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Spillover effects of Elon Musk his tweets on cryptocurrencies and Tesla on the price level of Tesla

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ABSTRACT

The goal of this paper is to determine if there are spillover effects in Musk's tweets on Tesla's price. The findings of this event study indicate that tweets have a different effect on the price of Tesla, Bitcoin and Dogecoin. While some tweets had statistically significant influence on the market, both positively and negatively, others did not. This suggests that the content, context, and time had a significant impact on investor sentiment and, as a result, Tesla's stock performance. When interpreting or generalizing these event study results caution should be exercised. Many other factors, next to the tweets of Musk, might have affected the prices of the assets.

Keywords: Spillover effects, Abnormal returns, Cumulative abnormal returns

JEL codes: Financial Statistics, Stock Market and Cryptocurrencies

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1 Introduction

Business tycoon Elon Musk, the CEO of Tesla and SpaceX, has established himself as a major player in the cryptocurrency industry. His tweets, especially those on Dogecoin and Bitcoin, affected the pricing greatly. Musk regularly mentions cryptocurrencies in his tweets, and publicly states his support for digital assets like Bitcoin, Dogecoin and Ethereum. His tweets have a severe impact on the crypto market since they can create sudden price changes. On April 14th, 2022, Musk started his acquisition of Twitter, Inc., and finished it on October 27th, 2022. Prior to the take-over of Twitter, the price of the Tesla stock was approximately $225 per share. However, the shares closed the financial year 2022 at roughly $123, declining about 45%. In comparison, during the same time period as the Nasdaq fell roughly 3%. More recently, on May 11th, 2023, Musk announced that he is stepping down as CEO of Twitter. The day this news became public the Tesla stock increased with $3.54 to a share price of $172.08. However, a day later those gains vanished, and the Tesla stock closed at a price of $167.98. Although none of Musk his tweets were about Tesla, the stock price was influenced.

The study on the impact that Musk's tweets can have on investor sentiment and the resulting price volatility in financial markets is a current academic subject. The proposed relation assumes that tweets about cryptocurrencies or Twitter have spillover effects and thus influence the price of Tesla. For example, if Musk posted a tweet announcing that Dogecoin would skyrocket in value, many might take it as financial advice. Shahzad, Anas & Bouri (2022) investigated the effect of Musk's tweets on the price explosiveness of Bitcoin and Dogecoin. They used four-hourly data from the period of January 1st, 2020, to June 19th, 2021, where they perform a BSADF. They found multiple bubble episodes in both coins. Musk his cryptocurrency-related tweets have contributed to the price explosivity of Bitcoin and Dogecoin. This research is in line with the research done by Ullah, Attah-Boakye, Adams & Zaefarian (2022) where they did a study about the effect of endorsements from celebrities and the government on Bitcoin's price volatility. The authors use panel data and run a panel regression of Bitcoin prices from Bloomberg from November 1st, 2019, till May 31st, 2021. They discovered that an increase in Bitcoin prices is considerably positively correlated with positive government and celebrity tweets. A total overview is given by Corbet, Lucey, Urquhart & Yarovava (2021) where they systematically analyse the growing breadth and depth of cryptocurrencies research that has been published since 2009 to 2018. They document what is currently known about cryptocurrencies. Their findings illustrate that there are ten important gaps in the literature and that people (just like any other investments) should temper their expectations.

Social media has developed into a useful tool to influence public opinion and behaviour, therefore research on the spillover effects of tweets, especially those of Musk, is timely and practical. The increased popularity of social media sites like Facebook, Reddit, and Twitter has opened up a new channel for the public to share information and viewpoints regarding the cryptocurrency and stock markets. Social media can therefore greatly affect many asset's values. Also, the crypto market is a relatively newish financial asset that is continuously developing. The market is very volatile and speculative because it is decentralized and generally unregulated. This makes it a perfect market for researching how spillover effects affect the financial market.

Research on the relationship between Musk’s tweets and cryptocurrency- and Tesla prices is relevant and realistic because it can offer important insights into the workings of spillover effects. A regulatory paper for example is Raza, Khan, Guesmi & Benkraiem (2023), where they study the impact of uncertain financial regulatory policies on the volatility of crypto markets using the GARCH-MIDAS model. They find that the volatility of cryptocurrencies is negatively and strongly correlated with the uncertainty of financial regulation policies. Meaning that the cryptocurrency market is strengthened by the sudden change in the uncertainty of financial regulation policy.
What we do not know yet, and thus my research question, is:

What are the spillover effects, and thus the impact, of Elon Musk's tweets on Tesla and cryptocurrencies, such as Bitcoin and Dogecoin, on the price level of Tesla?

The aim of this research is to determine whether there are statistically significant abnormal returns in financial markets due to the influence of influential individuals, such as Musk, on price levels. To test this hypothesis, an event study will be used. Similar to Ante’s (2023) research on the effects of tweets on price changes, the event study will be utilized to identify abnormal returns by comparing returns during the event window with the expected returns. These expected returns will be based on historical data. Spillover effects are detected when there are statistically significant abnormal returns on Tesla’s price during the event window of the Bitcoin and Dogecoin tweets. Data sources for this research will include Twitter for Musk his tweets, and Yahoo finance for the daily closing prices. The daily price data will range from January 1^{st}, 2019, to December 31^{st}, 2023. Scientific papers, such as Tandon, Revankar, Palivela, and Parihar (2021) and Fekrazad, Harun, and Sardar (2022), have conducted similar research.

Elon Musk his tweets about Twitter and cryptocurrencies have a big impact on the financial market and can cause big swings in the price of Tesla. As shown previously, after the announcement that Musk wanted to buy Twitter the price of a Tesla share dropped around 50% in half a year. The financial market is sensitive to Musk his tweets because it is well-known that they evoke both favourable and unfavourable reactions from investors and the media and thus, I expect to find spillover effects.

The remainder of this paper is structured as follows. Section 2 discusses the relevant literature and previous research. Section 3 is about the selected data. Section 4 will discuss the use of the event study. Section 5 discusses the results of the event study. Finally, section 6 will have the conclusion which is followed by the discussion about the limitations and the recommendations for further research.

2 Theoretical Framework

2.1 Cryptocurrency: background

In the ever-evolving worlds of banking and technology, cryptocurrencies have emerged as a disruptive force that is distorting conventional understandings of money and changing how we perceive and utilize it. The attraction and interest in cryptocurrencies have grown significantly since the introduction of Bitcoin in 2009. The creation of Bitcoin was motivated by the demand for a safe and decentralized digital currency. Due to their underlying blockchain technology, cryptocurrencies provide a new way to perform financial transactions, establish trust, and empower individuals worldwide.

