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Term Paper

Coin flipping?

The impact of @elonmusk on the prices of cryptocurrencies

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List of abbreviations

Aug.	August
CAR	Cumulative abnormal returns
BHAR	Buy and hold abnormal returns
o.c.	Own calculations
BTC	Bitcoin
DOGE	Dogecoin
ETH	Etherum
ADA	Cardano
LTC	Litecoin
Obs	Observations
Std. Dev.	Standard Deviation

Symbol directory

α_i, β_i	the parameters of the market model
$R_{m,t}$	the market index return
$u_{i,t}$	residual of the market model
$AR_{i,t}$	abnormal return of cryptocurrency i in time t
$E(R_{i,t})$	the expected return of cryptocurrency i in time t
t_0	event date
t_l	leakage information window
t_d	price delay window
CAR_i	cumulative abnormal return of cryptocurrency i
$\overline{CAR}$	mean of cumulative abnormal return
CAR_i	cumulative abnormal return of cryptocurrency i
$\hat{\sigma}^2$	estimated variance
$\overline{BHAR}$	mean of buy-and-hold abnormal return
$BHAR_i$	buy-and-hold abnormal return of cryptocurrency i
(T_1,T_2)	event window from time T_1 to T_2
N	number of cryptocurrencies
i	cryptocurrencies: BTC, DOGE, ETH, ADA, LTC

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1 Introduction

At the beginning of 2021, Donald Trump's Twitter account was permanently suspended because Twitter wanted to prevent him from inciting his followers to commit acts of violence through his tweets.[1] The role of social media in society has risen sharply in recent years and so has the influence of these platforms.

The study by Fan, Talavera and Tran from the Swansea University, for example, examined the connection between Trump's tweets and the development of stock prices.[2] Before his inauguration, it could be seen that the sentiment of his tweets influenced the performance of the S&P 500 stock returns.[3]

Like Trump, Elon Musk uses the Twitter platform very frequently. At the beginning of 2021, he increasingly tweeted about cryptocurrencies, 15 times in February 2021 alone.[4] With approximately 59 million followers (as of Aug. 21, 2021)[5], it is reasonable to assume that, as with Trump, Elon Musk could influence the course of cryptocurrencies through his tweets.

In a minute-by-minute framework, this topic was examined in the paper of Lennart Ante and a significant influence could be found.[6]

There are different models for the calculation of such an event study. Ante used the constant mean return model to calculate expected returns. Other than that, Ante chose tweets from which Elon Musk's opinion on cryptocurrencies was not directly evident. For example, the tweet from the 25th of December 2020, contained only an image, which included the Dogecoin symbol.

With clearly more provocative tweets such as "Dogecoin is dumb"[7] from 2nd of March 2021 which represent rather a negative position about cryptocurrencies, the question arises whether these also influence the market.

Therefore, as with Ante, the analyses of the impact of Elon Musk's tweets on cryptocurrencies will be the topic of this term paper.

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[1] Twitter Inc. (2021)
[2] Fan/Talavera/Tran (2018), p.3
[3] Fan/Talavera/Tran (2018), p.15
[4] https://twitter.com/elonmusk
[5] https://twitter.com/elonmusk
[6] Ante (2021), p.9
[7] https://twitter.com/elonmusk

Instead of the constant mean return model the market model is chosen. Using daily closing prices of various cryptocurrencies and the CCMIX index as well as tweets on the topic of Bitcoin, Dogecoin and cryptocurrencies from Elon Musk, it will be examined whether an impact can be found here as well.

In the following chapter, the research design is explained more in detail, and it is explained how the research question is going to be answered.

The choice of the data basis, as well as the data preparation are explained in the third chapter.

In the penultimate chapter, all empirical results are presented, subdivided according to the kind of method.

Finally, in the fifth and last chapter, a conclusion is drawn regarding the research question.

2 Methodology

2.1 Event study

In financial research, event study has been seen as one of crucial empirical methods to examine the market efficiency. For informationally efficient markets, there should be rapid response to the announcement event date and no further reaction towards the next trading days.[8] This paper carries out an event study in both short - term and long - term analyses with the help of the cumulative abnormal return approach (CAR) and the buy-and-hold abnormal return approach (BHAR). Both approaches are constructed based on the market model.

