Elon Musk, Twitter, and Dogecoin

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Abstract

One would expect Elon Musk, the richest man in the world with roughly 59 million Twitter followers, to be cautious when disclosing his investments or giving financial advice. This is far from reality, as Musk actively shows his interest in the cryptocurrency, Dogecoin, in his Twitter posts. Using the event study methodology, we analyze to what extent Musk's tweet activity affects Dogecoin's short-term return. Based on twenty-three tweets, we discover significant cumulative abnormal returns (CARs) in all tweets as well as significantly abnormal returns of up to 35.4% across different time frames. Furthermore, this study shows the significant impact that tweets of influential and well-known individuals can have on cryptocurrencies.

Introduction

Elon Musk has a large following on Twitter, the billionaire entrepreneur and business magnate has roughly 59 million Twitter followers as of July 2021. This puts him at #17 on the list of most followed accounts and #1 on the list of most followed businessmen. As such, the Musks' tweets carry more than just general thoughts and opinions. It Musk were to tweet about cryptocurrency—or any asset in general—several times a day, it is not farfetched for the market to interpret this as noise. In fact, Musk was charged twice in 2018 with securities fraud by the Securities and Exchange Commission (SEC) based on tweets about the share price of his company, Tesla Motors. In more recent cases, Musk has proven to be an advocate for Dogecoin based on his Twitter activity. In his defense, he claims his tweets about Dogecoin are jokes and went on Saturday Night Live (SNL) to call it a "hustle". Regardless of the intent, Musks' tweets seem to have an impact on the value of Dogecoin. Therefore, it is of interest to gauge the impact to which his tweets resulted in short-term changes in the coin's return.

This study investigates twenty-three tweets where Musk referred specifically to Dogecoin and analyzes to what extent these events affected return in the following minutes and hours. We expect most tweets to result in immediate increases in return or at least within an hour, mainly due to just how fast news is shared. Similarly, even Musks' tweets that are unrelated to Dogecoin are filled with comments about Dogecoin, perhaps indicating that the public has come to associate Musk with Dogecoin. We use the event study methodology to determine whether investor activity increased as a result of Musk tweeting about Dogecoin. Generally speaking, this activity is measured in terms of the difference in Dogecoin return before and after the tweet being posted. If the returns significantly increase in the later interval, then we can conclude that Musks' tweet had some influence on investment decisions.

Data

The two main sets of data used were a filtered batch of Elon Musk's twitter posts and historical intraday values for the currency pair DOGE:USDT. To maintain consistency, a fixed period is defined for all data from January 2021 to July 2021.

Through the Twitter API, we access all of Musks' tweets from this past year. Retweets and post replies were filtered out since they do not have the same outreach as tweets do. To elaborate, a tweet posted by Musk would appear in everyone's feed; however, a reply or retweet may always not. To ensure relevance to the topic, only tweets containing the case-insensitive keyword *doge* were kept. From the original 638 tweets, the 23 that were kept are described in Table 1. The tweets are assigned numerical values in the order they were posted to allow references to other tables and figures.

Historical minute data for Dogecoin was obtained through download via CryptoArchive[1], a database for intraday cryptocurrency data from the Binance exchange. The values were filtered to include only timestamps and closing prices. While the choice of interval was partly due to the accessibility of intraday data, using a larger interval such as 1-day would overlook cases where Musk tweeted multiple times in a day.

Figure 1 includes plots Dogecoin's price, return, and volume around every tweet. The red bar in each subplot indicates the exact time when the tweet was posted[2]. The price and volume

[1] CryptoArchive

[2] The subplot labeled "(10)" has the indicator incorrectly plotted. The correct version should have the indicator aligned with the other subplots.

movements alone could justify the significance of Musks' tweets; however, the next section formally proves this.

