FICCOMSS

Proceedings of Femfest International Conference on Economics, Management, and Business

Volume 1, 2023
https://ejournal.unida.gontor.ac.id/index.php/JTS/index

The Role of Social Media Influencers in the Cryptocurrency Market Performance Movement

Ronniko Agus Frinico
Faculty of Economics, Sultan Agung Islamic University, Jl. Kaligawe Raya KM. 4, Semarang, 50112, Central Java, Indonesia
*Corresponding author(s). E-mail(s): ronniko.silalahi@gmail.com

Abstract

During this pandemic, there are many people who just stay at home, so they think about investing in order to get additional income, one of which is investing in crypto, until finally crypto investment becomes a trend for people in Indonesia. The pump and dump pattern known in the cryptocurrency market shows that a high market capitalization makes a project in cryptocurrency healthy and not vulnerable to market manipulation. Many factors influence the increase or decrease in the price of cryptocurrencies, although this digital currency is known to be resilient to government intervention, there are many other factors that contribute to its price volatility. One of them is famous influencers such as Elon Musk, Michael Saylor, Changpeng Zhao, and many more. These influencers often tweet on social media such as Twitter, with a single positive or negative tweet that can increase or decrease the price of cryptocurrencies such as BTC and alternative cryptocurrencies.

Keywords; *Volume Trading, Influencer, Cryptocurrency, Media Social, Price*

Introduction

The purpose of this research is to test the variable abnormal return, cumulative abnormal return, and trading volume activity before and after the tweets made by social media (AR) influencers, especially Twitter social media, namely Elon Musk and Michael Saylor, on the price variable of Bitcoin. Conditions of changing abnormal returns, Crypto which has higher abnormal returns will attract greater investor interest, so that the demand for crypto is high and causes crypto prices to rise, this happens in the law of supply and demand. The concept of the influencer of social media influencers emerged from research conducted (Hamurcu 2022) who say that the role of social media influencers affects the movement of crypto prices. This research is also supported by (Hashemi Joo, Nishikawa, and Dandapani 2020) where market reactions are influenced by positive responses and negative responses which play a role in moving the price of crypto.

The activity of price movements from the crypto market itself is one of the things that investors hope for the opportunity to obtain capital gains obtained through the buying and selling process of cryptocurrency. Crypto price movements are partly influenced by the role of social media such as Instagram, Twitter, Telegram, and so on. In this study the social media used is Twitter. Twitter is a powerful platform for sharing information, many influential people in the crypto world always provide educational insights about crypto developments through Twitter social media such as Elon Musk, Saylor, and so on. As an example of the incident that occurred on March 24, 2021, Tesla CEO Elon Musk announced that the purchase of Tesla cars produced in America could already be purchased using Bitcoin, thus increasing the price of Bitcoin by more than 4%. This event shows that influencer Tweeters such as Musk and Saylor influence the rising price movement of Bitcoin, where Musk followers have 121 million followers in the world and Saylor has 2.8 million followers. The involvement of these social media influencers can help investors by adding unique insights and perspectives to make the right decisions in investing in crypto.

On the www.mediaindonesia.com website, 6 factors affect the price of bitcoin, namely: availability and demand, adoption of cryptocurrency into the real world, production costs for mining bitcoin, government regulations, influencer whales/important figures, and related news, and psychological factors. with the greed of investors who are tempted by high returns in the hope that crypto prices will rise high.

The research conducted (Hamza 2020) says that Cryptocurrency influencer social media has a positive effect on the price of bitcoin and the information contained in tweeters is very helpful in making Bitcoin buying strategies. Previous researchers said that signal responses from social media such as tweeters and Google trends partially affect the increase or decrease in the price of the cryptocurrency Bitcoin (Philippas et al. 2019). Furthermore, research conducted by (Mai et al. 2018) argues that not all responses from social media affect the price movements of cryptocurrency. According to research (Tio et al., 2022), social media has a positive and significant influence on the decision to buy cryptocurrency while research conducted by (Brans and Scholtens 2020) states that tweets from influencer Donald Trump do not cause significant stock returns, in this study it focuses on AR and CAR.

