the R^2 value is, the more the variance of the abnormal return is reduced, and the greater the return is. Therefore, the empirical two studies the relationship between the dynamic adjustment of the window range of the estimation window and the event window and the R^2 value of the regression model.

3.2.3 Empirical Study 1 - The Relationship Between Musk's Speech and Abnormal Return Rate in The Bitcoin Market

In empirical 3, the market index is the total market value of the cryptocurrency without bitcoin. The estimation window is set as [−30, −11], the event window is set as [−10, 10], and the post-event window is set as [11, 30]. The market model is established to calculate the abnormal return rate of the bitcoin market when events occur.

3.2.4 Empirical Study 2 - The Relationship Between Musk's Remarks and Ab-Normal Returns of Dogecoin Market

The impact of high-impact user's comments on social media on different cryptocurrency markets is different. In order to further explore the differences in the self-regulation ability of different cryptocurrency markets, empirical 4 uses Dogecoin market price as the research object of cryptocurrency. Based on the characteristics of the price trend of Dogecoin, the estimated window of the market model is set as [−90, −11], and the rest is consistent with the setting of empirical three, and the abnormal return rate of Dogecoin market is calculated when events 4 and 5 occur.

4 Results

4.1 Results of Correlation Analysis of Different Market Indices

In order to explore the relationship between the two indexes of 'Total Market Value of Crypto-currency with Bitcoin' and 'Total Market Value of Cryptocurrency without Bitcoin', the graph 1 has been showing the market value trend of the two since December 2020. It can be seen that the trend is highly correlated. Figure 2 uses median filtering technique and nonlinear method to smooth market noise. In addition, the time span of market data required for target events in this study is from December 4, 2020 to April 23, 2021, and the Person co-efficient of the two is 0.983(***) by using the data of this time period, which fully reflects the global synchronization. Figure 1 calculates the synchronization of sliding windows by setting the window width of 30 days, and shows the synchronization results at each moment. It can be seen from the figure that in January–February 2021, the Pearson co-efficient fluctuated abnormally from 0.9 to 0.5. This is because Bitcoin is in an upward channel during this period. Within a month, its price rose from USD 31645 on January 27, 2021 to USD 55630 on February 19, 2021.

