

How Elon Musk's Twitter activity moves cryptocurrency markets

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Abstract: Elon Musk, the richest person in the world, is considered a technological visionary and has over 44.7 million Twitter followers. We analyze to what extent Musk's Twitter activity affects short-term cryptocurrency returns and volume. Based on six recent cryptocurrency-related Twitter activities, we identify highly significant abnormal trading volume following each event. Furthermore, we discover significantly abnormal returns of up to 18.99% for Bitcoin and 17.31% for Dogecoin across different time frames. Nevertheless, not all tweets lead to significant abnormal returns. Our study shows the significant impact that social media activity of influential and well-known individuals can have on cryptocurrencies.

Keywords: Twitter; Bitcoin; Dogecoin; Event study; Social media

1 Introduction

On January 29, 2021, *Elon Musk*, at that time richest person in the world (Klebnikov, 2021), unexpectedly changed the bio¹ of his Twitter account to *#bitcoin*. The price of *Bitcoin* rose from about \$32,000 to over \$38,000 in a matter of hours, increasing its market capitalization by \$111 billion.

The relevance of Musk's tweets for financial markets has already become apparent in other contexts. His tweet “considering taking Tesla private at \$420” (Musk, 2018) resulted in a fraud charge and a penalty of \$40 million (U.S. Securities and Exchange Commission, 2018). Musk's endorsement of the encrypted messaging service *Signal* (Musk, 2021a) led to investors purchasing the unrelated *Signal Advance* stock, increasing the latter's market valuation from \$55 million to over \$3 billion (DeCambre, 2021).

¹ The Twitter bio is a prominent area on a Twitter account page where users can add a description of up to 160 characters.

In a recent talk on social media platform *Clubhouse*, Musk stated that Bitcoin is “on the verge of getting broad acceptance” and disclosed that he is “late to the party but [...] a supporter of Bitcoin” (Krishnan et al., 2021). This is in line with a tweet from May 2020 where Musk admitted to “only own[ing] 0.25 Bitcoins” (Musk, 2020a). In the talk, he claimed that his tweets about the cryptocurrency *Dogecoin* are only jokes (Krishnan et al., 2021). Regardless of whether they are meant in jest or in earnest, Musk's tweets seem to have an impact on the cryptocurrency market. Therefore, it is of interest to gain an understanding of the extent to which these tweets resulted in short-term changes of price or trading volume. We conduct an event study to investigate six Twitter events where Musk referred to cryptocurrency—specifically Bitcoin or Dogecoin—and analyze to what extent these events affected return and trading volume of the corresponding cryptocurrency in the following minutes and hours.

The study contributes to the literature on the impact and role of social media, specifically Twitter, and the influence of sentiment and investor attention on cryptocurrency markets. Various studies have analyzed the connection between cryptocurrency markets and Twitter activity. An increase in the number of related tweets result in short-term liquidity increases of Bitcoin (Choi, 2020), the number of Bitcoin-related tweets can explain Bitcoin trading volume or returns (Philippas et al., 2019; Shen et al., 2019) and Twitter sentiment can predict returns of cryptocurrencies (Kraaijeveld and De Smedt, 2020; Naeem et al., 2020; Steinert and Herff, 2018). Mai et al. (2018) show that social media users with comparatively lower activity drive effects on cryptocurrencies, which makes sense: their actions are unusual or unexpected. If Elon Musk were to tweet about cryptocurrency several times a day, the market would likely interpret this as noise in the medium term. While studies have investigated the impact of individual tweets on stock market returns (Brans and Scholtens, 2020; Ge et al., 2019; both articles study tweets of Donald Trump), to our knowledge, no study has analyzed the impact of individual tweets on the returns and trading volumes of cryptocurrencies.

2 Methods and data

We screen Elon Musk's recent Twitter history (twitter.com/elonmusk) and select six events where the accounts activity referred to cryptocurrency. These six events are only a selection of Musk's recent cryptocurrency-related Twitter activity and are described in Table 1. To ensure the timeliness and relevance of the results, we have decided to include only events from the years 2020 and 2021. For each of the events, we define the minute the first information was published or broadcasted on Twitter as event minute—some events consist of multiple actions. We identify which cryptocurrency the tweet or action refers to (2x Bitcoin, 4x Dogecoin) and retrieve corresponding minute by minute close prices, trading volume and number of trades from the cryptocurrency exchange Binance for 601 minutes before until 360 minutes after the event for BTC/USDT² and DOGE/USDT—the trading pairs that have the highest trading volume³.

² The reference pair USDT is Tether dollar, a blockchain-based stablecoin that pegs its value to the US Dollar. For the sake of simplicity, we will simply use the term dollar (\$) from now on.