Methods

The event study methodology is used to calculate what share of Dogecoin are attributable to Elon Musk's tweets. Return event studies help determine an event's impact in abnormal returns. Abnormal returns are the difference between expected returns ($\bar{R}_\iota$), or the returns that would have been realized if the event would not have taken place and the actual returns ($R_{i,t}$) of the asset. The return of an asset in prices is the difference between its value in the last time step ($t - 1$) and the current time (t) divided by the prior:

$$R_{\mathrm{t}} = = \frac{(P_{\mathrm{t}} - P_{t-1})}{P_{t-1}}$$

While actual returns can be found empirically, an approximation is required for expected returns. There are many complex pricing models that can do this; however, their effectiveness in terms of cryptocurrencies remains unclear. Thus, this paper calculates expected return by the constant-mean-returns model, which simply averages the returns within a pre-defined period:

$$\bar{R}_\iota = \frac{1}{T_1 - T_0} \sum_{t \in [T_0, T_1]} R_{it}$$

where T_0 and T_1 are the endpoints of the period and R_{it} is the return of the asset at observation i. Knowing the expected and actual return, we can now formally define abnormal return as:

$$\mathrm{A}R_{i,t} = R_{i,t} - \bar{R}_\iota$$

Since the returns are calculated over a pre-defined period, we can measure the total impact of an event over such period by adding up individual abnormal returns to create a cumulative abnormal return (CAR):

$$\mathrm{CAR}_i = \sum_{t \in [T_1, T_3]}^{T_3} AR_{i,t}$$

The timeline below shows the relevant period analyzed for every event:

where T_i represents the endpoints of a period spanning t minutes relative to the occurrence of an event (T_e). The colors differentiate two main windows:

1. The 5-hour period before the event, or $t \in [-360\ , -60]$ minutes is the *estimation* window and the values within this period are used to compute the expected return, or the value of Dogecoin far before Musk tweeted.

2. The 1-hour before and after period, or $t \in [-60\ , 60]$ minutes collectively make up the *event* window and the values within it are used to calculate the observed return, or the value of Dogecoin around the time when Musk tweeted. Optionally, additional time can be added to the event window, more formally known as the *post-event* window. Since the 1-hour prior to the event are insignificant for intraday event studies[3], this

[3] This follows the traditional event study methodology which suggests that the intraday context be handled with a pre-defined length--typically after the event when the CAR ceases to be statistically relevant (Ante and Fiedler, 2020).

paper adds an additional 1-hour to the end of the event window, i.e., $t \in [60\ ,120]$ minutes.

The length of the estimation window used is robust, as intraday event studies suggest at least 100-time steps (Ante and Fiedler, 2020) and ours includes three times that. While abnormal returns are evaluated at all points $t \in [0\ ,120]$, only fifteen-minute interval values are used for analysis. The next section discusses the results of the event study and includes t-tests. The standard deviation of all CAR values (S_{CAR}) is used to compute the t-statistic, so we define the t-statistic for the null $H_0: E(CAR_i) = 0$ as:

$$t_{CAR} = \frac{CAR_i}{S_{CAR}}$$

Results

Table 2 shows event study results. Each model refers to an individual Twitter event and shows the cumulative abnormal return (CAR) as well as the t-statistic over different windows, each starting at $t = 0$. For example, the first window row for each event represents the interval $t \in [0\ , 15]$, the second represents $t \in [0\ , 30]$, etc. This section will not analyze each event individually; instead, it will present noticeable patterns and reflect of them.

Significant CAR values are found in all events. The first and ninth events are particularly interesting as their respective values dramatically increase at 30 minutes and 120 minutes, perhaps highlighting the essence of this paper as the first tweet contained a single word, *Doge*. Some events show a pattern of decreased significance at 75 minutes, like the eleventh and twelfth events. This indicates that the original event window of 60 minutes may have been appropriate. Eight out of the twenty-three events lead to significantly positive CARs in the short

run at the 10% level, which follows the trends shown by their corresponding charts in Figure 2. The following summarizes two events that describe the magnitude of impact:

- Musk's one-word tweet: *Doge* resulted in significant CAR of 13.5% over a window of fifteen-minutes, and almost tripled fifteen-minutes later, peaking at 35.4%.
- The tweet referencing Dogecoin and another well-known figure, Lil X, had a CAR of 16.79% within the first fifteen minutes, which gradually fell towards 10% for the rest of the period.

These events illustrate the significant impact Elon Musks' tweets can have on Dogecoin return. It is funny to think that most of the tweets are just jokes—some are completely out of context-- yet the market reaction speaks towards serious issues regarding the influence that specific individuals have.