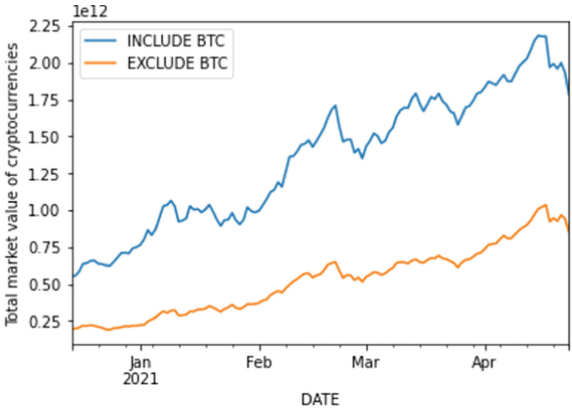

Fig. 1. Market Value Trend Map of Encryption Currency

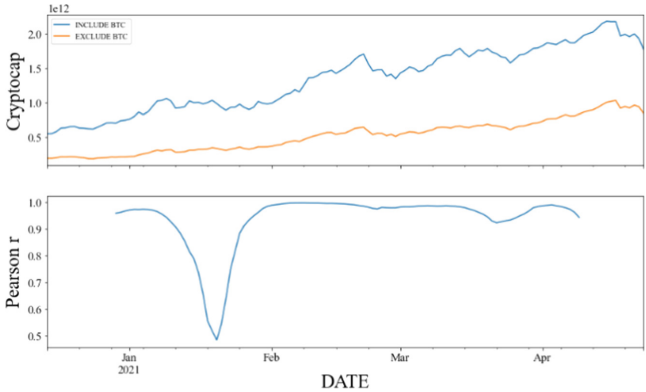

Fig. 2. Variation Chart of Two Index Pearson Coefficients

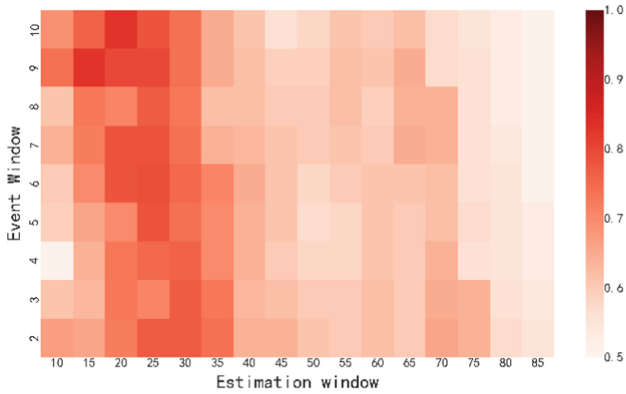

Fig. 3. Regression model 1 - fitting coefficient R2 thermal diagram

4.2 Results of Regression Model Para-Meters over Time Windows

The study takes Event 2 (Musk announced that Tesla supported Bitcoin payment) as an example to study the relationship between event window, estimation window range and the R^2 value of the regression model in the event analysis method. In the figure, the Y-axis indicates the range of the selected event window from two days before and after the event day to ten days, and increases in two days as a unit. The X-axis in the graph represents the range of the estimation window from the first ten days to eighty-five days, and increases in five days. Regression model 1 takes 'Total Market Value of Cryptocurrency without Bitcoin' as independent variable, and 'Bitcoin yield' as dependent variable. The average R^2 of the model is 0.6383, and the corresponding regression co-efficient R^2 of each parameter is shown in Fig. 3. Regression model 2 sets the independent variable as 'Total Market Value of Cryptocurrency with Bitcoin', and the others are consistent with model 1. After calculation, the overall mean R^2 is 0.9202. Figure 4 reflects the dynamic change of R^2 with parameters in regression model 2.

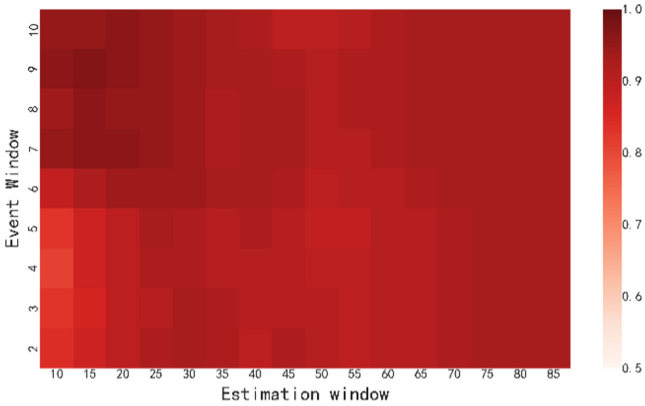

Fig. 4. Regression model 2 - fitting coefficient R2 thermal diagram

4.3 Results of Abnormal Return Statistics Corresponding to Events 1–5

The abnormal returns and cumulative returns corresponding to events 1–5 were calculated for this study. Event 1 represents Tesla's disclosure of the company's purchase of $1.5 billion in bitcoin. Using Event 1 as an example, Table 2 shows the impact of this event on the Bitcoin trading market. R_t represents the normal return on Bitcoin, R_{mt} represents the market index (Total market value of cryptocurrencies containing bitcoin) return, and $E(Rt)$ represents the return presented by the regression results. And AR_t represents the abnormal return of the Bitcoin in the trade date, CAR_t denotes the cumulative abnormal return from the first day of the event window.

In order to explore the influence of Musk's speech on the cryptocurrency market, this study adds Doge coin as a control group for supplementary research. Event 4 (Musk released dog coins related tweets), event 5 (Musk in the variety show called 'dog coin is a fraud'), using the same market model to calculate the corresponding data. The results of the abnormal returns statistics for other events can be found in Tables 3, 4, 5, and 6.