For both CAR and BHAR approaches, the null hypothesis is that the mean abnormal return is zero.[9] [10] One of the most important elements in an event study is to define the event window, which generally includes several days surrounding the day of the event.[11]

[8] Brooks (2014), p.634-635
[9] Kothari/Warner (2006), p.10
[10] Brooks (2014), p.635
[11] MacKinlay, A. (1997), p.14

Brooks (2014) suggests that it is common to analyze ten days before, and ten days after the announcement date for short-term event windows; for long-term event windows, one can conduct a period of several months or years.[12] Hence, the short-term event window in this study would be from time T_1= -10 to T_2=10, while the long-term window would be about three months after the announcement date of the event.

2.2 Short-term analysis – CAR approach

The market model (equation 1) is used to compute the expected returns of Bitcoin (BTC), Dogecoin (DOGE), Etherum (ETH), Cardano (ADA) and Litecoin (LTC) cryptocurrencies. By using linear regression with cryptocurrencies actual returns as dependent variables and actual market returns of the CCMIX as the independent variable, the expected returns are going to be calculated.

$$R_{i,t}=\alpha_i+\beta_i R_{m,t}+u_{i,t} \quad (1)$$

The expected return for cryptocurrency i on day t is computed as multiplying estimated β by the actual market returns (CCMIX). Brooks (2014) argues that the expected returns should be measured before the event window so that one would ensure these returns do not influence the nature of the event.[13] Therefore, the estimation window is comprised more than 300 days before the first event date (e.g., estimation window of 321 days from 01.01.2020 to 16.11.2020 before the first event date on 17.11.2020).

The abnormal returns (AR) are computed by eliminating the expected returns from actual crypto returns (equation 2).[14] Then the cross-sectional abnormal returns are measured by taking the mean $AR_{i,t}$ of the five cryptocurrencies.[15]

$$AR_{i,t}=R_{i,t}-E(R_{i,t}) \quad (2)$$

The event window is separated into three sub-sections: the event date $t_0 = [0]$, the leakage information window t_l = [-10;-1], and the price delay window t_d = [1;10].[16]

[12] Brooks (2014), p.635
[13] Brooks (2014), p.635
[14] MacKinlay, A. (1997), p.24
[15] MacKinlay, A. (1997), p.24

The cumulative abnormal returns are calculated by the sum of mean abnormal returns across five cryptocurrencies (equation 3), in which there are three values of CAR for (leakage information, announcement, and price delay window) each event.

$$CAR_i(T_1,T_2)=\sum_{t=T_1}^{T_2}\widehat{AR}_{it} \quad (3)$$

The effect of events on cryptocurrencies returns would be tested independently so that the t statistics is examined for each event. For each event, the mean of cumulative abnormal return is constructed across five cryptocurrencies and for every sub-section in the event window (equation 4).

$$\overline{CAR}=\frac{1}{N}\sum_{i=1}^{N}CAR_i \quad (4)$$

Finally, to conduct the t test (equation 7), the variance of average abnormal returns and the variance of cumulative abnormal return for cryptocurrency i is derived as follows in equation 5 and 6:[17]

$$\hat{\sigma}^2(\widehat{AR})=\frac{\sum_{i=1}^{N}(\widehat{AR}_i-\overline{AR})^2}{N-1} \quad (5)$$

$$\hat{\sigma}^2\left(CAR_i(T_1,T_2)\right)=(T_2-T_1+1)\hat{\sigma}^2(\widehat{AR}_{it}) \quad (6)$$

$$t_{CAR}=\frac{\overline{CAR}}{\hat{\sigma}^2\left(CAR_i(T_1,T_2)\right)}\times\sqrt{N} \quad (7)$$

2.3 Long-term analysis – BHAR approach

Besides CAR approach, the buy-and-hold abnormal return BHAR approach is used to detect the long-term abnormal return.[18]

$$BHAR_i=\left[\prod_{t=T_2}^{T_3}(1+R_{ti})-1\right]-\left[\prod_{t=T_2}^{T_3}\left(1+E(R_{ti})\right)-1\right] \quad (8)$$

One interesting difference between CAR and BHAR is that BHAR uses geometric returns for determining overall event period performance.[19] The last chosen Elon Musk's tweet was on 13.05.2021, thus the post-event period would be determined only within three months.