While the results agree with our expectations, there are noticeable limitations and unrecognized factors in our approach. The most obvious one is extending the estimation and event windows to get information past the two-hours studied in this paper. Also, abnormal (trading) volume (ATV) should have been measured in conjunction with abnormal return to determine whether Dogecoin was truly impacted by the tweet. Finally, until more robust models are created or adapted for cryptocurrencies, it may be difficult to evaluate their values accurately.

References

Ante, L., Fiedler, I., 2020. Market reaction to large transfers on the Bitcoin blockchain - Do size and motive matter? Financ. Res. Lett. https://doi.org/10.1016/j.frl.2020.101619

Ante, L., Fiedler, I., Strehle, E., 2020. The Influence of Stablecoin Issuances on Cryptocurrency Markets. Financ. Res. Lett. 101867. https://doi.org/10.1016/j.frl.2020.101867

Table 1. Twenty-three Dogecoin-related tweets posted by Elon Musk.

Event	Time	Text
1	2021-02-04 07:36	Doge
2	2021-02-04 08:15	Dogecoin is the people's crypto
3	2021-02-04 08:27	No highs, no lows, only Doge
4	2021-02-07 22:25	🎶 Who let the Doge out 🎶
5	2021-02-10 15:08	Bought some Dogecoin for lil X, so he can be a toddler hodler
6	2021-02-11 09:09	Frodo was the underdoge, All thought he would fail, Himself most of all.
7	2021-02-14 23:25	If major Dogecoin holders sell most of their coins, it will get my full support. Too much concentration is the only real issue imo.
8	2021-02-21 21:27	Dojo 4 Doge
9	2021-03-01 19:57	Doge meme shield (legendary item)
10	2021-03-06 04:40	Doge spelled backwards is Egod
11	2021-03-13 23:41	Doge day afternoon
12	2021-03-13 23:46	Origin of Doge Day Afternoon: The ancient Romans sacrificed a Dogecoin at the beginning of the Doge Days to appease the rage of Sirius, believing that the star was the cause of the hot, sultry weather.
13	2021-03-13 23:51	Why are you so dogematic, they ask
14	2021-04-01 10:25	SpaceX is going to put a literal Dogecoin on the literal moon
15	2021-04-15 04:33	Doge Barking at the Moon
16	2021-04-28 06:21	The Dogefather SNL May 8
17	2021-05-11 08:14	Do you want Tesla to accept Doge?
18	2021-05-13 22:45	Working with Doge devs to improve system transaction efficiency. Potentially promising.
19	2021-05-20 10:41	How much is that Doge in the window?
20	2021-05-24 19:50	If you'd like to help develop Doge, please submit ideas on GitHub & https://t.co/liAPQMFaQB @dogecoin_devs
21	2021-05-24 20:30	Someone suggested changing Dogecoin fees based on phases of the moon, which is pretty awesome haha
22	2021-07-01 08:44	Release the Doge!
23	2021-07-01 09:24	Baby Doge, doo, doo, doo, doo, doo, Baby Doge, doo, doo, doo, doo, doo, Baby Doge, doo, doo, doo, doo, doo, Baby Doge