³ Trading volume data were determined via [coingecko.com](https://www.coingecko.com).

Table 1. Six cryptocurrency-related events on Elon Musk's Twitter account.

Event	Date	Cryptocurrency mentioned	Content / activity on Twitter
1	29.01.2021	Bitcoin	<ul style="list-style-type: none"> - Changed Twitter Bio to <i>#bitcoin</i> (Musk, 2021b) - Tweeted: <i>In retrospect, it was inevitable</i> (Musk, 2021c), likely referring to the decision to change his Twitter bio
2	28.01.2021	Dogecoin	<ul style="list-style-type: none"> - Posted a picture about Dogecoin, specifically the cover of a magazine named <i>Dogue</i> (Musk, 2021d)
3	25.12.2020	Dogecoin	<ul style="list-style-type: none"> - Tweeted: <i>Merry Christmas & happy holidays</i> and posted a picture which includes, among other things, the Dogecoin symbol (Musk, 2020b)
4	20.12.2020	Dogecoin	<ul style="list-style-type: none"> - Tweeted: <i>One word: Doge</i> (Musk, 2020c) - Changed Twitter Bio to <i>Former CEO of Dogecoin</i> (Goodwin, 2020)
5	20.12.2020	Bitcoin	<ul style="list-style-type: none"> - Tweeted: <i>Bitcoin is my safe word</i> (Musk, 2020d) - Posted a picture about Bitcoin, specifically how Bitcoin keeps a person from living a productive life (Musk, 2020e) - Tweeted: <i>Bitcoin is almost as bs as fiat money</i> (Musk, 2020f)
6	18.07.2020	Dogecoin	<ul style="list-style-type: none"> - Tweeted: <i>Excuse me, I only sell Doge!</i> (Musk, 2020g) - Posted a picture about Dogecoin, specifically a cloud named <i>dogecoin standard</i> which is overrunning the global financial system (Musk, 2020h)

Event study methodology is used to calculate what share of the identified returns and trading volume is attributable to Elon Musk's Twitter activity. The expected return is calculated over an estimation period before an unexpected event and is compared to the observed return around the event. The difference between expected and observed return is the abnormal return that can be attributed to the occurrence of the event (Brown and Warner, 1985). In line with existing cryptocurrency market event studies (Ante et al., 2020; Ante and Fiedler, 2020), and considering the fact that the applicability of more complex assets pricing models remains unclear for cryptocurrency markets, we use the Constant Mean Return Model (Brown and Warner, 1985) for the calculation of expected returns. The model calculates the mean return over a time period—in our case a 9-hour period before the event ($t = -600$ to -60 minutes)—which represents a sufficient length to make the results robust (Armitage, 1995). Abnormal trading volumes are calculated in the same way. To ensure comparability between Bitcoin and Dogecoin we analyze trading volumes in USDT. In conformity with the literature (e.g. Ante, 2020; Campbell and Wasley, 1996; Chae, 2005), we use log-transformed trading volumes, more precisely a $\log(x+1)$ transformation to account for periods with zero trading volume.

3 Results

3.1 Descriptive statistics

Figure 1 through 6 show return, volume, price and number of trades from $t = -600$ to 360 minutes for the six events, where $t = 0$ is the minute the Twitter activity was initiated/posted. Figure 1 shows that the Twitter bio change to *#bitcoin* had an immediate effect on the Bitcoin

market. Minute by minute returns are below 0.5% in the six hours before the event and increase to over 2% after the event. Likewise, all other metrics display extreme increases after $t = 0$. For example, the Bitcoin price increases from just over \$32,000 to over \$38,000 within three hours. The increases shown in Figure 4 are even more extreme. For example, the average trading volume of DOGE/USDT in the 30 minutes before the event was about \$1,942 per minute with an average of 9 trades per minute. During the 30 minutes after the tweet, the average trading volume per minute was about \$299,330 with 775 trades per minute. The tweet stating “I only sell Doge” (Figure 6) also resulted in very strong short-term price and volume increases, which, however, already occur about 45 minutes before the tweet is published. After the actual tweet, we observe a further price increase and a new high in traded volume. This suggests that Musk’s tweet may have been a reaction to short-term price changes, which occurred due to videos on the social media platform TikTok encouraging Dogecoin investment (Voell, 2020).