[17] Brooks (2014), p.643
[18] Brooks (2014), p.643
[19] Brooks (2014), p.643

Particularly, the post event window is calculated from $[T_2; T_3]$=[10;100], which means 90 days after the event window. The BHAR of each cryptocurrency i is computed as equation 8. Afterwards, the average of buy-and-hold abnormal returns are constructed across all cryptocurrencies for each event in equation 9. Equation 10 and 11 are to carry out the t-statistics by calculating the variance of BHAR of cryptocurrency i and the t-test.

$$\overline{BHAR} = \frac{1}{N}\sum_{i=1}^{N} BHAR_i \quad (9)$$

$$\hat{\sigma}^2(BHAR) = \frac{\sum_{i=1}^{N}(BHAR_i - \overline{BHAR})^2}{N-1} \quad (10)$$

$$t_{BHAR} = \frac{\overline{BHAR}}{\hat{\sigma}^2(BHAR)} \times \sqrt{N} \quad (11)$$

3 Data

The purpose of this study is to explore the links between Elon Musk tweets and abnormal returns on cryptocurrencies. Thus, the cryptocurrencies daily data are employed, which are obtained from 1st January 2020 through 21st August 2021, including US Dollar closing prices from Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), Cardano (ADA) and Litecoin (LTC) (Yahoo, 2021).

In addition, 1600 tweets from the Elon Musk Twitter account are collected to analyze an event study. The programming language of Python is used for the filtering of the crypto-related Tweets including terms like "bitcoin", "dogecoin", and "cryptocurrency". Five tweets where randomly chosen to represent all the 22 founded cryptocurrency related tweets. Since there are tweets by Elon Musk on the same day among these 22, they were sorted out to avoid overlapping events. Furthermore, the crescent cryptocurrency market index (CCMIX), a rules-based cryptocurrency market index developed to assess the performance of the largest and most liquid cryptocurrencies, is considered to compute cryptocurrencies expected returns by conducting the market model.

Variable	Obs	Mean	Std. Dev.	Min	Max
Date	599	22214	173.0607	21915	22513
CCMIX	599	26047.43	20265.04	4882.84	73887.23
BTC	595	24096.94	17617.08	4970.788	63503.46
DOGE	595	0.0757355	0.1323623	0.001537	0.684777
ETH	595	1035.242	1008.515	110.6059	4168.701
ADA	595	0.5251888	0.6241718	0.023961	2.457702
LTC	595	107.478	74.2296	30.93088	386.4508

Table 1: Descriptive statistics (source: o.c.)

Table 1 shows the full dataset with descriptive statistics, including the closing prices of 5 cryptocurrencies during the period of 01.01.2020 and 21.08.2021, setting up a total of 599 observations, in which there are four missing values for each cryptocurrency. According to the CCMIX index, BTC, DOGE, ETH, ADA, and LTC are the top five currencies in terms of market capitalization, accounting for 91.41 percent of the total weight. It can be seen that BTC (with a weight of 56.26 percent in CCMIX) has a significant influence on the CCMIX index. The standard deviations of all cryptocurrencies are relatively high, indicating substantial price fluctuations throughout the studied time.

4 Empirical Results

4.1 Evaluation of the cumulative abnormal returns

Examining the t-test´s for the cumulative abnormal returns, less significant results are seen than previously expected (see Table 2).

	Leakage info (-10;-1)		Announcement (0)		Price delay (1;10)	
	$\overline{CAR}$	t-statistic	$\overline{CAR}$	t-statistic	$\overline{CAR}$	t-statistic
Event (1)	-2.83%	-0.5489	0.10%	0.0606	5.61%	1.0858
Event (2)	23.69%	2.1499 *	10.98%	3.1521**	-12.92%	-0.4910
Event (3)	6.96%	0.6217	-0.01%	-0.0023	-5.49%	-1.1726
Event (4)	23.39%	2.1659 *	7.47%	2.1881 *	16.82%	1.5574
Event (5)	7.81%	0.6978	20.77%	5.8698 ***	-1.12%	-0.1005

***, **, * indicate significance at the 1%, 5% and 10% level. (*with Df=4)*

Table 2: Average CAR and t-statistic (source: o.c.)

For the leakage window, there are two significant values. The first one on event two with a t value of 2.1499 and the second one on the fourth event with a t value of 2.1659.

With a mean CAR value of 23.69% in the leakage window and a gradually reduction to the announcement and price delay window an overreaction could be seen in event two. For the event one, three and five, even there are some slightly variations in the mean CARs, the null hypothesis cannot be rejected at any level of significant.

This suggests that in the case of the first, the third and the fifth event no information was previously available about a possible upcoming tweet.