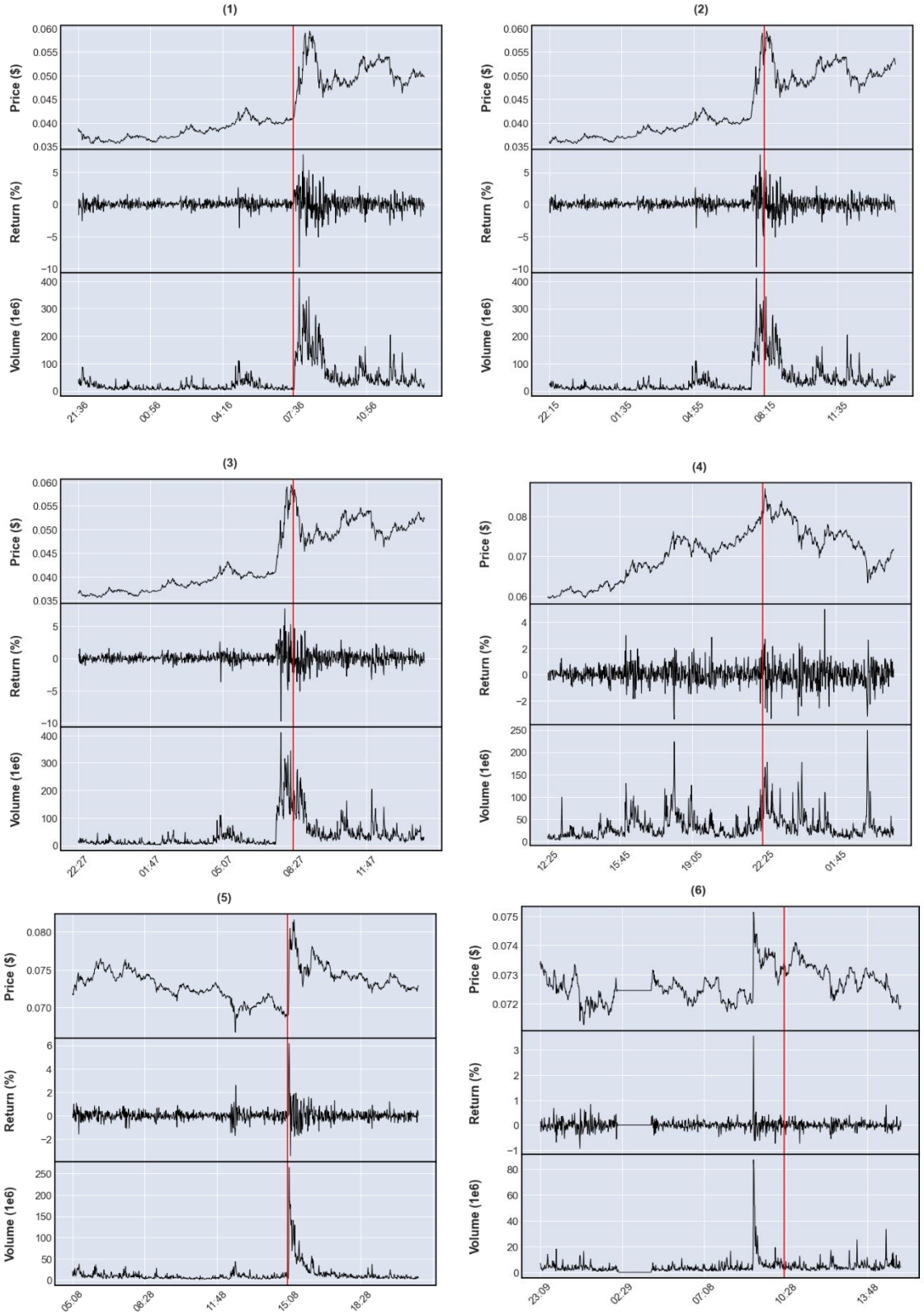
Table 2. Cumulative abnormal return (CAR) around Elon Musk's cryptocurrency-related twitter activities. The column "Window" shows the estimation window in minutes around the event starting at $t = 0$.