The other figures show less direct or extreme effects. For example, major price changes of Dogecoin around the publication of the *Doge* photo occur around three hours before and after the minute of the tweet (cf. Figure 2). This indicates that Musk’s tweet was likely a reaction to other market activity. Similar assumptions can be made for event three (*Merry Christmas*) and event five (*Bitcoin is my safe word*), as the most relevant market activities occur before the tweet. When looking at these two tweets, it is crucial to keep the context of the cryptocurrency market in mind. On the day of event five (December 20, 2020), Bitcoin reached its highest price ever at that time. Event three occurred only five days later. This suggests that Musk’s tweets were connected to this.

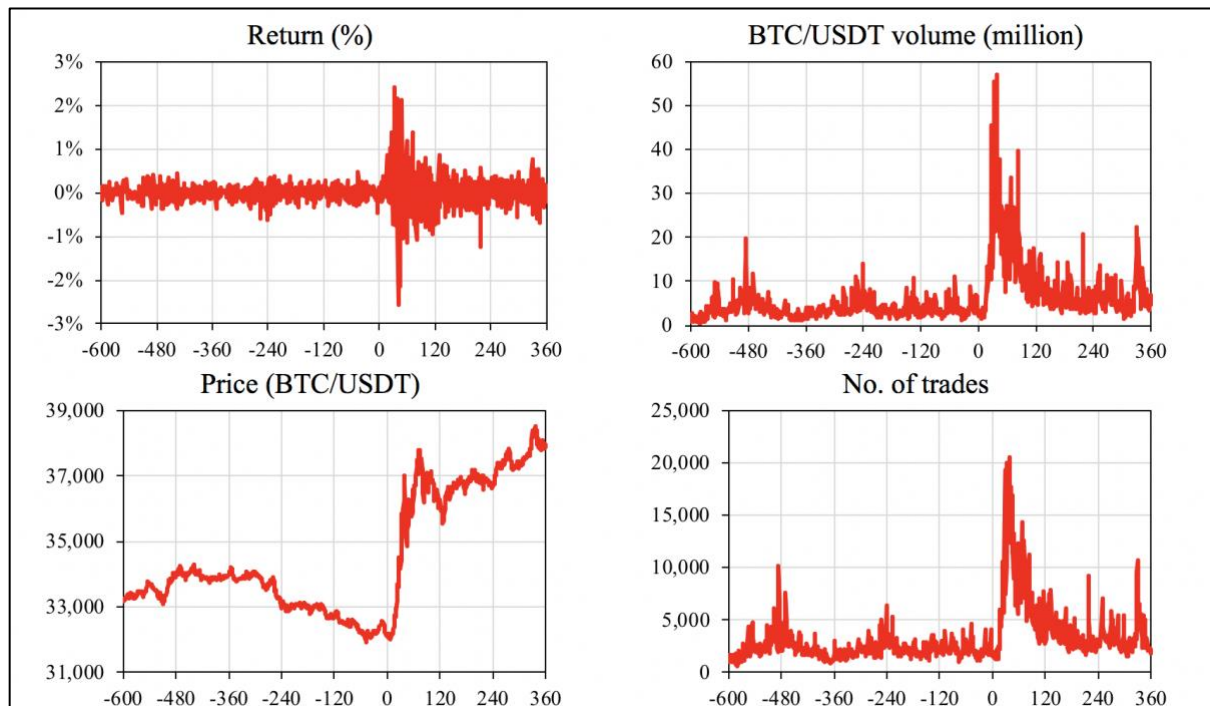


Figure 1. Return, volume, price and number of trades per minute around event number one (*Twitter bio change*).