Table 2. Statistical results of abnormal returns for Event 1

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
1/29/2021	0.1294	0.058	0.0441	0.0854	0.0854
1/30/2021	−0.039	−0.0009	−0.0067	−0.0323	0.053
1/31/2021	−0.0181	0.0044	−0.0021	−0.016	0.037
2/1/2021	0.0069	0.0201	0.0114	−0.0044	0.0326
2/2/2021	0.0347	0.0438	0.0318	0.0028	0.0354
2/3/2021	0.0497	0.0172	0.0089	0.0408	0.0763
2/4/2021	0.0269	0.0736	0.0575	−0.0307	0.0456
2/5/2021	−0.0003	0.0352	0.0244	−0.0248	0.0208
2/6/2021	0.0533	0.0296	0.0196	0.0337	0.0545
2/7/2021	−0.0246	−0.0281	−0.0302	0.0056	0.0601
2/8/2021	0.0895	0.0642	0.0494	0.0401	0.1002
2/9/2021	0.1003	0.0513	0.0383	0.062	0.1622
2/10/2021	−0.0233	0.0454	0.0332	−0.0565	0.1057
2/11/2021	0.0177	0.0306	0.0204	−0.0027	0.103
2/12/2021	0.0268	0.0395	0.0281	−0.0013	0.1017
2/13/2021	−0.0077	0.0281	0.0183	−0.026	0.0757
2/14/2021	0.0226	0.003	−0.0033	0.026	0.1016
2/15/2021	−0.0144	−0.0518	−0.0505	0.0361	0.1378
2/16/2021	0.0241	0.0264	0.0168	0.0072	0.145
2/17/2021	0.0408	0.0135	0.0057	0.0351	0.1802
2/18/2021	0.0184	0.0494	0.0367	−0.0183	0.1619

Table 3. Statistical results of abnormal returns for Event 2

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
3/14/2021	0.0251	0.012	0.0121	0.013	0.013
3/15/2021	−0.0419	−0.0282	−0.017	−0.025	−0.012
3/16/2021	−0.049	−0.0081	−0.0025	−0.0466	−0.0585
3/17/2021	0.0278	0.0295	0.0247	0.0031	−0.0554
3/18/2021	0.0076	0.0195	0.0175	−0.0099	−0.0652
3/19/2021	0.0154	−0.0021	0.0019	0.0135	−0.0518
3/20/2021	0.0179	0.0278	0.0235	−0.0056	−0.0573
3/21/2021	−0.0298	−0.028	−0.0168	−0.013	−0.0703

(*continued*)

Table 3. (*continued*)

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
3/22/2021	−0.0177	−0.0078	−0.0022	−0.0155	−0.0858
3/23/2021	−0.0297	−0.0207	−0.0115	−0.0182	−0.104
3/24/2021	0.0029	−0.0209	−0.0116	0.0146	−0.0894
3/25/2021	−0.0517	−0.0452	−0.0292	−0.0224	−0.1119
3/26/2021	0.0234	0.0492	0.0389	−0.0155	−0.1274
3/27/2021	0.0376	0.0307	0.0256	0.0121	−0.1153
3/28/2021	0.0078	0.0053	0.0072	0.0006	−0.1147
3/29/2021	0.016	0.0266	0.0226	−0.0066	−0.1213
3/30/2021	0.028	0.0284	0.0239	0.004	−0.1172
3/31/2021	0.0082	0.0101	0.0107	−0.0025	−0.1198
4/1/2021	0.0037	0.033	0.0273	−0.0236	−0.1433
4/2/2021	0.0088	0.0397	0.032	−0.0232	−0.1666
4/3/2021	−0.012	0.0071	0.0085	−0.0206	−0.1871

Table 4. Statistical results of abnormal returns for Event 3

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
5/3/2021	0.0132	0.0479	0.0207	−0.0075	−0.0075
5/4/2021	−0.0457	0.0074	−0.0047	−0.041	−0.0485
5/5/2021	0.0043	0.0347	0.0125	−0.0082	−0.0567
5/6/2021	0.0255	0.0517	0.0232	0.0024	−0.0543
5/7/2021	0.0016	−0.006	−0.0131	0.0147	−0.0396
5/8/2021	0.0218	0.0205	0.0036	0.0183	−0.0214
5/9/2021	−0.0064	−0.0003	−0.0095	0.0031	−0.0183
5/10/2021	−0.0183	−0.0078	−0.0142	−0.0041	−0.0224
5/11/2021	−0.0187	−0.0012	−0.0101	−0.0087	−0.0311
5/12/2021	−0.0402	0.0457	0.0193	−0.0595	−0.0907
5/13/2021	−0.0855	−0.0659	−0.0506	−0.0349	−0.1256
5/14/2021	0.0201	0.0619	0.0295	−0.0094	−0.135
5/15/2021	−0.0304	−0.0066	−0.0134	−0.017	−0.152
5/16/2021	−0.0379	−0.0393	−0.034	−0.004	−0.1559
5/17/2021	−0.0532	−0.0623	−0.0484	−0.0048	−0.1607