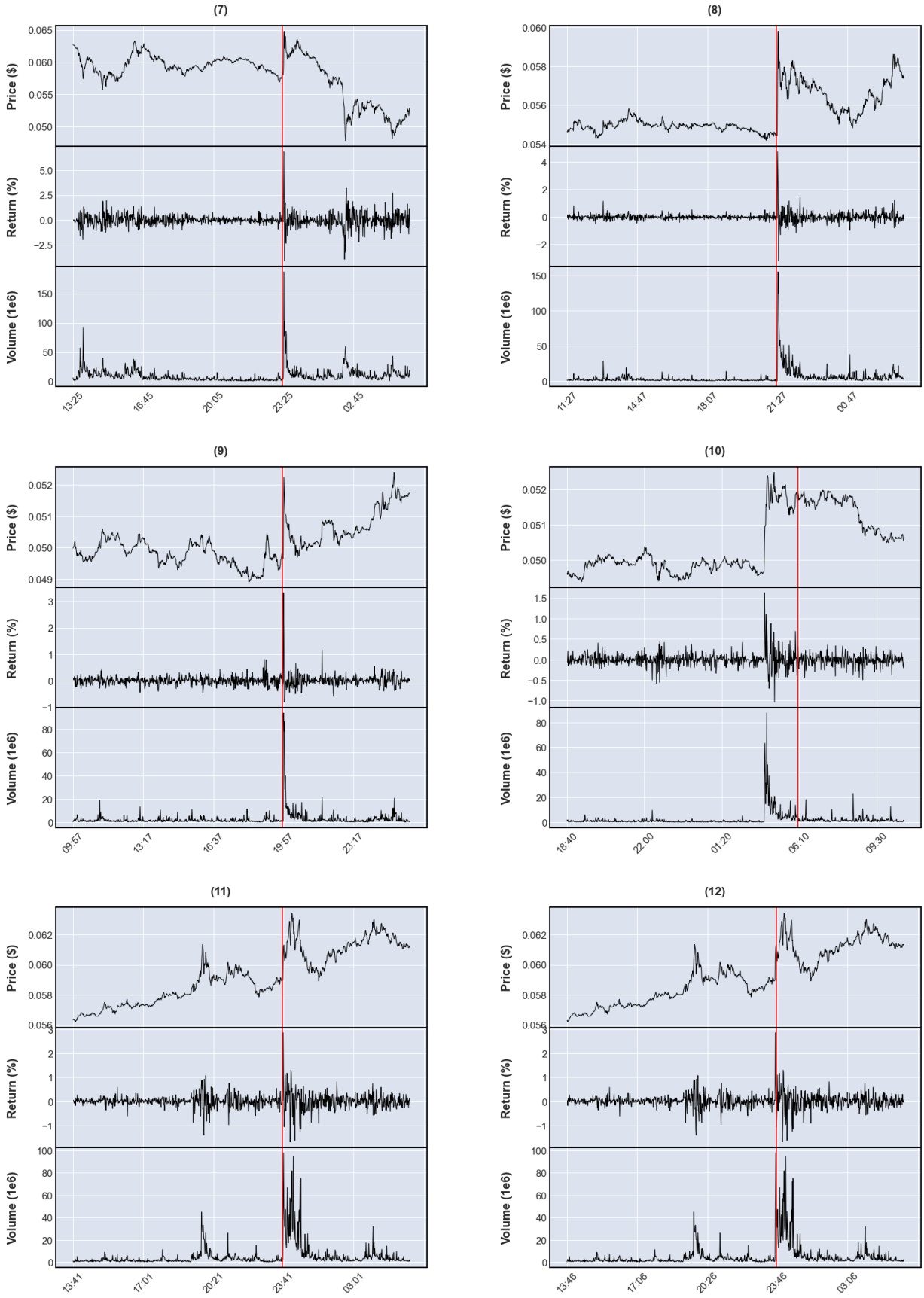
Event	**Window**	**CAR (%)**	***t*-statistic**	**Event**	**Window**	**CAR (%)**	***t* −statistic**
1	15	13.503	4.226	5	15	16.689	7.572
	30	35.396	12.293		30	9.398	4.952
	45	34.797	11.846		45	9.083	5.544
	60	28.459	10.164		60	8.935	6.088
	75	17.644	6.439		75	11.46	8.521
	90	18.236	6.912		90	10.556	8.489
	105	15.709	6.312		105	10.802	9.298
	120	17.079	7.195		120	8.361	7.597
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
2	15	2.765	1.269	6	15	1.243	1.297
	30	-12.301	-5.37		30	1.496	2.145
	45	-16.547	-7.235		45	1.724	2.987
	60	-15.254	-7.259		60	0.315	0.609
	75	-11.676	-5.935		75	1.382	2.941
	90	-15.035	-8.153		90	1.271	2.929
	105	-15.059	-8.678		105	2.302	5.67
	120	-16.7	-10.145		120	1.789	4.61
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
3	15	-13.047	-5.544	7	15	5.016	2.131
	30	-13.919	-5.73		30	6.687	3.876
	45	-15.096	-6.927		45	7.334	5.032
	60	-11.762	-6.059		60	6.045	4.716
	75	-15.732	-8.55		75	5.025	4.326
	90	-13.267	-7.764		90	5.186	4.88
	105	-14.204	-8.778		105	2.102	2.109
	120	-12.563	-8.21		120	2.115	2.253
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
4	15	2.208	1.414	8	15	6.001	3.383
	30	-1.144	-0.826		30	3.571	2.685
	45	1.343	1.125		45	6.408	5.728
	60	-1.271	-1.16		60	4.563	4.575
	75	-2.573	-2.535		75	5.395	5.875
	90	-5.279	-5.447		90	4.862	5.763
	105	-12.828	-11.941		105	5.36	6.806
	120	-9.932	-9.299		120	4.798	6.488