Research conducted by (Ante 2021) states that there is a significant increase in Bitcoin trading volume every minute with the acquisition of an abnormal return in the first minute of 1.46% and with a period of 30 minutes a cumulative abnormal return of 4.5%. Research by (Septiana et al., 2021) states that the factor of the increase in the price of Bitcoin cryptocurrency and alternative cryptocurrency coins is influenced by trading volume which shows the performance of Bitcoin currency and alternative coin currencies. (Demiralay and Golitsis 2021) found that trading volume and investor attention have a significant effect on dynamic cryptocurrency market price movements. Research conducted by (Gemici and Polat 2019) reveals that the positive relationship between price and trading volume is interrelated. Contrary to research conducted by (Dyhrberg, Foley, and Svec 2018) states that trading volume is positively correlated with Bitcoin price volatility, but negatively correlated with supply and demand. Another study conducted by (Balcilar et al. 2017) says that trading volume does not affect the price of cryptocurrency which is experiencing volatility

Therefore, this study provides a solution by providing an overview of the abnormal return and abnormal trading volume that will be obtained based on the positive responses expressed by social media influencers by applying the event study methodology. Besides that, this research is also a guide for investors and practitioners in managing information originating from Tweeters to make short-term and long-term investments

Literature Review and Hypothesis Development

Signal theory provides information that investors will take buying and selling actions based on the information them receive. Events that send a positive response will make the market react and vice versa if the market responds negatively, the market will not react. This study will provide an understanding of abnormal returns, cumulative abnormal returns, and trading volume activity.

AR (Abnormal Return)

The market reaction is indicated by a change in the price of the issuer concerned. This market reaction is measured using abnormal returns. If used with abnormal returns, it can be said that a response that has information content will provide an abnormal return to the market, whereas one that does not contain information will not provide an abnormal return. (Narto and Hasan 2021) says that abnormal returns are returns received by investors that are not the same. with the expected return due to information leakage. Abnormal has an impact on stock price fluctuations and investor behavior. When an event occurs that contains negative information for investors, it will cause a decrease in stock prices, trading volume and abnormal stock returns (Darmayanti, Mildawati, and Dwi Susilowati 2021). Based on the research above, the abnormal return is the difference between the actual profit rate and the expected profit rate. In testing market efficiency, abnormal returns are used as indicators that show the efficiency of a market. (Hartono 2013) in obtaining return expectations in using the following estimation models:

1. This Means a customized model. This model assumes that the expected return has a constant value equal to the average value of realized returns before the estimated period, ie

$$E(Rit) = \frac{\sqsubseteq Rit}{T}$$

Where: E(Rit) : The expected return of issuer i in the event period t
Rit : Actual Return of issuer i in the event period t
T : the length of the estimation period
The estimation period is generally the period before the event period, while the event period is the monitoring period or event window.

2. Market-adjusted model: A model that assumes that estimating returns on issuers is the market index return at that time. This model does not use the estimation period to form an estimation model. The estimated return is the same as the market index return.

$$E(Rit) = Rmt$$

Where (Rit) : The expected return of issuer i in event period i
Rmt: Issuer's return at time t

The results of the research conducted by (Fabiana Meijon Fadul 2019) did not find any positive influence from Twitter social media information on prices and abnormal returns obtained both before and after the event. (Brans and Scholtens 2020) also found that there was no positive effect on the abnormal returns obtained by investors both before and after Donald Trump's presidential election. (Tomić 2020) there was no significant effect of abnormal returns both before and after the bitcoin fork event. which is the same as research (Ante 2021) which states that there is a significant difference between abnormal returns before and after the mentions by Elon Musk. Therefore, our first hypothesis is as follows:

Hypothesis 1: there are differences in abnormal returns before and after mentions by social media influencers.

CAR (Cumulative Average Return)

Cumulative average return means the sum of abnormal returns from the previous day in a certain period (Balcilar et al. 2017), the number of abnormal returns offers another point of view based on event responses that provide an unusual amount of return (Fabiana Meijon Fadul 2019). Social media influencers such as Musk respond very quickly to the market and return to normal quickly too so the CAR achieved has a positive effect on all event periods (Ante 2021).

Based on the description above, the cumulative average return can be defined as the total amount of return earned. To determine CAR comparisons during the period before the event, it can be seen the effect of an event on stock prices in a period. The formula for finding CAR is as follows:

CARit = Σta=t AR

Where: AR is the abnormal return of issuer i in period i

The results of the study (Hafidz and Isbanah 2020) show that there is a difference in CAR before and after the revision of the ratification of the revision of the KPK law. However, different research (Ante, Fiedler, and Strehle 2021) found that there was no cumulative abnormal return effect before and after the information on the issuance of a new stablecoin. Therefore, we propose the second hypothesis as follows:

Hypothesis 2: there is a difference in cumulative abnormal return (CAR) before and after being mentioned by social media influencers.