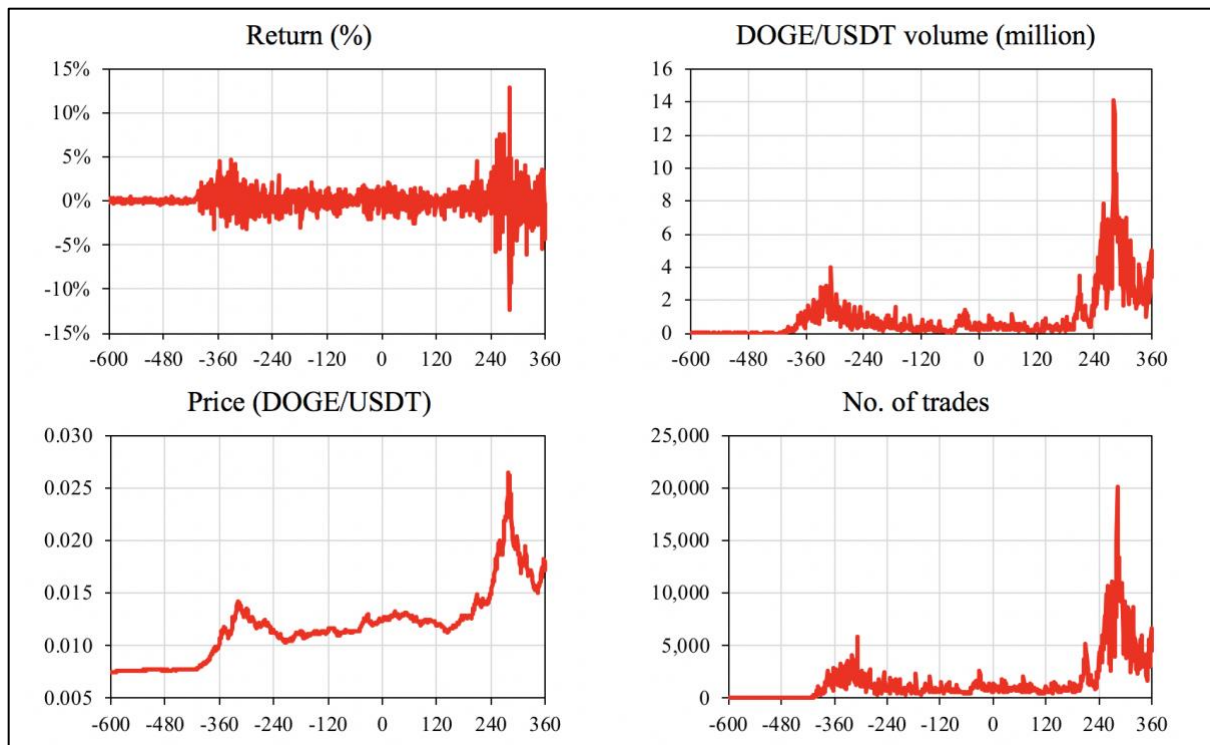


Figure 2. Return, volume, price and number of trades per minute around event number two (*Dogue*).

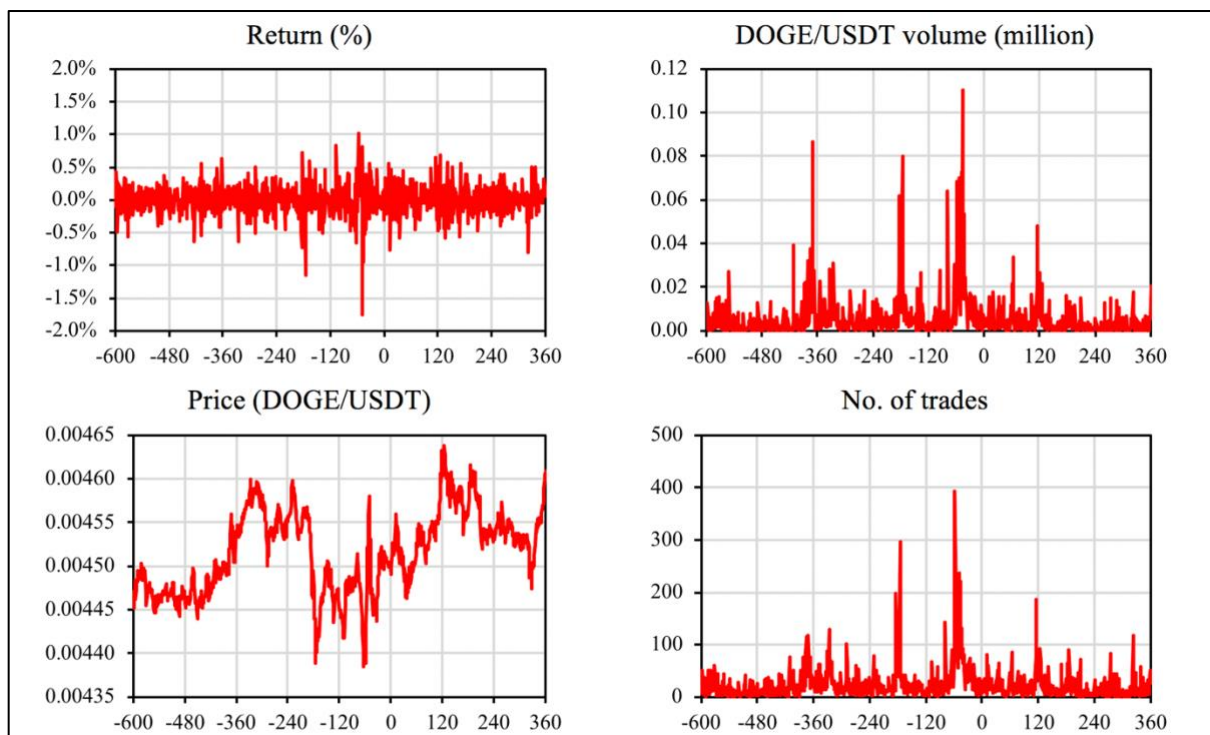


Figure 3. Return, volume, price and number of trades per minute around event number three (*Merry Christmas*).