No information was leaked before the event period. Only in the case of events two and five were reactions from cryptocurrencies before the tweet appeared.

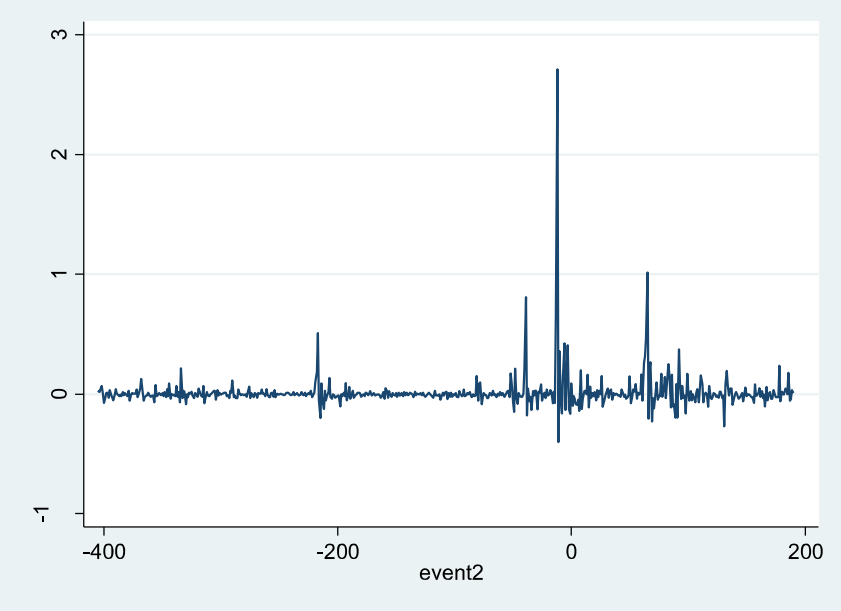
Since this is an online platform, it is rather unlikely that information was leaked beforehand in the classic sense. Leaking is often understood as the unauthorized publication of information. In this context, it would mean much more that Elon Musk's opinion regarding cryptocurrencies had already become known before the tweet was published.

In the time period of event two, Elon Musk also tweeted about cryptocurrencies the day before and three days before. It's the same for the fourth event, where he tweeted five days prior about cryptocurrencies. This may have possibly led to this significant value in the leakage window, as followers were already prepared for his opinion.

At event time zero, there are three significant events. In addition to the second and fourth event, as in the leakage window, the fifth event also has a significant t test with a value 5,8698 at a 99 % confidence interval (see Table 1).

Here, the respective tweets of Elon Musk seem to have an influence on the returns of the cryptocurrencies.

When looking at the scatter plot of the abnormal returns of event two for example, a deflection of these can also clearly be seen at time zero (see graph 1). The same results can be seen for the fourth and fifth event as well.



Graph 1: AR of Dogecoin at the 2nd event (source: o.c.)

Returns suddenly turned out to be significantly higher for a short period of time than they had been before.

These results can also be interpreted well in terms of content. For example, Elon Musk tweeted at the second event "bought some dogecoin for lil x, so he can be a toddler holder"[20]. This tweet is clearly one of the more provocative tweets at which many crypto enthusiasts probably looked at least twice. Quite apart from whether one evaluates this tweet as an endorsement of cryptocurrencies or as a metaphor against Dogecoin.

Elon Musk's tweet can thus be seen as the decisive factor for these abnormal returns. There are no significant values for the other events. Here, his tweets apparently did not lead to significant abnormal returns on the event date.

For the last time window to be analyzed, there are also no significant values for any of the events. They are all below the value of 2.13 which defines the acceptance or rejection range. It can therefore be assumed that if the cryptocurrencies have an impact, then only on the event day itself. In addition, Elon Musk tweets frequently about this topic, so that other events could also fall in this period.

4.2 Evaluation of the buy and hold abnormal returns

There are no significant values for the post event window (see table 3).

	Post event window (10;90)	
	$\overline{BHAR}$	t-statistic
Event (1)	-346.39%	1.3342
Event (2)	136.58%	1.2156
Event (3)	120.56%	1.2381
Event (4)	7.02%	0.7056
Event (5)	-10.26%	-0.7878

***, **, * indicate significance at the 1%, 5% and 10% level. (*with Df=4)*

Table 3: Average BHAR and t-statistics (source: o.c.)