Trading Volume Activity

Trading volume is used in trading on the cryptocurrency market to find out if the cryptocurrency has liquidity. This liquidity shows a characteristic of cryptocurrency where good liquidity means buyers make decisions when buying and selling cryptocurrencies on the market and converting them into cash. In a study conducted by (Pradita et al., 2019) there are three factors related to trading volume and the Bitcoin market price, namely (1) trading volume is related to information on the market, and investors' personal information is depicted through trading volume where trading volume is a good indicator in investing, (2) the price of bitcoin reflects complete information from the cryptocurrency market, so investing in bitcoin can see changes in trading volume, (3) The short-term impact is related to trading volume, where investing in the short term has an effect on trading volume.. By definition – the definition above, the definition of trading volume is the number of assets traded between sellers and buyers to measure the liquidity of an asset. The formula for finding trading volume is as follows:

$$Volume\ trading\ \frac{= (number\ of\ shares\ traded\ at\ time\ t)}{(number\ of\ shares\ outstanding\ at\ time\ t)}$$

According to research (Balcilar et al. 2017) that trading volume can predict returns, but trading volume cannot predict fluctuations in the price of Bitcoin. A study conducted by (Gemici and Polat 2019) reveals that the positive relationship between price and trading volume is interrelated. previous researchers (Dyhrberg, Foley, and Svec 2018) stated that trading volume is positively correlated with Bitcoin price volatility, but negatively correlated with demand and supply, but on the contrary in research (Hafidz and Isbanah 2020) found no difference in total trading volume before and after the ratification of the revision of the 2019 KPK Law and subsequent researchers (Vaddepalli and Antoney 2017) found that there was no effect of Bitcoin trading volume on economic factors, financial openness and internet penetration.

Hypothesis 3: there are differences in trading volume activity (TVA) before and after being mentioned by social media influencers

Event Study

Event study studies events that cause a market reaction to an event whose information is conveyed through announcements (Fabiana Meijon Fadul 2019). Event studies can test the content of information, it is hoped that there will be a market reaction when the information is received by the market. There is a market reaction marked by a change in the price of the cryptocurrency itself. To measure the existence of this market reaction by using abnormal returns which are marked by changes in the price of cryptocurrencies. If the abnormal return is used as an indicator to measure this reaction, then the information content is positive and can provide an abnormal return on the market, and vice versa, if the information content is negative, it is estimated that it will not provide an abnormal return on the market.

Event study theory is research that examines the effect of information on cryptocurrency prices. Event study research generally describes an empirical financial research technique that allows researchers to assess the effect of an event on the price of a cryptocurrency. Market analysts who wish to test the impact of information conveyed by a social media influencer will test market reactions to observe changes in cryptocurrency prices after information contains positive and negative responses (Abraham 2021).

Social Media and Influencers

Research (Mai et al. 2018) says that social media can provide precise and fast information directly where traditional media cannot provide information as fast as social media. Other researchers (Pentescu et al, 2015) say that social media is a group of internet-based applications as a means of creating and exchanging information in the form of content for its users. Through this social media, influencers will provide education and knowledge regarding useful content for their followers. (Whatmough 2018) states that influencers are people who have great influence in conveying messages conveyed through newspapers, TV or speeches in front of many people. Influencers who have a large number of followers and have a strong influence on their followers (Tokopedia, 2022) influencers can be divided into three, namely:

- Mega Influencer: has more than one million followers
- Macro Influencers: have followers between 100,000 people and up to 1 million people
- Micro Influencer: have followers between 1000 people to 100,000 people

A study conducted by (Mai et al. 2018) found that the response from social media is an important indicator of changes in Bitcoin prices. Another study conducted by (Bizzi and Labban 2019) found that social media influences consumer behavior toward interest in trading decisions.

Research Methods

The type of research being conducted is event study and comparative research which will compare existing indicators such as AAR, CAAR, and TVA investors before and after getting news information from Twitter social media influencers such as Elon Musk and Michael Saylor in comparing which influencers most influential on the movement of the price of bitcoin. The social media taken in this study is Twitter, where the research data consists of Elon Musk and Michael Saylor's tweet data from November 1, 2020, to December 31, 2021. To obtain tweet data using the Python programming language version 3.10, it is then converted to Excel data.

The type of research data is quantitative with secondary data taken through the website www.coingecko.com. The population taken in this study is by comparing 12 event tweets originating from crypto influencers Elon Musk and Michael Saylor.

Results and Discussion

The data processed in this study describes the average abnormal return (AAR) in a period of 5 hours before mentions made by influencers and 5 hours after mentions are made on Twitter social media. The movement of average abnormal returns influenced by social media influencers Elon Musk and M Saylor can be seen in Figure 1.