The concept of cryptocurrencies was initially inspired by the need for a digital payment system free from centralized banks and governments. In a whitepaper titled "A Peer-to-Peer Electronic Cash System" published in 2008, the mysterious creator of Bitcoin, Satoshi Nakamoto, described the underlying concepts and technical foundations of this revolutionary digital currency. The ground-breaking path of Bitcoin that has seen the launch of thousands of competitive cryptocurrencies and blockchain-based services.

Blockchain, the fundamental technology that powers cryptocurrencies, is a distributed ledger that keeps track of and validates transactions across numerous computers, or nodes, in a network. A chain of earlier blocks is added to the bundle of transactions to create an immutable record of all transactions. With the help of this decentralized ledger, the system is more secure and trustworthy because no one entity can change or modify the transaction history.

Numerous factors have contributed to the mass acceptance, but also to the mass disgust of cryptocurrencies. Rejeb, Rejeb and Keong (2021) studied the role of cryptocurrencies in modern finance. They combine earlier research using a narrative literature review method to gain insights into the benefits and disadvantages of using cryptocurrency. The findings show that cryptocurrencies provide customers and corporations with lower transaction costs, more efficiency, improved security and privacy, significant benefits from diversification, alternative funding options, and financial inclusion. There are several difficulties with incorporating cryptocurrency into modern finance. The lack of regulatory standards, the possibility of criminal activity, high energy and environmental costs, usage bans and limits imposed by regulations, security and privacy issues, and the extreme volatility of cryptocurrencies.

2.2 The impact of information: Efficient Market Hypothesis

In the realm of economics, market efficiency is a topic that is heavily researched. According to the Efficient Market Hypothesis (EMH), prices precisely match all available information (Fama, 1970). The intersection of the supply and demand curves yield the equilibrium price. This price is acceptable to both consumers and producers. When new information becomes available, this equilibrium often alters. For instance, if deemed important, the publication of a news item or a tweet by well-known individuals can affect the equilibrium price.

From platforms like MySpace, which reached a million monthly users in 2004, to Facebook nowadays, which had 2.26 billion members in 2018, the importance and use of social media has increased exponentially (Ortiz-Ospina, 2019). Everyone is always able to express their opinion. Sayce (2022) estimates that in 2016, there were approximately 500 million tweets per day which averages 6,000 tweets every second. For financial models, systems, and theories, the vast amount of data available through social media presents difficulties. Both buyers and sellers must learn how to recognize, process, and evaluate information effectively and efficiently. As the EMH strongly depends on the tastes and behaviors of market players, this worries critics of the model. The Adaptive Markets Hypothesis (AMH), an update of the EMH, acknowledges that the way information is represented in prices depends on the market environment, the number of participants, and the characteristics of each member (Lo, 2004). Following this, the market efficiency is dependent on external factors.

While most studies (e.g., Bollen et al., 2011 for stocks and Steinert and Herff, 2018 for the crypto market) concentrate on general feelings or moods in relation to the market, some studies (e.g., Brans and Scholtens, 2020) have shown that the social media activity of influential people can affect stocks. Using a sample of 100 tweets from Donald Trump, former president of the United States, Brans and Scholtens conducted an event analysis. They discovered that the tweets had no apparent influence. However, they did see a significantly negative market reaction. Particularly unfavorable tweets led to particularly negative market movements when the emotion of the tweets was considered.

A study by Huynh (2021) gives a textual analysis with spillover effects that investigates the relationship between the sentiment in the tweets of former US President Donald Trump and price and volume activity in the Bitcoin market. He discovers that negative sentiment is a predictor of Bitcoin returns, trading volumes, realized volatility, after analyzing 13.918 tweets from January 2017 to January 2020. A Granger-causal relationship between sentiment and volatility exists exclusively for negative sentiment. He also discovers a time-varying correlation between Trump's Twitter mood and the Bitcoin market. This study further extended the COVID-19 period and discovered that the Bitcoin market during the epidemic can be predicted using Trump's attitude.

2.3 Exploitation of information: Market manipulation

Market manipulation is the use of illegal methods to unfairly affect the cost, worth, or trading activity of financial assets or instruments. It entails deliberate activities intended to manipulate the markets for one's own benefit or to mislead other market players. Market manipulation threatens the fairness and integrity of financial markets, reducing investor trust and perhaps resulting in substantial loss of money. For the financial ecosystem to remain transparent, trustworthy, and efficient, market manipulation must be identified and combated.

Market manipulation can take many different forms, and as financial instruments and technology development, so can its methods. Insider trading, pump-and-dump scams, and end-of-day manipulation are a few frequent examples of market manipulation (Aitken, Cumming, & Zhan, 2015). Although each of these techniques employs a distinct set of tactics and strategies, their fundamental goals are the same: to deceive market circumstances, manipulate prices, or take advantage of knowledge gaps for individual or collective gain. The tweets of Musk could be viewed as a form of market manipulation, section 2.3.2 will review this more in depth.

2.3.1 Insider trading

Insider trading involves the purchase or sale of stocks, bonds, or other securities based on non-public information about a company. Insider trading occurs when individuals who have access to confidential information use that information to engage in trading activities and gain profits. Raj Rajaratnam was convicted of the biggest insider trading scandal. He was the founder and manager of the Galleon Group and ran a complex insider trading scam from 2003 until 2009. He gathered sensitive information from managers, consultants, and other insiders at various businesses. Rajaratnam and his trading network profited from the material non-public knowledge by trading stocks and other securities using this privileged information until he was caught in 2011.

The question of whether insider trading restrictions accelerate, or slow down technological innovation is explored in the research of Levine, Lin, and Wei (2017). Using more than 80.000 industry-country-year observations ranging 74 economies from 1976 to 2006, they find that establishing insider-trading restrictions encourages innovation determined by patent intensity, scope, effect, generality, and originality. The findings also support the notion that restricting insider trading encourages innovation by enhancing the value of innovative activities and the flow of equity financing to them. Finally, they point out that being found guilty of insider trading frequently has a damaging impact on a company's long-term worth.

Meulbroek (1992) discovers that the stock market recognizes the possibility of informed trade and incorporates this knowledge into the stock price using previously unavailable data on illegal insider trading from the Securities and Exchange Commission. An abnormal return averages 3% on an insider trading day and insider trading days account for over half of the pre-announcement stock price run-up seen before takeovers. The market recognizes the insider trading because of the insider's trade volume as well as other trade-specific details.

2.3.2 Pump-and-dump

The next form of market manipulation is referred to as "pump-and-dump". It is frequently associated with both the stock and cryptocurrency market. This method involves spreading false or misleading information and using deceptive advertisements or statements to artificially increase the price of a particular asset. The movie “The wolf of Wallstreet” entails such a pump-and-dump scheme.