Event	**Window**	**CAR (%)**	***t*-statistic**	**Event**	**Window**	**CAR (%)**	***t*-statistic**
9	15	2.284	2.252	13	15	3.881	5.328
	30	1.49	2.007		30	1.648	2.386
	45	0.746	1.182		45	-0.594	-0.908
	60	1.447	2.6		60	-2.079	-3.538
	75	1.238	2.475		75	-1.905	-3.471
	90	1.541	3.368		90	-3.312	-6.447
	105	1.589	3.743		105	-2.124	-4.399
	120	3.055	7.412		120	-0.789	-1.707
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
10	15	3.722	5.862	14	15	12.02	11.833
	30	3.843	6.742		30	12.936	9.976
	45	4.13	8.484		45	15.932	13.398
	60	3.373	7.701		60	19.135	17.516
	75	3.161	7.792		75	25.529	22.754
	90	3.703	9.693		90	19.55	17.816
	105	3.494	9.749		105	19.181	18.321
	120	3.624	10.695		120	17.681	17.331
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
11	15	2.772	4.67	15	15	7.416	9.548
	30	2.372	3.423		30	7.29	9.027
	45	3.537	5.528		45	8.445	11.586
	60	-0.398	-0.633		60	6.58	9.335
	75	-1.331	-2.31		75	6.622	10.116
	90	-1.936	-3.573		90	5.282	8.561
	105	-2.02	-3.922		105	5.496	9.383
	120	-0.969	-1.981		120	1.743	2.983
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
12	15	1.709	2.514	16	15	15.797	8.168
	30	2.263	3.139		30	10.266	6.001
	45	0.977	1.458		45	12.531	8.671
	60	0.302	0.499		60	10.269	7.969
	75	-1.384	-2.463		75	7.99	6.793
	90	-1.119	-2.143		90	9.868	9.095
	105	-1.234	-2.477		105	11.694	11.518
	120	0.285	0.601		120	11.241	11.743

Event	**Window**	**CAR (%)**	***t*-statistic**	**Event**	**Window**	**CAR (%)**	***t*-statistic**
17	15	5.862	4.764	21	15	-3.495	-4.592
	30	5.698	5.653		30	-3.5	-6.095
	45	5.294	6.174		45	-3.692	-7.432
	60	3.699	4.78		60	-4.754	-10.774
	75	4.145	5.768		75	-5.692	-12.673
	90	5.799	8.753		90	-5.87	-13.849
	105	5.001	7.945		105	-5.295	-13.315
	120	4.232	7.112		120	-4.866	-12.618
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
18	15	13.202	6.893	22	15	0.803	0.715
	30	13.199	7.877		30	-1.545	-1.886
	45	10.396	7.051		45	-0.194	-0.25
	60	8.981	6.879		60	-0.76	-1.108
	75	10.89	9.191		75	-0.45	-0.706
	90	12.061	10.991		90	-0.706	-1.197
	105	9.179	8.925		105	-1.8	-3.25
	120	9.803	10.093		120	-1.294	-2.475
Event	Window	CAR (%)	*t*-statistic	Event	Window	CAR (%)	*t*-statistic
19	15	8.23	3.408	23	15	2.159	3.156
	30	5.282	2.94		30	2.208	3.952
	45	5.6	3.766		45	2.33	4.933
	60	7.673	5.912		60	0.593	1.368
	75	7.163	6.092		75	1.087	2.731
	90	6.533	6.028		90	1.171	3.18
	105	8.934	8.782		105	1.917	5.458
	120	10.901	11.259		120	2.724	8.167
Event	Window	CAR (%)	*t*-statistic				
20	15	1.392	1.307				
	30	0.949	1.195				
	45	3.079	3.111				
	60	2.881	3.287				
	75	3.768	4.752				
	90	2.742	3.758				
	105	2.441	3.58				
	120	1.263	1.915				

Figure 1. Dogecoin closing prices, returns, and trading volume for every tweet around the time it was posted. The red vertical lines indicate the exact time it was posted.