(*continued*)

Table 4. (*continued*)

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
5/18/2021	−0.0074	0.0174	0.0016	−0.009	−0.1697
5/19/2021	−0.1722	−0.2502	−0.1663	−0.0059	−0.1756
5/20/2021	0.0433	−0.0149	−0.0186	0.0619	−0.1137
5/21/2021	−0.0225	−0.0244	−0.0246	0.0021	−0.1115
5/22/2021	−0.021	−0.0838	−0.0619	0.0409	−0.0706
5/23/2021	−0.0654	−0.1254	−0.088	0.0226	−0.048

Table 5. Statistical results of abnormal returns for Event 4

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
1/18/2021	0.0044	0.0196	0.0362	−0.0318	−0.0318
1/19/2021	0.0206	0.0324	0.0563	−0.0356	−0.0674
1/20/2021	−0.0547	−0.0467	−0.0676	0.0129	−0.0545
1/21/2021	−0.0296	−0.0555	−0.0813	0.0517	−0.0028
1/22/2021	−0.0475	−0.0461	−0.0666	0.019	0.0162
1/23/2021	0.0506	0.0435	0.0737	−0.0231	−0.0069
1/24/2021	0.0164	0.0035	0.011	0.0054	−0.0015
1/25/2021	−0.0214	0.0463	0.0781	−0.0995	−0.101
1/26/2021	−0.0408	−0.0515	−0.0751	0.0343	−0.0667
1/27/2021	−0.0569	−0.0305	−0.0421	−0.0148	−0.0815
1/28/2021	1.0604	0.0343	0.0593	1.0011	0.9196
1/29/2021	0.9758	0.0861	0.1404	0.8354	1.755
1/30/2021	−0.4859	−0.0264	−0.0357	−0.4502	1.3049
1/31/2021	0.0425	−0.0098	−0.0098	0.0522	1.3571
2/1/2021	0.0057	0.0121	0.0246	−0.0189	1.3382
2/2/2021	−0.1799	0.0382	0.0653	−0.2452	1.093
2/3/2021	0.0968	0.0389	0.0664	0.0304	1.1234
2/4/2021	0.3039	0.043	0.0729	0.231	1.3544
2/5/2021	0.0192	0.0138	0.0271	−0.0079	1.3464
2/6/2021	0.0577	0.0456	0.077	−0.0192	1.3272
2/7/2021	0.3073	−0.0274	−0.0374	0.3446	1.6718

Table 6. Statistical results of abnormal returns for Event 5

Trade date	Rt	Rmt	E(Rt)	ARt	CARt
4/29/2021	0.0301	−0.008	0.0347	−0.0046	−0.0046
4/30/2021	0.0326	0.032	0.1024	−0.0698	−0.0744
5/1/2021	0.1215	0.0367	0.1105	0.011	−0.0634
5/2/2021	0.0497	−0.002	0.0447	0.0049	−0.0585
5/3/2021	0.0755	0.0306	0.1002	−0.0246	−0.0831
5/4/2021	0.206	−0.0179	0.0178	0.1882	0.1051
5/5/2021	0.1836	0.0211	0.0839	0.0997	0.2048
5/6/2021	−0.0069	0.0393	0.1148	−0.1217	0.0831
5/7/2021	0.0368	-0.0019	0.045	−0.0082	0.0749
5/8/2021	0.0694	0.0211	0.0839	−0.0146	0.0603
5/9/2021	−0.1828	−0.004	0.0414	−0.2242	−0.1639
5/10/2021	−0.1188	−0.0141	0.0243	−0.1431	−0.307
5/11/2021	0.0004	−0.0076	0.0353	−0.0349	−0.3419
5/12/2021	−0.0923	0.0062	0.0588	−0.151	−0.4929
5/13/2021	−0.0365	−0.0771	−0.0825	0.046	−0.4469
5/14/2021	0.1901	0.0502	0.1333	0.0568	−0.3901
5/15/2021	0	−0.017	0.0194	−0.0194	−0.4095
5/16/2021	−0.0538	−0.0391	−0.0181	−0.0357	−0.4452
5/17/2021	−0.0276	−0.0585	−0.051	0.0234	−0.4218
5/18/2021	0.0117	0.0073	0.0606	−0.0489	−0.4707
5/19/2021	−0.3534	−0.2232	−0.3303	−0.0231	−0.4938