Via deceptive advertising, high-pressure sales tactics, and promoting incorrect or inaccurate information about the companies the protagonist and his associates pushed penny stocks. When the price of these penny stocks had risen significantly, they sold all their shares leaving the buyers with big losses.

The first test in the research by Hamrick et al. (2018) examines the volume of Bitcoin pump and dump activity on Discord and Telegram, two very popular platforms with 130 million and 200 million users, respectively. Both platforms are the most frequently used distribution channels for cryptocurrency pump-and-dump schemes because of their immense popularity and ability to control large groups of users. They found 1.051 pump signals on Discord and 3.767 on Telegram over a six-month period in 2018. More than 300 cryptocurrencies were advertised in various schemes. These comprehensive data provide the first estimate of the extent of pump-and-dump schemes across cryptocurrencies and suggest that they are widespread and frequently extremely profitable. They also found that the rank of the coin the most important factor for assessing the pump's profitability is (the rank is based on market capitalization/volume). As a result, pumping unknown, low-volume coins is much more profitable than pumping coins that are dominating the ecosystem.

In certain cases, investors are more likely to pay inflated prices, especially when influential figures, persuade them to invest in a certain type of cryptocurrency. This can occur due to a domino effect or a fear of missing out. For instance, when Elon Musk tweeted on April 1st, 2021, "*SpaceX is going to put a literal Dogecoin on the literal moon.*" the price of Dogecoin experienced a price surge of approximately 16% in just one day (CoinMarketCap). Plausibly, Musk later clarified that the tweet was intended as a joke, as it was posted on April Fools' Day (Krishnan et al., 2021). Despite the temporary surge in Dogecoin's value following positive tweets from influential figures like Musk, it is important to note that the cryptocurrency market's popularity remains highly volatile and that the effect is not permanent (Verma, 2022).

2.3.3 End-of-day

End-of-day (EOD) manipulation, sometimes referred to as closing manipulation, is the act of manipulating stock prices or their closing values at the close of a trading day. This type of market manipulation seeks to improve public perception of an assets pricing. A well-known example of EOD manipulation is the “London Whale” in 2012. It involved a trader named Bruno Iksil who worked for JPMorgan in London. The goal of Iksil's transactions in the credit derivatives market was to reduce the bank's exposure to risk. However, his investments suffered severe losses. To account for his losses Iksil manipulated the end of the day. He would make significant deals right before the market closed to manipulate prices in his advantage. Iksil intended to conceal the true size of the losses and keep market players from spotting the weakness of JPMorgan's positions by giving the appearance of liquidity and stability. Eventually the fraud was discovered, and JPMorgan faced losses in the billions of dollars.

The study of Aitken, Cumming, and Zhan (2015) investigated the connection between high-frequency trading (HFT) and EOD price dislocation on 22 exchanges worldwide from January 2003 to

June 2011. The data consisted of actual surveillance systems which registered a suspected EOD price dislocation which is used the same across all exchanges. Their results, in contrast to recent media concerns, shows that HFT has greatly reduced the frequency and degree of EOD price dislocation. The impact of HFT has the greatest effect on days that an option expires or at the end of a month occurs when EOD price disruption is more likely to be caused by market manipulation.

The topic of EOD manipulation has been thoroughly studied in the mergers and acquisitions industry. EOD stock price manipulation can affect both the target and the acquiring company. The target company may manipulate its stock to increase value prior to the acquisition to obtain a higher price, while the acquiring company may attempt to manipulate its own stock to reduce acquisition costs (Cumming et al. 2020).

2.4 Spillover effects of information

Spillover effects, commonly referred to as externalities, are when the result of an economic action go beyond the parties immediately involved. When the acts of one economic agent or sector have unforeseen costs or advantages for other economic agents or sectors. These consequences can be positive or negative. The collapse of the US subprime mortgage market, which sparked the 2008 global financial crisis, is a clear illustration of spillover effects. Due to this crisis, there was a considerable drop in lending, a freeze on the credit market, and a loss of confidence. Global financial markets' interconnectivity and the spread of toxic assets caused significant losses for financial institutions all around the world. Globally, the effects could be seen as stock markets fell, housing prices declined, and the rising unemployment rate.

In his important work "The Economics of Welfare", published in 1920, Pigou first addressed externalities. Pigou's primary research focus was on the harmful effects of market activity when third parties are forced to cover costs that are not their own. Pigou's research established the theoretical foundation for interpreting externalities, but Coase's 1960 publication, "The Problem of Social Cost," presented opposition to the popular believe. Coase argued that market players can internalize externalities through voluntary transactions where property rights are properly established, and transaction costs are low. He emphasized the cost of negotiating as well as the role that imprecise property rights play in producing spillover effects. Since Coase, numerous economists have looked into spillover effects and what they mean in different contexts.

The impact of spillover effects extends beyond the stock market alone and also contains the cryptocurrency market. The impacts of spillover both within the cryptocurrency market and from the cryptocurrency market to other financial markets are examined by Lui and Serletis (2019). They examine the connection between the volatility and returns of the top cryptocurrencies using GARCH-in-mean models. According to the study, the top cryptocurrencies exhibit statistically significant shock and volatility exchanges, with considerable consequences to the overall cryptocurrency market. The cryptocurrency market's spillover effects on other financial markets in sophisticated economies, such as the US, Germany, the UK, and Japan, are also strongly supported by Lui and Serletis' research. The results show how the cryptocurrency market and conventional financial markets are intertwined and how changes in the cryptocurrency market can affect and spread shocks to other financial sectors. This means that policymakers and market participants ought to pay attention to cryptocurrencies since they have the potential to affect overall financial stability.

The US, UK, Germany, Japan, and France are the five main stock markets that Tsai's (2014) study evaluates for spillover effects. The study measures the degree to which spillover effects affect each of these marketplaces and finds that information transmission has significantly increased since 1998. Notably, information is often shared to other foreign markets through the German and American stock markets. “Results show that the US stock market shows three periods during which its net spillover effect exceeds zero: the period prior to 1997, the dot-com bubble from 2000 to 2002, and the subprime mortgage crisis and Lehman Brothers bankruptcy from 2007 to 2008”. Additionally, there is a significant association between the fear index and the US stock market's spillover effects into other markets, showing the importance of both positive fundamental information and non-fundamental elements like fear in the transmission process. Overall, the analysis highlights the existence of asymmetries as well as the tendency for both non-fundamental and favorable fundamental information to spread throughout the US stock market and have an impact on other connected markets. With an emphasis on the function of information flow and non-fundamental elements in influencing market behavior, these insights offer light on the dynamics of spillover effects in international stock markets.