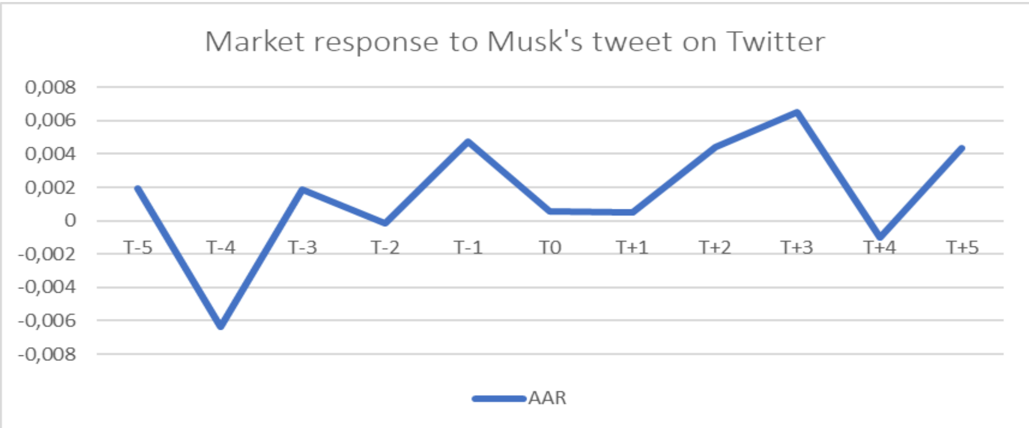

Figure 1. Market Response to Musk's tweet on Twitter

Based on the image in the chart above, it can be seen that Musk's tweets in the previous 5 hours did not show price movements, but at T0 to T3 or from 0 hours to 3 hours after Musk's tweet, the crypto market response responded quickly and returned to normal. quickly. Investors start buying and selling Bitcoin starting in the 180-minute period. Musk's tweets based on the research only took effect about 3 hours or 180 minutes after Musk's tweet. The influence of the Musk influencer on the price movement of Bitcoin can be seen the difference with the influence of the Saylor influencer. The movement of the average abnormal return on influencer M Saylor on the crypto market can be seen in Figure 2.

The movement of the Average abnormal return from Saylor's influence from the beginning of the tweet at T0 to T-1 to T-4 did not change significantly. The market response to Saylor's tweets had no effect both before the tweets and after the tweets on social media Twitter on the average abnormal return.

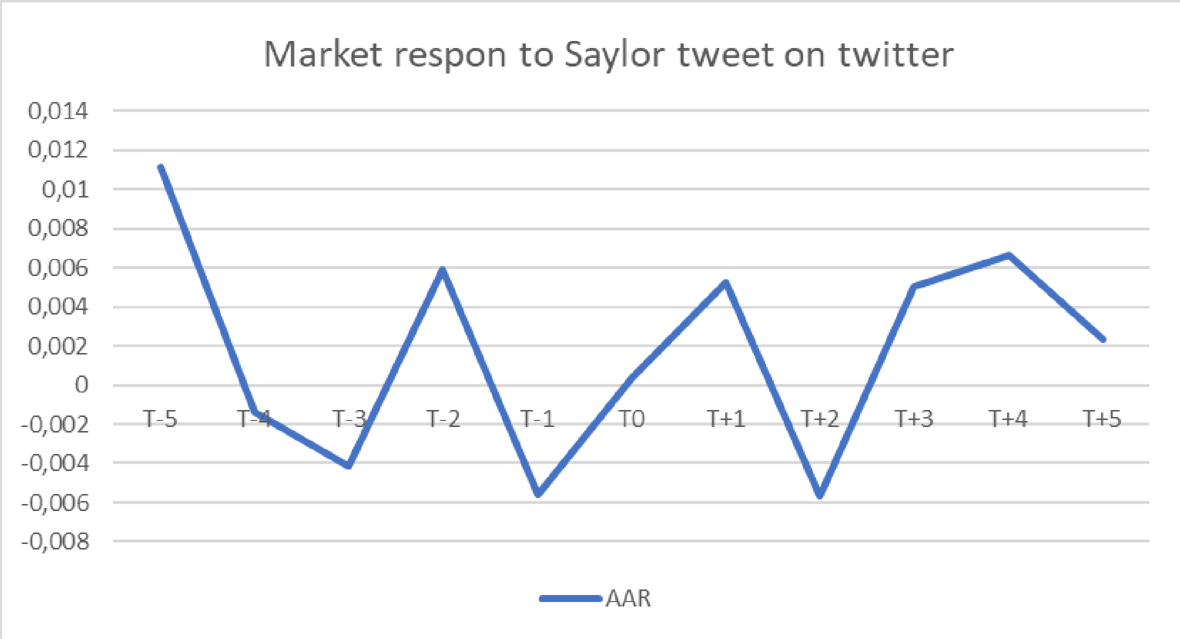

Figure 2. Market Response to Saylor's tweet on Twitter

Descriptive Statistical Test Results

Descriptive statistical testing of the research sample total are 12 events where each event from the influencers consisted of 6 events for 5 hours before and after the tweets of the influencers on social media Twitter which obtained the minimum value, mean, and standard deviation for AAR, CAR, and TVA from each -respectively crypto influencers namely Musk and Saylor