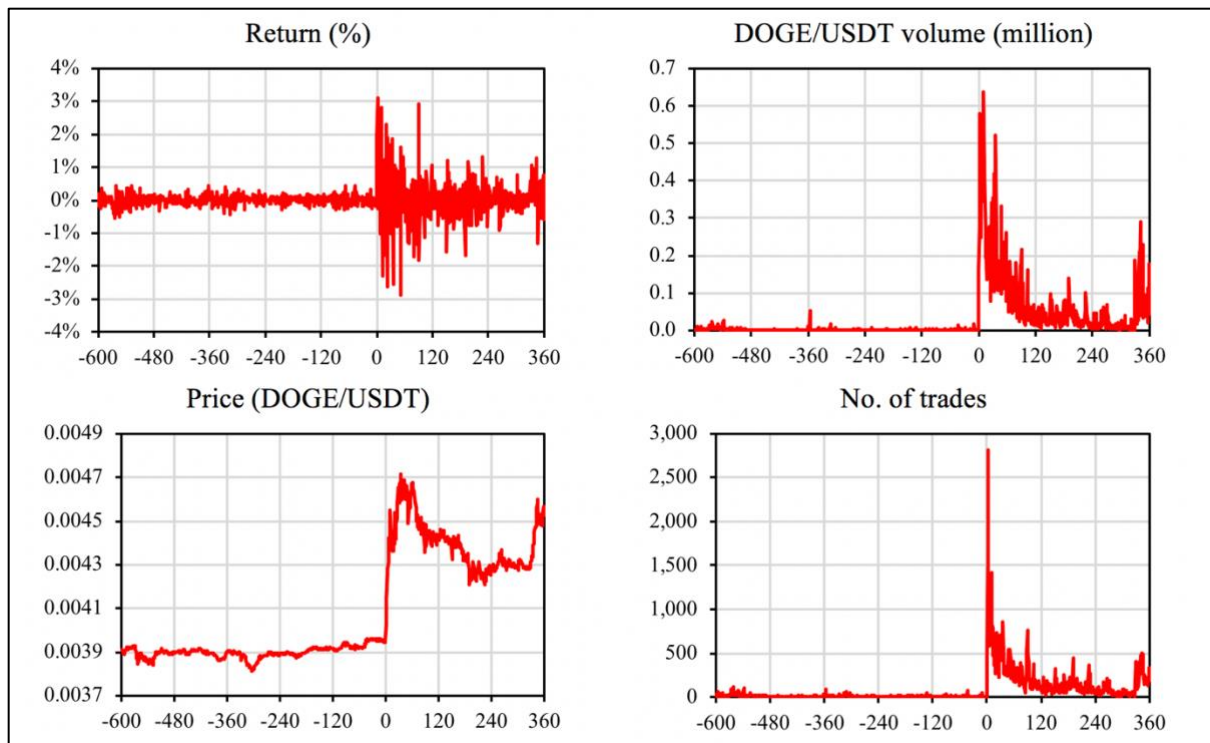


Figure 4. Return, volume, price and number of trades per minute around event number four (*One word: Doge*).