3 Data

The aim of this paper is to determine whether there are spillover effects in Musk's tweets on the price of Tesla. This section discusses the two sources are used to retrieve information about Musk's tweets, and the price of Tesla, Bitcoin and Dogecoin.

The tweets from Elon Musk's official Twitter account (twitter.com/elonmusk) are retrieved using Twitter's open and publicly available API. The timespan reaches from January 2, 2019, to December 31, 2021. January 1, 2019, is not available since the stock exchange is closed on New Year's Day. To maintain data accuracy, only Elon Musk's original tweets are included in the dataset; retweets and duplicates are not selected. To ensure relevance to the hypothesis, only tweets that explicitly mentioned Tesla, Bitcoin, or Dogecoin are included in the dataset. The dataset consists of fifteen tweets total, each giving the opportunity for a new event study.

The dataset consists of fifteen tweets total (more detailed depiction in appendix A). Five concerning Tesla, five concerning Bitcoin and five concerning Dogecoin. These tweets are shown in table 3.1 below and briefly discussed what Musk presumably meant.

Table 3.1 *The tweets of Musk and their interpretation*

No.	Asset	Content	Interpretation
1	Tesla	*"Tesla made 0 cars in 2011, but will make around 500k in 2019"*	Here Musk wanted to emphasize the growth Tesla had gone through in just 9 years.
2	Tesla	*"Tesla stock price is too high imo."*	The abbreviation "imo" stands for in my opinion and Musk thought that the stock price of Tesla was too high.
3	Tesla	*"Tesla will make fabulous short shorts in radiant red satin with gold trim."*	Using colorful language Musk described a new product which Tesla was going to produce. One interpretation of the tweet could be that this was Musk's response to the short sellers in the market.
4	Tesla	*"Strange that moved valuation, as Tesla is very much a production ramp problem, not a demand problem"*	Musk talked about the confusing variations and adjustments that happened in Tesla's valuation. After that, he explained that Tesla's primary problem was a production ramp-up, not one of customer demand.

(Continues on next page)

Table 3.1 *(continued)*

No.	Asset	Content	Interpretation
5	Tesla	*“Much is made lately of unrealized gains being a means of tax avoidance, so I propose selling 10% of my Tesla stock.”*	Musk was talking about unrealized gains and tax evasion. He admitted that the accumulation of unrealized gains without triggering tax requirements is still a topic of debate and criticism.
6	Bitcoin	*“Bitcoin is my safe word”*	A “safe word” is commonly used as a reference in a close relationship. Users of Twitter wondered what Musk meant by tweeting this. However, Musk responded to his own tweet by saying: “*Just kidding, who needs a safe word anyway!?”*. Revealing the jokingly intent of the tweet.
7	Bitcoin	*"Tesla's action is not directly reflective of my opinion. Having some Bitcoin, which is simply a less dumb form of liquidity than cash, is adventurous enough for an S&P500 company."*	Musk wanted to explain that Tesla's investment in Bitcoin does not represent his opinion of the cryptocurrency personally.
10	Bitcoin	*"To clarify speculation, Tesla has not sold any Bitcoin"*	Musk reacted on speculations that Tesla sold its Bitcoin holdings.
11	Dogecoin	*“Dogecoin might be my fav cryptocurrency. It’s pretty cool.”*	Musk directed a lot of attention to Dogecoin with this positive tweet.
12	Dogecoin	*"Dogecoin is the people's crypto"*	This tweet emphasized Musk's support for Dogecoin as a cryptocurrency that is driven by the larger community as opposed to a particular group or corporation.
13	Dogecoin	*"Doge spelled backwards is Egod"*	Musk gave a fun edge to the discussion surrounding Dogecoin which came with a lot of attention.

(Continues on next page)

Table 3.1 *(continued)*

No.	Asset	Content	Interpretation
14	Dogecoin	*“Doge Barking at the Moon”*	This tweet could represent the path and focus that Dogecoin has received in the world of cryptocurrencies.
15	Dogecoin	*"SpaceX launching satellite Doge-1 to the moon next year"*	With this tweet Musk said that his company SpaceX would launch a satellite called Doge-1 into space and would be paid for in Dogecoin.

Yahoo finance provided the daily closing price of Tesla in US dollar. The data covers the same timespan as Musk’s tweets, from January 2nd, 2019, to December 31st, 2021, to guarantee consistency. The daily closing price information offers a thorough in-depth analysis of Tesla's price changes over the course of the study. This enables us to study the effect of Musk's tweets on Tesla's stock price.

Yahoo finance also provided the daily closing price of Bitcoin and Dogecoin in US dollar. The data covers the same timespan as Musk’s tweets, from January 2, 2019, through December 31, 2021, to guarantee consistency. The daily stock price information offers a thorough in-depth analysis of Bitcoin’s and Dogecoin’s price changes over the course of the study. This enables us to study the spillover effects in Musk's tweets on Tesla's stock price.

4 Method

In this part of the paper the research method will be discussed. The goal is to determine whether there are spillover effects in Musk's tweets on the price of Tesla. Therefor we conduct an event study analysis. An event study method is frequently done to analyse the market response to particular events, such as business announcements or in this example, tweets. We make use of an event study method because it has advantages over other statistical methods. The first advantage is that it offers a clear framework and defined technique when it comes to spillover effects, which makes it easy to be recreated by other researchers. In addition, when using time-series data it effectively spots abnormal returns or other significant changes connected to the tweets.

4.1 Event study

Firstly, the expected return (ER) is calculated over the estimated period before the tweet of Musk. The ER is compared to the observed return on each day. The difference between these two returns is the abnormal return (AR). The magnitude of the AR can be attributed to the tweet of Musk (Brown and Warner, 1985). Also following Brown and Warner (1985), the Constant Mean Return Model is used to determine the ER where it calculates the log return ($\log(\frac{p_t}{p_{t-1}})$) over the closing prices. The ER over the estimation period is given by the average log return and represented in the following formula:

$$(1) \qquad ER_{ti} = \frac{\sum ER_{\text{estimation window}}}{n}$$

Where t is the time and i corresponds with the tweet. The number of observations in the estimation period is given by n.

Secondly, the ARs are represented by the difference between the observed returns and the ERs:

$$(2) \qquad AR_{ti} = R_{ti} \text{ -} ER_{\text{estimation window}}$$

Where t is the time and i corresponds with the tweet.

Thirdly, because this is a multiple event study these ARs can be combined so it becomes a Cumulative Abnormal Return (CAR):

$$(3) \qquad CARti = \sum AR_{ti}$$

Where t is the time and i corresponds with the tweet.