Tabel 1. Descriptive Statistics of Musk

	N	Minimum	Maximum	Mean	Std. Deviation
AARsebelum	6	.00050	.00880	.0044333	.00300644
AARsesudah	6	.00370	.02140	.0138667	.00665663
CAARSebelum	6	.00053	.00884	.0044447	.00301256
CAARSesudah	6	.00374	.02138	.0138635	.00663721
AAVsebelum	6	-358553629,00	355829331,00	-42404229,1667	252304528,70470
AAVsesudah	6	-342246111,00	535198717,00	38426756,1667	293812389,11824
Valid N (listwise)	6				

From Table 1, it can be seen that the AAR before and after has the Mean and standard deviation at 0.0044333 and 0.0138667 and 0.00300644 and 0.0665663. Meanwhile, Table 2 shows that the AAR before and after has the Mean and standard deviation at 1325570.83 and 1410922.50 and 6641901.33 and 3732199.40.

Tabel 2. Descriptive Statistics of Saylor

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
AARsebelum	6	-4959586	14130261	1325570,8	6641901,3
AARSesudah	6	-2008542	8439466	1410922,5	3732199,4
CARSebelum	6	-7343887	10010161	242500,17	7556726,8
CARSesudah	6	-928295	7559116	3045139,7	3536816,5
Volsebelum	6	-289681605	234508955	-55903880	213450132
VolSesudah	6	-14118129	520718367	136588550	199660761

Normality Test Results

After carrying out the descriptive statistical tests carried out for the normality test, the purpose of this test is to conclude whether the data to be processed by the researcher is normally distributed or not normally distributed. For testing the normality test using Kolmogorov – Smirnov with Asymp.Sig (2-tailed) results from AAR, CAR, and TVA. If the test data results are below 0.05, it means that the data is not normally distributed**.**

Tabel 3 : Uji Normalitas Musk

Data	Sig.	Kesimpulan
T-5	0,38	Normal
T-4	0,63	Normal
T-3	0,01	Tidak Normal
T-2	0,89	Normal
T-1	0,02	Tidak Normal
T-0	0,73	Normal
T1	0,56	Normal
T2	0,99	Normal
T3	0,01	Tidak Normal
T4	0,46	Normal
T5	0,37	Normal
ARRSebelum	0,96	Normal
ARRSesudah	0,69	Normal
CAARSebelum	0,96	Normal
CAARSesudah	0,69	Normal
AVSebelum	0,87	Normal
AVSesudah	0,81	Normal

Tabel 4 : Uji Normalitas Saylor

Data	Sig.	Kesimpulan
T-5	0,65	Normal
T-4	0,0004	Tidak Normal
T-3	0,93	Normal
T-2	0,14	Normal
T-1	0,03	Tidak Normal
T-0	0,01	Tidak Normal
T1	0,01	Tidak Normal
T2	0,38	Normal
T3	0,08	Normal
T4	0,88	Normal
T5	0,00070	Tidak Normal
ARRSebelum	0,06	Normal
ARRSesudah	0,11	Normal
CAARSebelum	0,15	Normal
CAARSesudah	0,37	Normal
AVSebelum	0,55	Normal
AVSesudah	0,04	Tidak Normal

In the normality test, Musk obtained three data that were not normally distributed, namely at T=3, T-1, and T3 which were obtained in the normal test below 0.05, so that later on the data that was not normally distributed, the Wilcoxon test was carried out. In the Saylor normality test, six data are not normally distributed, namely at T-4, T-1, T0, T1, T5, and after AV.