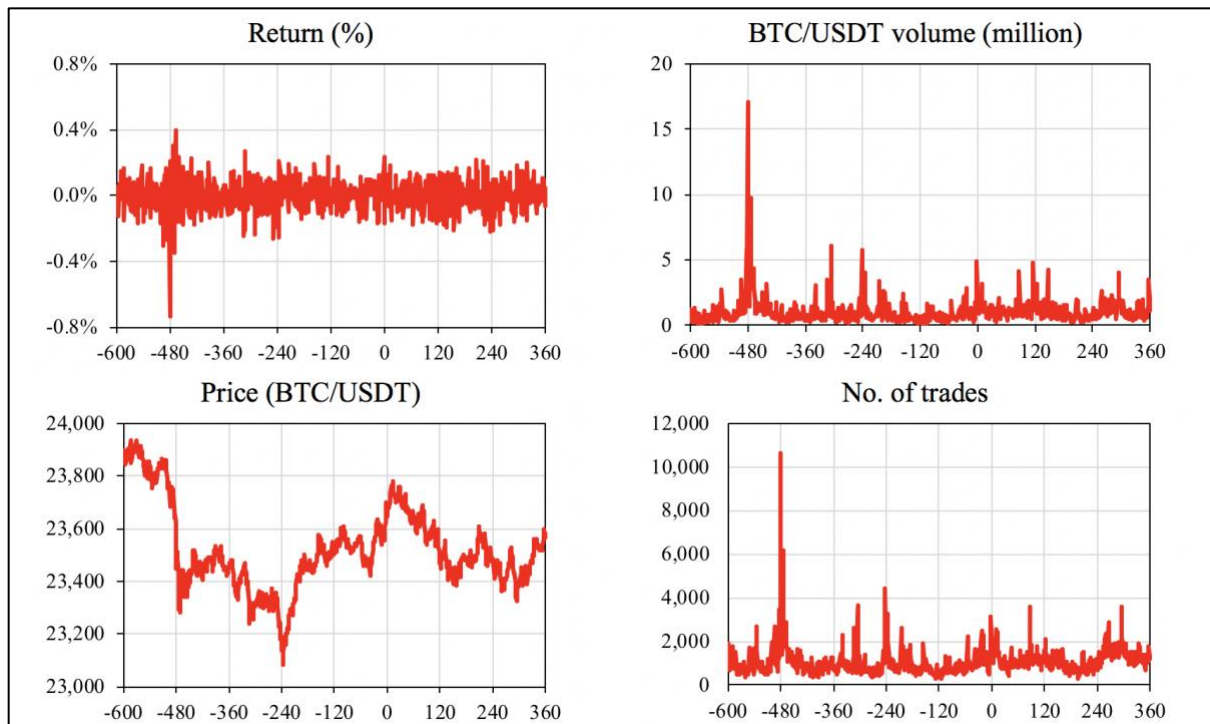


Figure 5. Return, volume, price and number of trades per minute around event number five (*Bitcoin is my safe word*).

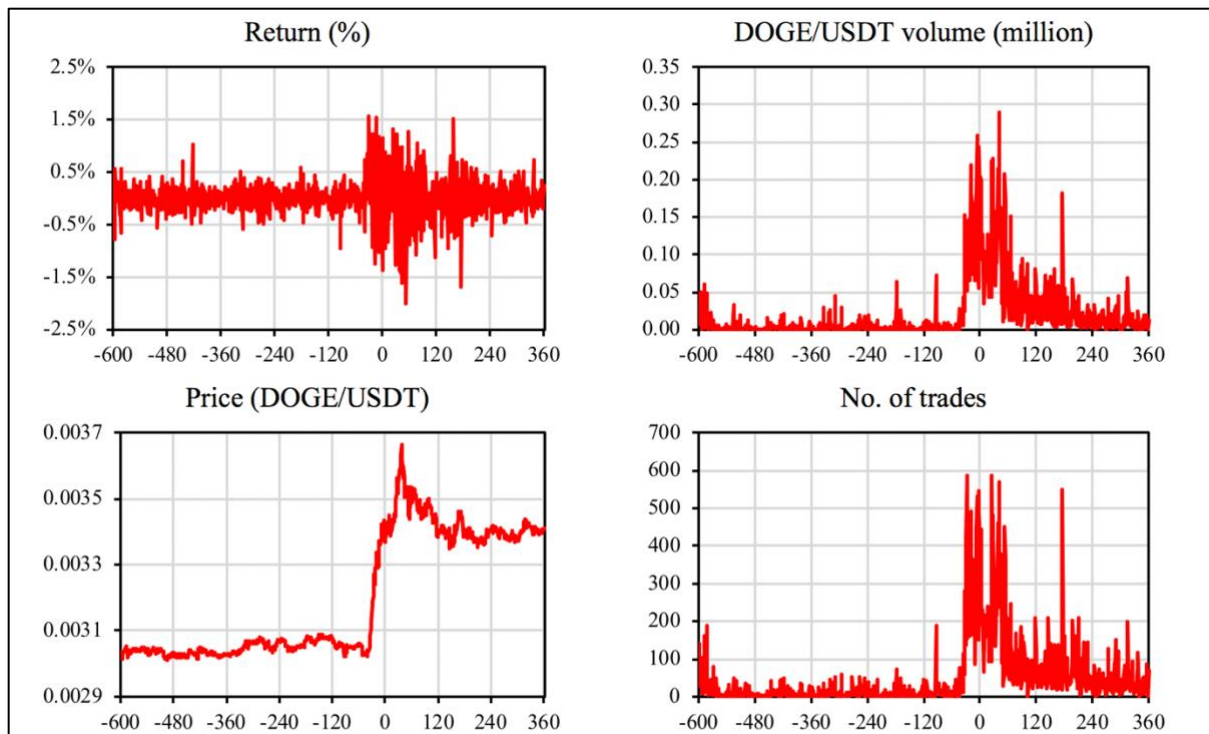


Figure 6. Return, volume, price and number of trades per minute around event number six (*I only sell Doge*).