4.2 Spillover effects

The goal of this paper is to measure if there are spillover effects in Musk's tweets on Tesla's price. A t-test is used to see whether the ARs and CARs are statistically significant. The same as in the study of Ante (2023).

A t-test has the following hypothesis:

H_0= Musk's tweets have no significant differences between the means of the expected AR and the observed AR ($\mu = \mu_0$)

H_a= Musk's tweets Musk have significant differences between the means of expected AR and the observed AR ($\mu \neq \mu_0$)

In a t-test the first step is to calculate the t-statistic. The t-statistic is determined as the difference between the sample means divided by the standard error of the difference:

$$T = \frac{\bar{X} - \mu_0}{\sigma/\sqrt{n}}$$

Here: the observed value of the return on Tesla, Bitcoin and Dogecoin is $\bar{X}$, the expected return on Tesla, Bitcoin and Dogecoin is μ_0, standard deviation σ, and the number of observations n. However, the standard deviation of Tesla, Bitcoin and Dogecoin is unknown. Therefor an estimated standard deviation of the sample group, S , is calculated:

$$S = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

Finally, the degrees of freedom (df) has to be determined. The formula for the degrees of freedom is: df = n-1. After completion of step two we get a critical value or p-value. When this value is compared to the level of significance, the null hypothesis is either accepted or rejected.

5 Results of the event study

Tables 5.1 to 5.3 show the ARs for Tesla, Bitcoin, and Dogecoin. They are divided in three different tables because of the different assets mentioned in the tweets. The ARs reflect whether the asset outperformed the markets expectation (positive AR) or underperformed (negative AR). The level of significance is shown by the p-value for each AR. When the p-value of the AR is statistically significant it means that the observed AR is not likely the result of random chance.

Table 5.1 *Event study results for the abnormal returns of Tesla*

Tweet	Day(s)	TSLA	
		AR	p-value
1	-2	1,41289%	0,69018
	-1	-0,66126%	0,85185
	0	-0,94386%	0,78986
	1	-3,74768%	0,29435
	2	1,25681%	0,72283
2	-2	3,72662%	0,40376
	-1	-2,62836%	0,55585
	0	-11,14728%	0,01288**
	1	7,91829%	0,07660*
	2	0,64444%	0,88514
3	-2	6,43316%	0,14238
	-1	3,30662%	0,45035
	0	7,33671%	0,09446*
	1	12,33042%	0,00509***
	2	1,00928%	0,81772
4	-2	2,83151%	0,50224
	-1	1,36504%	0,74631
	0	11,54817%	0,00634***
	1	-1,00305%	0,81210
	2	1,5162%	0,71935
5	-2	0,90252%	0,83102
	-1	-1,04889%	0,80413
	0	-5,37216%	0,20426
	1	-13,18336%	0,00189***
	2	3,84024%	0,36401

*Note. The tweets are numbered and are all regarding Tesla specifically. The event study consists of two days prior the tweet, -2, to two days after the tweet, 2. The abnormal returns are calculated for each day and have a matching p-value. Here the significance stars represent a significance level of 1%, 5% and 10%. Where *$p<0,1$, ** $p<0,05$ and *** $p<0,01$.*

Table 5.1 shows that the first tweet has none statistically significant ARs. However, the day after the tweet, has a noticeable negative AR of -3,7% but is not statistically significant at the 5% level.

The second tweet impacted the stock performance of Tesla significantly. Both days prior the tweet of Musk were both not statistically significant. But there was a negative statistically significant AR reported on the day of the tweet. This negative AR of -11,1% can be attributed to the negative tone of the tweet stating that Musk regarded the stock price of Tesla being too high. The first day after the tweet had a positive AR at the 10% significance level.

The third tweet showed positive statistically significant ARs both on the day of the tweet and the day after. The day after the tweet showed a higher significant effect, at the 1% significance level, while the day of the tweet, at a 10% level.

When the fourth tweet was posted, the market reacted positively and significantly. The tweet resulted in an AR of 11,5% which is significant at the 1% level. The day after the tweet, however, had a negative AR of -1% but is not statistically significant.

The last tweet regarding Tesla had a statistically significant effect the day after the tweet. Reporting an AR of -13,2% which is significant at the 1% level. The second day after the tweet caused a rebound of the stock with a notable positive AR of 3,8% but was not statistically significant.

Overall, the tweets of Musk about Tesla have had statistically significant results on the stock price of Tesla.

Table 5.2 *Event study results for the abnormal returns of Bitcoin and Tesla*

Tweet	Days	BTC		TSLA	
		AR	p-value	AR	p-value
6	-2	6,34477%	0,16694	4,71184%	0,30449
	-1	0,98942%	0,82919	5,31908%	0,24645
	0	-2,06915%	0,65190	-7,18676%	0,11756
	1	4,37688%	0,34012	-1,94703%	0,67120
	2	-2,72865%	0,55193	0,40565%	0,92952
7	-2	5,27296%	0,24301	-0,23588%	0,95832
	-1	-1,43475%	0,75059	-1,83653%	0,68411
	0	7,57473%	0,09374*	-1,25315%	0,78130
	1	-3,73887%	0,40762	-9,41558%	0,03736**
	2	-10,58044%	0,01938**	-2,69409%	0,55065
8	-2	-7,49092%	0,10242	1,86096%	0,68460
	-1	0,05562%	0,99031	-1,60019%	0,72688
	0	-4,47081%	0,32931	-5,35903%	0,24237
	1	-2,42179%	0,59710	1,16977%	0,79846
	2	6,50027%	0,15629	-3,86721%	0,39873

(Continues on next page)

Table 5.2 *(continued)*

Tweet	Day	BTC		TSLA	
		AR	p-value	AR	p-value
9	-2	1,0541%	0,81541	-2,2915%	0,61184
	-1	-14,25753%	0,00166***	-4,91703%	0,27640
	0	0,19594%	0,96539	-3,52525%	0,43507
	1	-0,17911%	0,96836	2,71716%	0,54738
	2	-13,96115%	0,00207***	-2,60474%	0,56407
10	-2	0,19417%	0,96567	-3,52139%	0,43523
	-1	-0,18088%	0,96802	2,72102%	0,54652
	0	-13,96292%	0,00204***	-2,60088%	0,56437
	1	-1,94262%	0,66682	-0,20734%	0,96335
	2	-15,99989%	0,00041***	-2,91273%	0,51863

*Note. The tweets are numbered and are all regarding Bitcoin specifically. The event study consists of two days prior the tweet, -2, to two days after the tweet, 2. The abnormal returns are calculated for each day and have a matching p-value. Here the significance stars represent a significance level of 1%, 5% and 10%. Where *$p<0,1$, ** $p<0,05$ and *** $p<0,01$.*

Table 5.2 shows the ARs of Bitcoin and Tesla when Musk tweets about Bitcoin specifically. Tweet number six did generate noticeable ARs for Bitcoin and Tesla. The Tesla stock dropped -7,2% on the day of the tweet and the Bitcoin price increased by 3,4% the day after. All the ARs however were not statistically significant at the 5% level.