Table 4 : one simple test Musk

Data	Sig.	Kesimpulan
T-5	0,607	tidak terdapat AR yg signifikan
T-4	0,087	tidak terdapat AR yg signifikan
T-3	0,605	tidak terdapat AR yg signifikan
T-2	0,962	tidak terdapat AR yg signifikan
T-1	0,358	tidak terdapat AR yg signifikan
T-0	0,883	tidak terdapat AR yg signifikan
T1	0,933	tidak terdapat AR yg signifikan
T2	0,28	tidak terdapat AR yg signifikan
T3	0,418	tidak terdapat AR yg signifikan
T4	0,641	tidak terdapat AR yg signifikan
T5	0,048	Terdapat AR yg signifikan
ARRSebelum	0,01535	Terdapat AR yg signifikan
ARRSesudah	0,037	Terdapat AR yg signifikan

Table 5 : one simple test Saylor

Data	Sig.	Kesimpulan
T-5	0,0542	tidak terdapat AR yg signifikan
T-4	0,3450	tidak terdapat AR yg signifikan
T-3	0,2267	tidak terdapat AR yg signifikan
T-2	0,5244	tidak terdapat AR yg signifikan
T-1	0,4630	tidak terdapat AR yg signifikan
T-0	0,1150	tidak terdapat AR yg signifikan
T1	0,3450	tidak terdapat AR yg signifikan
T2	0,1425	tidak terdapat AR yg signifikan
T3	0,7044	tidak terdapat AR yg signifikan
T4	0,4776	tidak terdapat AR yg signifikan
T5	0,1730	tidak terdapat AR yg signifikan
ARRSebelum	0,6456	tidak terdapat AR yg signifikan
ARRSesudah	0,3969	tidak terdapat AR yg signifikan

The first hypothesis testing reads that there are differences in abnormal returns before and after being mentioned by social media influencers. Simple one test in table 4 (Musk one simple test) obtained significant data on T5, ARR before and after ARR, whereas in table 5 (one simple Saylor test) no significant AR (abnormal return) was found. To see a comparison of the hypotheses, there is an average abnormal return before and after mentioning tweets on Twitter social media, which can be seen in the test below

Table 6 : Paired samples Test Musk

Paired Samples Test Musk Tweet

Indikator	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
AARsebelum - AARsesudah	-,00943333	,00541652	,00221128	-,01511762	-,00374905	-4,266	5	,008

The significant effect of Musk's tweets can be seen in the paired samples test above, that there is a difference in the average abnormal return before and after Musk's tweets on Twitter. The response of the crypto market to Musk's tweet had a significant effect, while the result was 0.008 in sig 2-tailed table 6 above. This result is indicated by a significant value of 0.008 <0.05, so the results of the first hypothesis are accepted these results support the first hypothesis and are in line with research (Ante 2021) and are also supported by research conducted (Tomić 2020).

The paired samples test on Saylor's tweet can be seen in the table below:

Tabel 7 : Paired Samples Test Tweet Saylor

Indikator	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
AARsebelum - AARSesudah	-85351,6666667	8471922,5096580	3458647,8815102	-8976089,0866651	8805385,7533318	-,025	5	,981

Saylor's paired sample test on the average abnormal return before and after has no significant effect. The test results obtained sig 2 tailed around 0.961. Where the significance value is 0.961 > 0.05, this result is not following the first hypothesis so the results of the first hypothesis for the Saylor influencer are rejected. Based on the research results above, Saylor's tweet where the crypto market did not respond significantly. Comparing the two influencers, it can be concluded that the influence of Musk's tweets has a significant effect on the response of the crypto market.

For testing the second hypothesis, there is a difference in cumulative abnormal return (CAR) before and after being mentioned by social media influencers.

Paired Samples Test CAR Musk Tweet

Indikator	Paired Differences					t	df	Sig. (2-tailed)
				the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
CARSebelum - CARSesudah	-12150744,00	6430091,26	2875624,23	-20134756,82	-4166731,18	-4,225	4	,013

Testing the second hypothesis, the cumulative average value before and after the influencer Musk obtained results in Sig.2 tailed of 0.013, where the significance value is 0.013 <0.05 so that the two hypotheses of Musk's tweets have different cumulative abnormal returns before and after. These results are following the second hypothesis and the results of the hypothesis are accepted. This hypothesis is supported by research (Thomson 2021) and research (Ante, Fiedler, and Strehle 2021)

Paired Samples Test Saylor

Indikator	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
CARSebelum - CARSesudah	-881879,40	9074345,93	4058170,87	-12149168,05	10385409,25	-,217	4	,839

Testing the second hypothesis, the cumulative average before and after the Saylor influencer obtained a Sig 2 tail result of 0.839, where the significant result was 0.839 > 0.05 so the second hypothesis from Saylor's tweet was rejected.

Paired Samples Test Musk

Indikator	Paired Differences					t	df	Sig. (2-tailed)
				the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
TVAsebelum - TVAsesudah	-287868848,2	147905140,1	66145189,5	-471517335,9	-104220360,5	-4,352	4	,012

The third hypothesis test is that there are differences in trading volume activity (TVA) before and after being mentioned by social media influencers, the results of paired sample testing are 0.012. The significance result is 0.012 <0.05 so the third hypothesis is accepted, namely the existence of different trading volume activities before and after. The findings of this study are in line with the findings (HAMURCU 2022) which stated that there was a significant increase in different trading volume activities before and after.