3.2 Event study results

Table 2 shows event study results. Each model refers to an individual Twitter event and shows cumulative abnormal return (CAR) as well as cumulative abnormal trading volume (ATV) over different time periods, each starting with the minute the information is published in Twitter ($t = 0$).

We identify significant CARs in four of the six events. In particular, events one and four stand out. The change of Musk’s Twitter bio to *#bitcoin* resulted in significantly positive CARs which already amounted to 6.31% after 30 minutes and reaches the peak of 18.99% over a period of six hours. The tweet *One word: Doge* resulted in a significant CAR of 8.17% over the five minutes after publishing before reaching a peak of 17.31% over the period of one hour after the tweet. Thereafter, the—still strongly positive—CARs remain insignificant.

For event two, we identify a significantly negative CAR of -13.42% over a period of two hours, while the *Merry Christmas* message (event three) resulted in a significantly positive CAR of 1.43% over ten minutes. Nevertheless, the identified CARs for both events remain insignificant for all other event windows. For the events five and six, all CARs are insignificant.

Table 2. Cumulative abnormal return (CAR) and cumulative abnormal log trading volume (CAV) around Elon Musk’s cryptocurrency-related twitter activities. The column “Window” shows the estimation window in minutes around the event starting in $t = 0$.

Event	(1) <i>Twitter bio change</i>		(2) <i>Dogue</i>		(3) <i>Merry Christmas</i>		(4) <i>One word: Doge</i>		(5) <i>Bitcoin is my safe word</i>		(6) <i>I only sell doge</i>	
Crypto	Bitcoin		Dogecoin		Dogecoin		Dogecoin		Bitcoin		Dogecoin	
Window	CAR	<i>t</i> -statistic	CAR	<i>t</i> -statistic	CAR	<i>t</i> -statistic	CAR	<i>t</i> -statistic	CAR	<i>t</i> -statistic	CAR	<i>t</i> -statistic
0 to 5	0.01%	0.01	1.85%	0.59	0.60%	1.37	8.16%	2.23**	0.07%	0.28	1.84%	1.07
0 to 10	0.20%	0.35	-0.75%	-0.22	1.43%	2.10**	14.30%	3.01***	0.27%	0.87	2.26%	1.03
0 to 30	6.31%	2.48**	2.47%	0.41	-0.07%	-0.05	16.23%	1.99**	0.19%	0.43	5.11%	1.44
0 to 60	13.19%	2.07**	-1.63%	-0.22	0.95%	0.50	17.31%	1.73*	-0.00%	-0.00	3.59%	0.62
0 to 120	13.18%	1.97**	-13.42%	-1.82*	2.92%	1.19	11.78%	1.01	-0.50%	-0.59	0.84%	0.12
0 to 180	15.03%	1.76*	-11.60%	-0.97	1.97%	0.61	9.88%	0.82	-0.37%	-0.33	1.13%	0.15
0 to 240	15.24%	1.72*	-1.08%	-0.07	1.52%	0.43	8.60%	0.67	-0.24%	-0.17	0.95%	0.12
0 to 300	17.29%	1.91*	24.93%	0.66	1.56%	0.42	8.36%	0.65	-0.44%	-0.31	-0.06%	-0.01
0 to 360	18.99%	2.04**	10.11%	0.24	3.39%	0.84	14.13%	1.06	0.51%	0.32	0.98%	0.12
Window	CAV	<i>t</i> -statistic	CAV	<i>t</i> -statistic	CAV	<i>t</i> -statistic	CAV	<i>t</i> -statistic	CAV	<i>t</i> -statistic	CAV	<i>t</i> -statistic
0 to 5	-1.70	-2.57**	11.01	9.36***	3.77	3.70***	40.82	35.00***	3.45	4.59***	3.45	40.08***
0 to 10	-2.21	-2.40**	19.81	15.81***	6.21	2.82***	76.56	56.71***	8.18	6.83***	56.86	28.95***
0 to 30	20.67	3.83***	58.34	21.28***	10.82	2.21**	204.33	75.57***	15.62	7.11***	158.62	56.50***
0 to 60	81.44	10.23***	112.12	34.66***	13.61	1.44	388.63	94.86***	23.40	7.00***	309.31	58.51***
0 to 120	162.85	18.19***	203.22	35.96***	18.62	1.13	694.58	72.06***	47.72	9.90***	549.16	51.24***
0 to 180	208.27	20.55***	297.58	43.66***	6.75	0.35	950.93	66.40***	65.58	10.78***	768.34	56.53***
0 to 240	239.35	20.92***	453.62	42.25***	-25.44	-1.12	1204.90	71.32***	55.21	6.93***	953.56	55.98***
0 to 300	275.05	22.66***	711.77	35.08***	-82.70	-2.94***	1413.98	67.21***	84.78	9.59***	1107.84	51.07***
0 to 360	310.51	23.58***	941.23	40.93***	-127.48	-3.89***	1662.65	68.28***	98.72	10.33***	1248.92	48.43***