Tweet number seven, on the day of the tweet and two days after the tweet Bitcoin had an AR of 7,6% and -11,6% which were both statistically significant. Both on the 10% level and the second day after the tweet at a significance level of 5%, resulting in spillover effects.

The eighth tweet showed no statistically significant effect on the ARs of Bitcoin and Tesla. On the day of the tweet Bitcoin dropped -4,5% and Tesla dropped -5,4%.

In tweet 9, the day before the tweet and the second day after the tweet show negative statistically significant impacts on Bitcoin's ARs. The price dropped around -14,3% the day prior to the tweet and -14% the second day after the tweet. These ARs were highly significant at the 1% level. However, none of the ARs for any day were statistically significant at the 5% level for Tesla.

The last tweet about bitcoin showed that on the day of the tweet and the second day after the tweet had statistically significant impacts on Bitcoin's ARs. The ARs for these days were highly significant at the 1% level. None of the ARs for Tesla were statistically significant at the 5% level.

Table 5.3 *Event study results for the abnormal returns of Dogecoin and Tesla*

Tweet	Days	DOGE		TSLA	
		AR	p-value	AR	p-value
11	-2	1,76782%	0,58110	0,6256%	0,84501
	-1	16,23965%	0,00002***	3,45753%	0,27859
	0	13,31269%	0,00025***	-0,96618%	0,76188
	1	11,92367%	0,00080***	2,23462%	0,48354
	2	15,23460%	0,00005***	-8,41218%	0,00867***
12	-2	-10,85318%	0,01718**	3,35466%	0,46031
	-1	17,15705%	0,00018***	-2,59287%	0,56818
	0	34,38974%	0,00000***	-1,04869%	0,81742
	1	-12,88532%	0,00471***	-0,23407%	0,95890
	2	51,61660%	0,00000***	0,80722%	0,85895
13	-2	23,14764%	0,00000***	-6,43701%	0,15571
	-1	-8,62300%	0,05739*	17,51845%	0,00012***
	0	-4,20737%	0,35320	-1,23714%	0,78479
	1	-0,56997%	0,89988	4,19882%	0,35418
	2	-1,69462%	0,70836	-1,25685%	0,78144
14	-2	27,61044%	0,00000***	7,82196%	0,08570*
	-1	25,19487%	0,00000***	-4,45137%	0,32765
	0	40,36828%	0,00000***	0,47584%	0,91663
	1	68,71491%	0,00000***	-0,29840%	0,94766
	2	10,22785%	0,02476**	-3,88298%	0,39313
15	-2	-13,17323%	0,00369***	-1,51469%	0,73758
	-1	16,01034%	0,00043***	0,91634%	0,83937
	0	-43,22688%	0,00000***	-7,06703%	0,11836
	1	8,24755%	0,06847*	-2,30580%	0,61004
	2	-24,62953%	0,00000***	-4,93133%	0,27557

*Note. The tweets are numbered and are all regarding Dogecoin specifically. The event study consists of two days prior the tweet, -2, to two days after the tweet, 2. The abnormal returns are calculated for each day and have a matching p-value. Here the significance stars represent a significance level of 1%, 5% and 10%. Where *$p<0,1$, ** $p<0,05$ and *** $p<0,01$.*

The next five tweets in table 5.3 are explicitly about Dogecoin. Tweet eleven had a statistically significant effect on Dogecoin's ARs on all days within the event window except for the second day before the tweet. The ARs were highly significant at the 1% level. Not one of the ARs of Tesla were statistically significant, indicating that there weren't any spillover effects.

In tweet twelve, all the days had statistically significant impact on Dogecoin's ARs. The ARs for these days were significant at the 5% level and after the second day prior to the tweet all at a 1% level. Additionally, the day of the tweet had highly significant ARs at the 1% level, indicating significant market responses to the tweet. However, none of the ARs for any day were statistically significant at the 10% level for Tesla, meaning that there weren't any spillover effects.

The thirteenth tweet only shows that on the two days prior the tweet had statistically significant impact on Dogecoin's ARs with an increase of 23,1% and the day before the tweet a decline of 8,6%. This had a high level of significance at the 1% and 5% level. Tesla had a significant increase of 17,5% in their ARs the day before the tweet. This increase is significant at the 1% level, and thus showed that there were spillover effects in this tweet about Dogecoin.

All the ARs of Dogecoin are statistically significant in the fourteenth tweet. All on the 5% level and except the second day after the tweet also on the 1% level. Only the second day prior to the tweet was significant on a 10% for Tesla and thus indicates that there were spillover effects in this tweet about Dogecoin.

Similarly, to tweet fourteen are all Dogecoin's ARs are statistically significant at a 1% level apart from the day after the tweet which is significant at 10% level in tweet fifteen. None of the ARs were statistically significant for Tesla, so no spillover effects in this tweet from Musk.

Tables 5.4 to 5.6 show the CARs for Tesla, Bitcoin, and Dogecoin. They are divided in three different tables because of the different asset mentioned in the tweets. The CARs reflect the market's total reaction during the event window. The level of significance is shown by the p-value for each CAR. When the p-value of the CAR is statistically significant it means that the CAR observed is not likely the result of random chance.