Paired Samples Test Saylor

Indikator	Paired Differences					t	df	Sig. (2-tailed)
				Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
TVAsebelum - TVAsesudah	-275.253.692	518.229.950	231.759.479	- 918.721.164	368.213.780	- 1	4	0,301

The third hypothesis test in testing different trading volume activities before and after Saylor's paired sample test is 0.301. These findings are contrary to the results of the third hypothesis where the significance is 0.301 > 0.05. The results of Saylor's third hypothesis were rejected

Conclusion

Based on the results of the analysis and hypothesis testing above, the researcher can draw the following conclusions:

1. The first hypothesis provides an illustration that states that crypto influencers such as Musk have a significant influence on the movement of the average

abnormal return, while in the influence of Saylor in the first hypothesis there is no difference between the average abnormal return before and after. The impact of Musk's tweets can be seen three hours after Musk shared his tweets on social media Twitter
2. The second hypothesis and the third hypothesis of Musk's tweets make the cumulative average return and trading volume activity have a significant effect on the movement of abnormal returns and trading volume activity while the influence of Saylor's tweets found no difference in CAR and TVA both before and after
3. This research is very sensitive in terms of data collection and the samples used because the data used in this study are of a trading age and in a short period.

Acknowledgment and Limitation

In this study there are limitations and deficiencies, there are some suggestions that researchers convey in terms of deficiencies and limitations in this study:
1. The sample used can be added to the period from hours to minutes so that the test results get even better accuracy
2. the number of events studied is added, the period can be more than 2 years to see in detail the influence of crypto influencers
3. During the study event, research can be done within minutes interval to see the effect of the crypto market response to influencer tweets
4. For future research, could add other influences of crypto such as Anthony Pompliano and Nayib Bukele.

Reference

Abraham, M. 2021. "An Event Study Analysis of Bitcoin and Altcoins under COVID-19." *African Review Of Economics And Finance-Aref* 13 (2): 7–24.

Ante, Lennart. 2021. "How Elon Musk's Twitter Activity Moves Cryptocurrency Markets." *SSRN Electronic Journal*, no. 16: 1–28. https://doi.org/10.2139/ssrn.3778844.

Ante, Lennart, Ingo Fiedler, and Elias Strehle. 2021. "The Influence of Stablecoin Issuances on Cryptocurrency Markets." *Finance Research Letters* 41: 101867. https://doi.org/10.1016/j.frl.2020.101867.

Authors, For. 2019. "Relationship Is Bitcoin a near Stock ? Linear and Non-Linear Causal Evidence from a Price – Volume Relationship." https://doi.org/10.1108/IJMF-06-2017-0107.

Balcilar, Mehmet, Elie Bouri, Rangan Gupta, and David Roubaud. 2017. "Can Volume Predict Bitcoin Returns and Volatility? A Quantiles-Based Approach." *Economic Modelling* 64 (August 2016): 74–81. https://doi.org/10.1016/j.econmod.2017.03.019.

Bizzi, Lorenzo, and Alice Labban. 2019. "The Double-Edged Impact of Social Media on Online Trading: Opportunities, Threats, and Recommendations for Organizations." *Business Horizons* 62 (4): 509–19. https://doi.org/10.1016/j.bushor.2019.03.003.

Brans, Heleen, and Bert Scholtens. 2020. "Under His Thumb the Effect of President Donald Trump's Twitter Messages on the US Stock Market." *PLoS ONE* 15 (3): 1–11. https://doi.org/10.1371/journal.pone.0229931.

Chania, Mutia Fitri, Oyami Sara, and Isfenti Sadalia. 2021. "Analisis Risk Dan Return Investasi

Pada Ethereum Dan Saham LQ45." *Studi Ilmu Manajemen Dan Organisasi* 2 (2): 139–50. https://doi.org/10.35912/simo.v2i2.669.

Darmayanti, Novi, Titik Mildawati, and Fitriah Dwi Susilowati. 2021. "Dampak Covid-19 Terhadap Perubahan Harga Dan Return Saham." *EKUITAS (Jurnal Ekonomi Dan Keuangan)* 4 (4): 462–80. https://doi.org/10.24034/j25485024.y2020.v4.i4.4624.

Demiralay, Sercan, and Petros Golitsis. 2021. "On the Dynamic Equicorrelations in Cryptocurrency Market." *Quarterly Review of Economics and Finance* 80: 524–33. https://doi.org/10.1016/j.qref.2021.04.002.