***, **, * indicate significance at the 1%, 5% and 10% level.

Five of the events lead to significantly positive ATVs in the short run—only event one actually has a significantly negative ATV in the first ten minutes after the tweet. ATVs become significantly positive for all events once the event window reaches the span of 31 minutes ($t = 0$ to 30). In three of the models we identify a significant positive ATV in each estimation window examined. This can also be seen in the figures presented above, where the increase in trading volume is very strong—especially for the in comparison to Bitcoin smaller and less efficient cryptocurrency Dogecoin. For event three, the ATVs are significantly positive during the short term, while they become significantly negative in the longer term (300 minutes and more) compared to the 9-hour observation period.

4 Concluding remarks

We investigate the impact of Elon Musk's Twitter messages on cryptocurrency markets. By applying event study methodology, the impact of six Twitter events from 2020 and 2021 on return and trading volume of the mentioned cryptocurrency is analyzed. Across all events, we identify significant increases in trading volume that are attributable to the events. Four of the Twitter activities are likely only reactions to previous market events and relate to little or no significant price reactions. The other two events, however, do not seem to be reactions but independent actions which result in huge increases in trading volumes and large and significant positive abnormal returns:

- Musk's Twitter bio change to *#bitcoin* resulted in significant CAR of 6.31% over 30 minutes, which increased to 13.19% over one hour and peaked at 18.99% over a period of 7 hours.
- Musk's tweet *One word: Doge* resulted in significant CAR of 8.17% over a window of five minutes, peaking at 17.31% over the period of one hour.

These two events illustrate the significant impact Elon Musk's Twitter activity can have on cryptocurrency markets. While the Twitter bio change might have been meant to be a serious sign of support for Bitcoin, the tweet about Dogecoin was a joke—as Musk later admitted himself (Krishnan et al., 2021). Considering that a joke made by the richest person in the world has caused such a significant market reaction illustrates the impact of influential individuals on cryptocurrency markets. While Musk's behavior and communication can be deemed positive or funny in nature (and therefore arguably uncritical), similar research has already revealed that negative tweets can also have a negative impact on financial returns (e.g. Brans and Scholtens, 2020; Ge et al., 2019). This is also conceivable for cryptocurrency markets.

The presented results show that individual tweets can have a significant influence on returns and trading volumes of cryptocurrencies, and can therefore be a basis for a great deal of further research. While Elon Musk is likely to be an extreme example in terms of influence via social media, there is a huge number of comparatively less influential individuals, groups or companies who communicate their opinions on cryptocurrencies via social media. A systematic classification of influencers in terms of their short-term impact on cryptocurrencies may represent a promising research approach. This becomes especially relevant against the background of coordinated manipulation via so-called pump and dump schemes, in which the

prices of cryptocurrencies are artificially driven up (Mirtaheri et al., 2019; Pacheco et al., 2020). Additionally, the existence of informed trading could be analyzed based on trading volumes before specific social media events (Ante, 2020; Feng et al., 2018) or by analyzing the associated transparent flow of cryptocurrencies and stablecoins (Ante et al., 2021). Another promising avenue could be the analysis of corporate announcements, such as *Michael Saylor*, CEO of Nasdaq-listed *MicroStrategy Inc.* announcing the corporate acquisition of Bitcoins (Saylor, 2020).

Our results lead to the question under which conditions people in the public eye should comment on specific cryptocurrencies. If a single tweet can potentially lead to an increase of \$111 billion in Bitcoin's market capitalization, a different tweet could also wipe out a similar value. No simple or quick “solution” to that challenge is foreseeable, as individuals should naturally be allowed to express themselves freely and cryptocurrency markets are still relatively unregulated compared to, for example, stock markets, where similar challenges exist (e.g., Ge et al., 2019).

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Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on request.

Conflicts of interest

Not applicable.

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The Blockchain Research Lab promotes independent science and research on blockchain technologies and the publication of the results in the form of scientific papers and contributions to conferences and other media. The BRL is a non-profit organization aiming, on the one hand, to further the general understanding of the blockchain technology and, on the other hand, to analyze the resulting challenges and opportunities as well as their socio-economic consequences.

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