Table 5.4 *Event study results for the cumulative abnormal returns of Tesla*

Tweet	Window	TSLA	
		CAR	p-value
1	[-2, -1]	0,75163%	0,91545
	[-2, 0]	-0,19223%	0,98556
	[-2, 1]	-3,93991%	0,78095
	[-2, 2]	-2,68310%	0,87952
2	[-2, -1]	1,09826%	0,90281
	[-2, 0]	-10,04902%	0,45845
	[-2, 1]	-2,13073%	0,90571
	[-2, 2]	-1,48629%	0,94729
3	[-2, -1]	9,73978%	0,27491
	[-2, 0]	17,07649%	0,20358
	[-2, 1]	29,40691%	0,10370
	[-2, 2]	30,41619%	0,17507

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Table 5.4 *(continued)*

Tweet	Window	TSLA	
		CAR	*p*-value
4	[-2, -1]	4,19655%	0,62260
	[-2, 0]	15,74472%	0,22335
	[-2, 1]	14,74167%	0,38942
	[-2, 2]	16,25787%	0,44699
5	[-2, -1]	-0,14637%	0,98631
	[-2, 0]	-5,51853%	0,66671
	[-2, 1]	-18,70189%	0,27786
	[-2, 2]	-14,86165%	0,48763

*Note. The tweets are numbered and are all regarding Tesla specifically. The event window starts at two days prior the tweet, -2, and includes a new day to create a cumulative effect until two days after the tweet, 2. The cumulative abnormal returns are calculated for each newly included day and have a matching p-value based on the outcome of the t-test. Here the significance stars represent a significance level of 1%, 5% and 10%. Where *p<0,1, ** p<0,05 and *** p<0,01.*

Table 5.4 depicts that the none of the tweets show any CARs that were statistically significant at the 10% level. Tweets three, four and five however did show relatively big reactions on the price of Tesla. During the entire event window of tweet three and four the effect was 30,4% and 16,3%. The tweet effect generated a negative response during tweet five causing a drop of -14,9%.

Table 5.5 *Event study results for the cumulative abnormal returns of Bitcoin and Tesla*

Tweet	Window	BTC		TSLA	
		CAR	*p*-value	CAR	*p*-value
6	[-2, -1]	7,33419%	0,43021	10,03092%	0,28289
	[-2, 0]	5,26504%	0,70461	2,84416%	0,83759
	[-2, 1]	9,64192%	0,60298	0,89713%	0,96131
	[-2, 2]	6,91327%	0,76508	1,30278%	0,95506
7	[-2, -1]	3,83821%	0,67370	-2,07241%	0,81995
	[-2, 0]	11,41294%	0,40599	-3,32556%	0,80764
	[-2, 1]	7,67407%	0,67379	-12,74114%	0,48580
	[-2, 2]	-2,90637%	0,89837	-15,43523%	0,49924
8	[-2, -1]	-7,43530%	0,42347	0,26077%	0,97748
	[-2, 0]	-11,90611%	0,39322	-5,09826%	0,71324
	[-2, 1]	-14,32790%	0,44041	-3,92849%	0,83167
	[-2, 2]	-7,82763%	0,73490	-7,79570%	0,73594
9	[-2, -1]	-13,20343%	0,15430	-7,20853%	0,43102
	[-2, 0]	-13,00749%	0,34465	-10,73378%	0,43436
	[-2, 1]	-13,18660%	0,47099	-8,01662%	0,66030
	[-2, 2]	-27,14775%	0,23870	-10,62136%	0,64140

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Table 5.5 *(Continued)*

Tweet	Window	BTC		TSLA	
		CAR	p-value	CAR	p-value
10	[-2, -1]	0,01329%	0,99883	-0,80037%	0,92991
	[-2, 0]	-13,94963%	0,31110	-3,40125%	0,80331
	[-2, 1]	-15,89225%	0,38564	-3,60859%	0,84287
	[-2, 2]	-31,89214%	0,16797	-6,52132%	0,77451

*Note. The tweets are numbered and are all regarding Bitcoin specifically. The event window starts at two days prior the tweet, -2, and includes a new day to create a cumulative effect until two days after the tweet, 2. The cumulative abnormal returns are calculated for each newly included day and have a matching p-value based on the outcome of the t-test. Here the significance stars represent a significance level of 1%, 5% and 10%. Where *p<0,1, ** p<0,05 and *** p<0,01.*

In table 5.5 hereabove, there is no evidence of statistically significant CARs for all the tweets during their event window on the 5% significance level. There were no spillover effects in the overall market reaction in the tweets about Bitcoin on the price of Tesla. For Bitcoin however the CARs for the entire event window highlighted some big effects. Tweet seven started with a 3,8% increase in the first window, rising to 11,4% in the second window and dropping to an effect of -2,9% during the entire window. Tweets nine and ten had a cumulative drop to -27,1% and -31,9%.

There were no spillover effects in the tweets about Bitcoin to Tesla. Tweet seven caused the biggest overall response. Starting at a cumulative drop of -2,9% which ended at -15,4% during the entire event window.

Table 5.6 *Event study results for the cumulative abnormal returns of Dogecoin and Tesla*

Tweet	Window	DOGE		TSLA	
		CAR	p-value	CAR	p-value
11	[-2, -1]	18,00747%	0,00844***	4,08313%	0,52667
	[-2, 0]	31,32016%	0,00272***	3,11695%	0,74667
	[-2, 1]	43,24383%	0,00201***	5,35157%	0,67762
	[-2, 2]	58,47843%	0,00097***	-3,06061%	0,84897
12	[-2, -1]	6,30387%	0,49306	0,76179%	0,93372
	[-2, 0]	40,69361%	0,00567***	-0,28690%	0,98334
	[-2, 1]	27,80829%	0,13655	-0,52097%	0,97731
	[-2, 2]	79,42489%	0,00153***	0,28625%	0,99003
13	[-2, -1]	14,52464%	0,11958	11,08144%	0,23093
	[-2, 0]	10,31727%	0,45367	9,84430%	0,47444
	[-2, 1]	9,74730%	0,59457	14,04312%	0,44441
	[-2, 2]	8,05268%	0,72465	12,78627%	0,57657

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Table 5.6 *(continued)*

Tweet	Window	DOGE		TSLA	
		CAR	p-value	CAR	p-value
14	[-2, -1]	52,80531%	0,00000***	3,37059%	0,71340
	[-2, 0]	93,17359%	0,00000***	3,84643%	0,77981
	[-2, 1]	161,88850%	0,00000***	3,54803%	0,84658
	[-2, 2]	172,11635%	0,00000***	-0,33495%	0,98834
15	[-2, -1]	2,83711%	0,75581	-0,59835%	0,94766
	[-2, 0]	-40,38977%	0,00579***	-7,66538%	0,57610
	[-2, 1]	-32,14222%	0,08583*	-9,97118%	0,58539
	[-2, 2]	-56,77175%	0,01779**	-14,90251%	0,51471

*Note. The tweets are numbered and are all regarding Dogecoin specifically. The event window starts at two days prior the tweet, -2, and includes a new day to create a cumulative effect until two days after the tweet, 2. The cumulative abnormal returns are calculated for each newly included day and have a matching p-value based on the outcome of the t-test. Here the significance stars represent a significance level of 1%, 5% and 10%. Where *p<0,1, ** p<0,05 and *** p<0,01.*

In table 5.6 the eleventh tweet showed statistically significant effects on its cumulative abnormal returns during the entire event window. All the CARs were highly significant at the 1% significance level, representing significant overall market responses to the tweet. For Tesla however none of the CARs were statistically significant at the 5% level.