5 Discussions

Aiming at the parameters of event window and estimation window in event analysis method, previous studies mostly rely on subjective experience to set artificially. On this basis, this study takes the two parameters as variables to quantitatively study the influence of their changes on the fitting coefficient R^2 of regression model. In addition, in view of the fact that the cryptocurrency market has not yet formed a stable and widely accepted market index, this study compares the performance of two index in the market model and the relationship between them, and constructs the research model of Bitcoin price fluctuation from the perspective of objective data and subjective consideration. The results of the discussion are as follows.

a) This paper provides an idea for a quantitative study on the setting of parameters for the event analysis method. The cryptocurrency market Bitcoin accounts for a

disproportionately high market capitalisation weighting and when a single investment underlying accounts for a dis-proportionately high market index, the index is not representative. At the same time, the study compares the synchronisation relationship between the two indices, which are highly correlated. And after filtering the anomalous market noise with the median filtering technique, the trends are also extremely consistent, which can indicate that the "total market capitalisation of cryptocurrencies without bitcoin" index is both representative and stable, expanding the idea of researching price volatility in the cryptocurrency field.

b) Based on the empirical results, the event 1–5 abnormal returns and cumulative abnormal returns are plotted separately in Fig. 5, whereby the reaction of the bitcoin price to Musk's release of information on Tesla's policy towards bitcoin can be visualized.

Figure 5-a corresponding to Event 1 is taken as an example for analysis. Firstly, the abnormal return rate of bitcoin in the event window fluctuates by nearly 4% on the event day. The abnormal return rate return rate on the first day after the event reaches the maximum positive value of about 6%, and the cumulative abnormal return rate also reaches the maximum positive value of about 9%, indicating that Tesla's purchase of bitcoin has a substantial positive impact on the price of bitcoin.

On the day of the event, investors buy bitcoin in large quantities under the stimulation of good news. However, on the second day after the event, with short-seeing speculators entering the market rapidly, the price of bitcoin has been greatly adjusted, and the abnormal return rate reaches the minimum negative value of 6.1%. From five to ten days after the event, the abnormal return rate gradually stabilized.

Secondly, the volatility of the abnormal return rate on the first six days of the event decreased, and the cumulative abnormal return rate within the first two days was close to 0, indicating that the Bitcoin market did not expect Tesla to announce its purchase of Bitcoin. Third, combined with the cumulative yield curve, this event has a significant positive impact on the bitcoin market.

c) In order to measure the impact of high-impact users on the price trends of different markets, this study explores the factors behind the impact differences by analysing the volatility of the Bitcoin and Dogecoin markets in the face of news shocks. Figure 5-d shows that when Musk made good comments, the abnormal rate of return on the day of dog-dog coins could rise by about 100%. Figure 5-f shows that after Musk released his bullish remarks, the maximum decline in the abnormal return on dog money can reach 20%.

As the opinion leader of cryptocurrency market, Musk is also the investor of cryptocurrency. Behind the frequent tweets about Dogecoin, Musk's related comments have also influenced the movement of Dogecoin market funds. On the contrary, there are a large number of institutional investors in the Bitcoin market. They arbitrage against unusual market fluctuations caused by information disclosure in a timely manner. This move keeps the market price relatively stable.