There are different interpretations for this occasion. On the one hand, it could be due to the fast pace of cryptocurrencies.

[20] https://twitter.com/elonmusk

Compared to stocks, they can be traded 24 hours a day, seven days a week. This could lead to the fact that if tweets have an impact on cryptocurrencies, it can be seen directly.

On the other hand, it may be due to the fact that other events occur within the ninety-day window. For example, in the event window from the second event also falls the third and fourth event. In addition to the six tweets considered, Elon musk has also tweeted much more frequently on the topic of cryptocurrencies. From November 2020 to May 2021, 22 times alone. This may lead to these insignificant results.

4.3 Determinants of potential Ars

There are several reasons for the occurrence of potential abnormal returns. We are still in the middle of the Corona crisis. Many areas of the economy have probably been greatly affected by it. The exact extent is probably still difficult to determine. Thus, it seems likely that the Corona crisis could also be responsible for such abnormal returns. In the last two years there were always new resolutions which caused the most different emotions with the people. This also led to constantly changing attitudes towards politics and the economy.

5 Conclusion

The aim of this work was to empirically investigate the impact of Elon Musk's tweets on cryptocurrencies.

In the end, the initial assumption could be partially disproved. An influence of tweets on cryptocurrencies could be found, but it is significantly smaller and less clear than assumed at the beginning.

For example, no influence at all could be found when looking at the post event window. This is attributed to the fast-moving nature of cryptocurrencies and tweets. In very short periods of time, Elon Musk tweets about cryptocurrencies again and again, so no clear influence could be determined in the long term.

In the short-term calculations, there were two significant tweets. Depending on the content of the tweets, these can thus apparently influence the cryptocurrencies. However, to be able to say this unambiguously, there are two other important factors that have to be included and analyzed in the investigation.

First, as previously mentioned, the tweets have to be examined in terms of content as well. Possibly negative or provocative tweets could have a stronger influence than more neutral tweets. This is only a conjecture which has not been investigated in detail in this work.

The other factor that must be examined is the factor of Elon Musk´s followers. Although almost 60 million people follow him, it is not entirely clear how many of these are actually involved with the topic of cryptocurrencies. If a major part of them have other interests, tweets on other topics would have a much greater influence on them than tweets about cryptocurrencies. This could be one reason why no clear influence could be found.

Finally, this work can be seen as an introduction to the topic of the impact of Elon Musk´s tweets. However, as explained before, there are still some factors that need to be investigated before a clear statement can be made.

Appendix

File	TweetID	Date	Dogecoin	Bitcoin	Crypto
Tweet1182.txt	1,32846E+18	16.11.2020 23:02	0	1	0
Tweet264.txt	1,32859E+18	17.11.2020 16:41	0	1	0
Tweet903.txt	1,34057E+18	20.12.2020 09:21	0	1	0
Tweet65.txt	1,37462E+18	31.12.2020 06:19	0	1	0
Tweet872.txt	1,35824E+18	07.02.2021 03:24	1	0	0
Tweet381.txt	1,35893E+18	09.02.2021 01:09	0	0	1
Tweet131.txt	1,35952E+18	10.02.2021 16:08	1	0	0
Tweet860.txt	1,36109E+18	15.02.2021 00:25	1	0	0
Tweet1529.txt	1,3626E+18	19.02.2021 04:01	0	1	0
Tweet1087.txt	1,36327E+18	21.02.2021 00:42	0	0	1
Tweet335.txt	1,36681E+18	02.03.2021 18:50	0	0	1
Tweet1476.txt	1,37045E+18	12.03.2021 20:00	0	1	0
Tweet1024.txt	1,37088E+18	14.03.2021 00:51	1	0	0
Tweet66.txt	1,37462E+18	24.03.2021 08:02	0	1	0
Tweet506.txt	1,37499E+18	25.03.2021 08:33	1	0	0
Tweet730.txt	1,37757E+18	01.04.2021 12:25	1	0	0
Tweet1167.txt	1,38077E+18	10.04.2021 08:44	0	0	1
Tweet714.txt	1,3828E+18	15.04.2021 23:10	1	0	0
Tweet1353.txt	1,38682E+18	27.04.2021 01:15	0	1	0
Tweet1451.txt	1,39052E+18	07.05.2021 06:24	0	0	1
Tweet44.txt	1,3926E+18	13.05.2021 00:06	0	1	0
Tweet787.txt	1,39152E+18	16.05.2021 03:20	0	0	1

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