Dyhrberg, Anne H., Sean Foley, and Jiri Svec. 2018. "How Investible Is Bitcoin? Analyzing the Liquidity and Transaction Costs of Bitcoin Markets." *Economics Letters* 171: 140–43. https://doi.org/10.1016/j.econlet.2018.07.032.

Fabiana Meijon Fadul. 2019. THE EFFECT OF SOCIAL MEDIA ACTIVITY ON THE MARKET –CASE ELON MUSK, EVIDENCE FROM THE US". Lappeenranta–Lahti University of Technology LUT

Gemici, Eray, and Müslüm Polat. 2019. "Relationship between Price and Volume in the Bitcoin Market." *Journal of Risk Finance* 20 (5): 435–44. https://doi.org/10.1108/JRF-07-2018-0111.

Hafidz, Maulana Faizal, and Yuyun Isbanah. 2020. "Analisis Komparatif Abnormal Return Dan Trading Volume Activity Berdasarkan Political Event (Event Study Pada Pengesahan RUU KPK 2019)." *Jurnal Ilmu Manajemen* 8 (3): 829. https://doi.org/10.26740/jim.v8n3.p829-838.

HAMURCU, Cagri. 2022. "Can Elon Mask's Twitter Posts About Cryptocurrencies Influence Cryptocurrency Markets By Creating A Herding Behavior Bias?" *Fiscaoeconomia* 6 (1): 215–28. https://doi.org/10.25295/fsecon.1028730.

Hamza, Shakirullah. 2020. "The Effect of Tweets Made by Cryptocurrency Opinion Leaders on Bitcoin Prices." *Saudi Journal of Economics and Finance* 4 (12): 569–89. https://doi.org/10.36348/sjef.2020.v04i12.005.

Hashemi Joo, Mohammad, Yuka Nishikawa, and Krishnan Dandapani. 2020. "Announcement Effects in the Cryptocurrency Market." *Applied Economics* 52 (44): 4794–4808. https://doi.org/10.1080/00036846.2020.1745747.

Mai, Feng, Zhe Shan, Qing Bai, Xin (Shane) Wang, and Roger H.L. Chiang. 2018. "How Does Social Media Impact Bitcoin Value? A Test of the Silent Majority Hypothesis." *Journal of Management Information Systems* 35 (1): 19–52. https://doi.org/10.1080/07421222.2018.1440774.

Narto, E, and M Hasan. 2021. "Dampak Over Reaksi Pasar Dan Abnormal Return Terhadap Harga Saham Emiten Pada Cluster Sub-Sektor Food and Beverage Di …." *Journal of Accounting Science and Technology* 1 (1): 123–30.

Pengaruh, Analisis, Influencer Sosial, R Aditya Rayhan Zanesty, Tio Arya, Dewa Prakasa, Intania Chantika, Nur Aini Rakhmawati, and Departemen Sistem Informasi. 2022. "ANALISIS PENGARUH INFLUENCER SOSIAL MEDIA TERHADAP KEPUTUSAN MASYARAKAT INDONESIA" 15 (1): 44–59.

Philippas, Dionisis, Hatem Rjiba, Khaled Guesmi, and Stéphane Goutte. 2019. "Media Attention and Bitcoin Prices." *Finance Research Letters* 30: 37–43. https://doi.org/10.1016/j.frl.2019.03.031.

Sihombing, Septiana, Muhammad Rizky Nasution, and Isfenti Sadalia. 2021. "Analisis Fundamental Cryptocurrency Terhadap Fluktuasi Harga: Studi Kasus Tahun 2019-2020."

Jurnal Akuntansi, Keuangan, Dan Manajemen 2 (3): 213–24. https://doi.org/10.35912/jakman.v2i3.373.

Thomson, Liam. 2021. "Abnormal Returns of Corporations Adopting Bitcoin as a Treasury Asset: An Event Study." *Erasmus School of Economics*, no. August.

Tomić, Nenad. 2020. "Measuring the Effects of Bitcoin Forks on Selected Cryptocurrencies Using Event Study Methodology." *Industrija* 48 (2): 21–36. https://doi.org/10.5937/industrija48-26003.

Vaddepalli, Surendar, and Laly Antoney. 2017. "Are Economic Factors Driving BitCoin Transactions? An Analysis of Select Economies." *Journal of Emerging Issues in Economics, Finance & Banking* 6 (2): 2215–27.

Whatmough, Danny. 2018. "7. Influencers." *Digital PR*, 87–98. https://doi.org/10.1108/978-1-78756-619-420181008.