As a result, commentary from opinion leaders tends to be limited. Therefore, the comments of opinion leaders are often limited. Other Crypto-currency markets, such as Dogecoin, have the characteristics of low market value and concentrated chips. Behind the good or bad news, they often represent the inflow and outflow of market

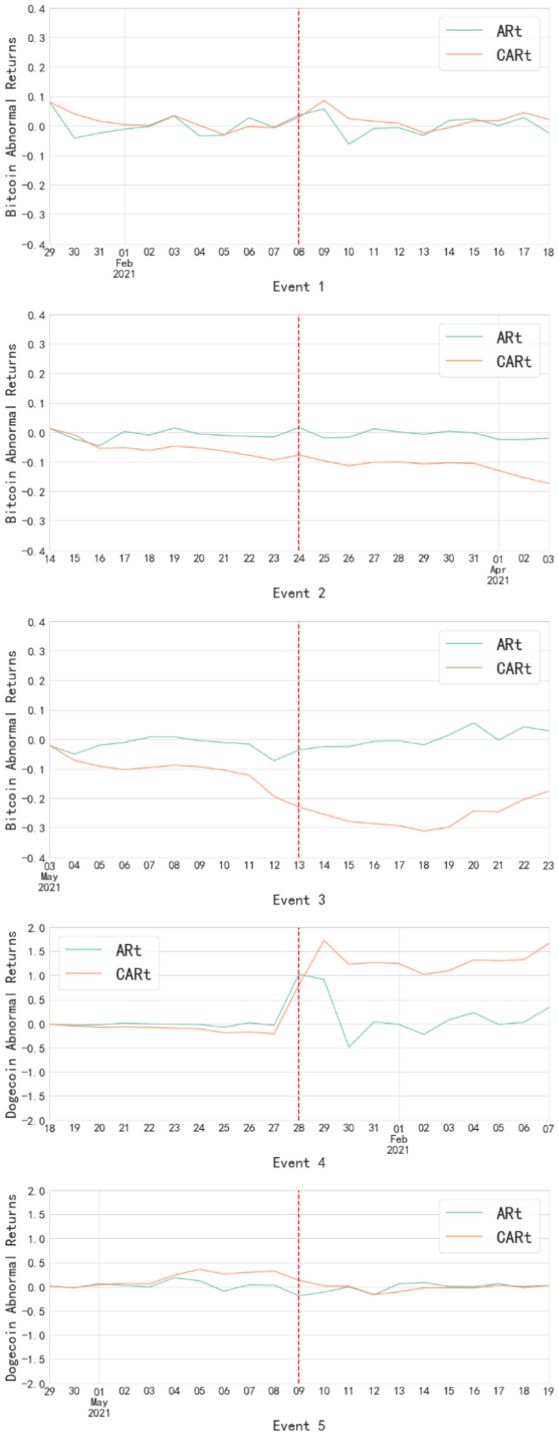

Fig. 5. Event 1–5 Abnormal Return and Cumulative Abnormal Return Curve

funds. The impact of their statements on the market is usually essentially accompanied by abnormal changes in funds, rather than just the impact of information, and thus the abnormal return range is much larger than the bitcoin market.

6 Conclusions

Based on the price information of Bitcoin and Dogecoin, this paper studies the impact of high-impact user comments on the cryptocurrency market. It is found that when the bitcoin market is in the upward channel, favourable information occurs frequently, and high-impact users' comments are only favourable promoters to promote the rise. Due to the existence of key investors, excessive abnormal returns cannot be formed. Conversely, when the bitcoin market is in a downward channel, the adverse comments of high-impact users can cause extreme panic in the market. And the large number of noise traders selling in a frenzy to follow the trend created a terrible trampling effect, with abnormal returns falling far more than the good news.

To a certain extent, the conclusion of this study shows that the opinion leader effect measured in this paper exists and has good applicability for the study of price fluctuation in cryptocurrency market. However, due to the lack of relevant literature, the measurement of opinion leader effect in this paper is still an attempt, there is room for improvement and perfection. In addition, the window setting of the event analysis method itself is uncertain, which has great subjectivity. Moreover, the fitting degree R^2 calculated by OLS regression in the market model cannot accurately measure the quality of the prediction results, which is also the limitation of this paper.

The directions can be further investigated in this paper include the following three points.

a) Firstly, the potential factors that cause abnormal fluctuations in the cryptocurrency market can be sorted out by modules. And the influence degree of each factor can be examined in more detail. b) Secondly, we further study the difference between the positive returns brought by good news and the negative returns caused by bad news. Combined with the different returns and loss psychological utility values of different types of investors, the next step in the research could be the next empirical research based on prospect theory. c) Finally, when the event analysis market model predicts the normal return of the market, the neural network and deep learning technology can be used to improve the accuracy of the prediction and improve the credibility of the conclusion.

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