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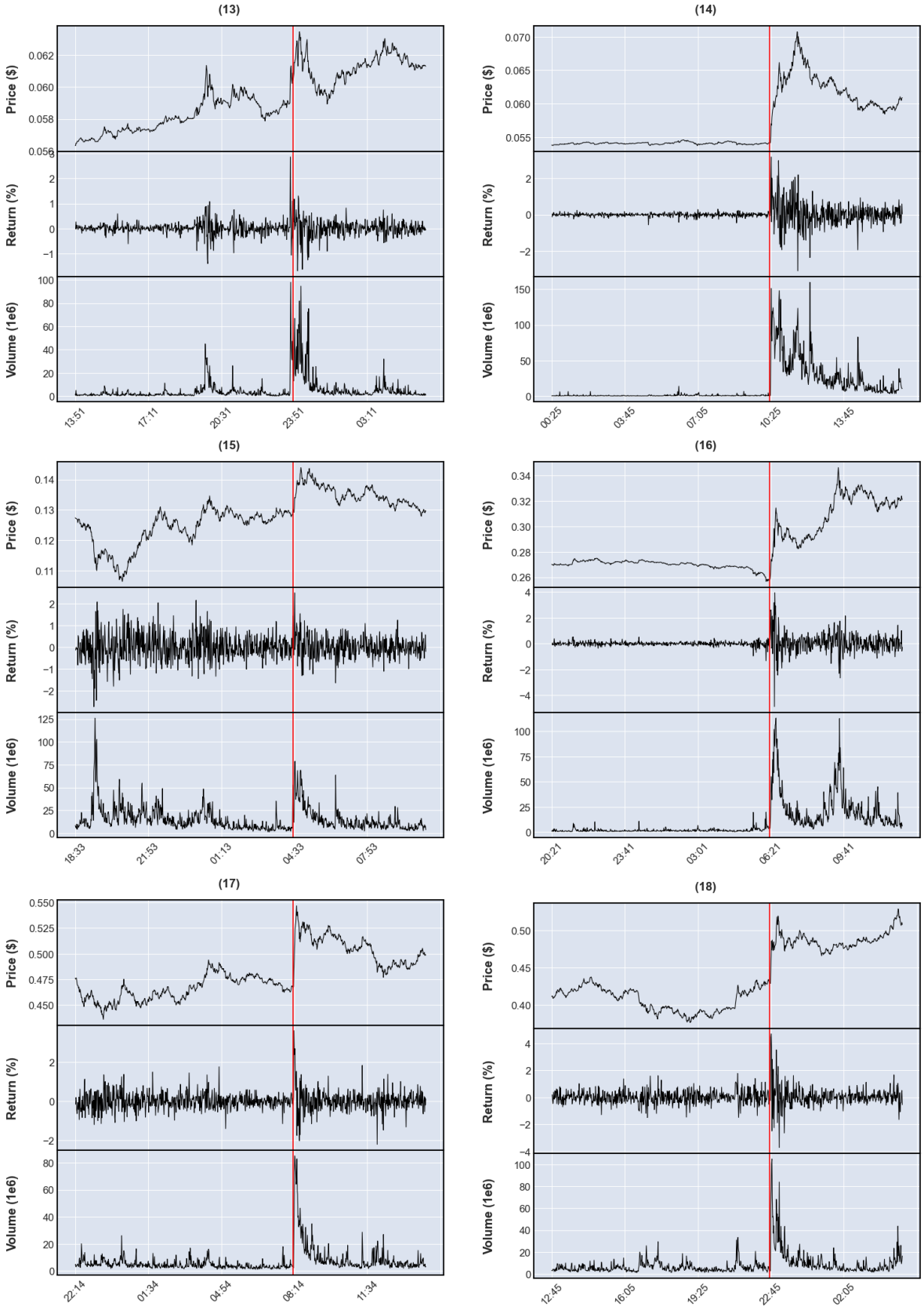
(13)
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