In response to the twelfth tweet Dogecoins CARs were statistically significant at the 1% level in the window of [-2, 0] and the entire window. Their cumulative effects amounted to 79,4%. There was no statistically significant spillover effect in this tweet about Dogecoin to Tesla.

Tweet thirteen showed no statistically significant CARs for both Dogecoin and Tesla. It did cause the biggest positive overall market reaction on the Tesla CAR with an effect of 12,8%. Causing the log return on the Tesla increase, and thus the stock price.

Tweet fourteen depicts highly statistically significant CARs for Dogecoin at the 1% level. The total cumulative effect was 172,1%. This enormous increase caused no statistically significant CARs and thus spillover effects for Tesla on the 5% level.

The final tweet about Dogecoin caused statistically significant CARs for Dogecoin. The second event window, [-2, 0], resulted in a CAR of -40,4% which is significant at the 1% level. The third window, [-2, 1], let the CAR increase to -32,1% which is significant at the 10% level. The final and entire event window let the CAR decrease again to -56,8% which is statistically significant at the 5% level. Once again there was no statistically significant CAR for Tesla and thus no spillover effect. Tweet fifteen however resulted in the biggest cumulative effect on the tesla stock with a response of -14,9%.

To sum up all the results table 5.7 shows all the tweets combined with an answer to whether they are statistically significant. If only one of the days or event window observations has a significant effect the answer is yes. Same goes for whether there are spillover effects.

Table 5.7 *Final overview of all the tweets, their significance and spillover effects*

No.	Significant effect on AR	Spillover effect on AR	Significant effect on CAR	Spillover effect on CAR
1	No	-	No	-
2	Yes	-	No	-
3	Yes	-	No	-
4	Yes	-	No	-
5	Yes	-	No	-
6	No	No	No	No
7	Yes	Yes	No	No
8	No	No	No	No
9	Yes	No	No	No
10	Yes	No	No	No
11	Yes	Yes	Yes	No
12	Yes	No	Yes	No
13	Yes	Yes	No	No
14	Yes	Yes	Yes	No
15	Yes	No	Yes	No

The results of this paper are in line with the research of Shahzad, Anas and Bouri (2022) where they show that the tweets of Musk about Bitcoin contributed to the price explosivity of Bitcoin and Dogecoin related tweets contributed to Dogecoin price explosivity. Their conclusion states that there is a clear role of (influential) individuals in the creation of price bubbles. As shown in table 5.7 only two out of ten Bitcoin or Dogecoin related tweet did not generate significant returns.

Ante (2021) results are also in line with the results of this paper. Ante (2021) said that Musk's tweets do influence the cryptocurrency market. His research showed that Dogecoin yielded more abnormal returns than Bitcoin due to the tone of the tweets. Dogecoin was mainly positive while Bitcoin consisted of both. The different tones in musk's tweets about bitcoin canceled out the effect.

The last research that yields similar results is the research of Ullah, Attah-Boakye, Adams and Zaefarian (2022). They show that positive celebrity endorsements and government sentiments are significantly associated with positive changes in the price of Bitcoin.

Contrary to the results of this paper are the results of Tandon, Revankar, Palivela and Parihar (2021) they found that not one single person can control the prices of cryptocurrencies. Bitcoin has known free falls of its value in the past and Musk tweeting about it had some minor influence but was not the cause. The reason why the results could differ is that they forecast the price of Bitcoin using the Augmented Dickey Fuller test while this paper uses historical data.

6 Conclusion & Discussion

This paper has the following research question: *"What are the spillover effects, and thus the impact, of Elon Musk's tweets about Tesla and cryptocurrencies, such as Bitcoin and Dogecoin, on the price level of Tesla?"*. The corresponding hypothesis is: "*Musk's tweets have significant differences between the means of the expected AR and the observed AR"* if this hypothesis is rejected the alternative is accepted which is that there are no significant differences.

An event study was performed on the abnormal returns and the cumulative abnormal returns of Tesla, Bitcoin and Dogecoin. This paper investigated the spillover effects on price level of Tesla when Musk tweets about Tesla, Bitcoin and Dogecoin.

When Musk tweets about his own company Tesla it makes sense that it has a direct effect on the price of Tesla. Table 5.1 shows that there are statistically significant abnormal returns on the day of the tweet and/or the day after. Only tweet one does not report significant abnormal returns which could be explained by comparing the content of the tweet.

Table 5.2 and 5.3 depict the abnormal returns when Musk tweets about Bitcoin and Dogecoin. Only a few days for a few tweets about Bitcoin how statistically significant abnormal returns for Bitcoin. Dogecoin on the other hand shows for almost every day for each tweet statistically significant abnormal returns. When looking at the statistical significance of the abnormal returns for Tesla in these tables, a conclusion is that there are spillover effects in the tweets of Musk. This is in tweet seven, eleven, thirteen and fourteen.

Tables 5.4 to 5.6 show that only for Dogecoin the cumulative abnormal returns are statistically significant. The difference between the statistical significance between Dogecoin and Bitcoin and Tesla is that Dogecoin is far more volatile and the other two. The results of the cumulative abnormal returns for Tesla do not indicate that there are spillover effects in the overall market response.

In short, the findings of this event study indicate that tweets have converging effects on the stock of Tesla. While some tweets had statistically significant influence on the market, both positively and negatively, others did not. This suggests that the content, context, and time had a significant impact on investor sentiment and, as a result, Tesla's stock performance. When interpreting or generalizing these event study results, caution should be exercised. Many other factors, apart from the tweets of Musk, might have affected the prices of the assets.

6.2 Limitations

This paper employs abnormal returns and cumulative abnormal returns as its primary analytical techniques to examine the effect of Musk's tweets on the values of Tesla, Bitcoin, and Dogecoin. While the analysis sheds light on the relationship between Musk's tweets and price changes in these assets, it is essential to consider several limitations.

Firstly, the focus of this paper is solely on Musk's individual tweets concerning Tesla, Bitcoin, and Dogecoin to measure spillover effects on Tesla. Other influential people or external factors that may also influence the pricing of these assets are not taken into account. As a result, the results may not solely represent the effect of the tweet.

Secondly, this paper uses a t-test to assess the statistical significance of the abnormal returns and the cumulative abnormal returns. While t-tests are commonly used in finance research due to their simplicity, they do have their limitations. Especially when dealing with complex and dynamic financial data. They suffer from several biases, such as non-normality of financial data, heteroscedasticity, and endogeneity.

Only having a total event window of 756 closing price observations, the study size is rather small. Therefor the generalizability of the conclusion of this study is difficult.

Additionally, this study ignores intraday price fluctuations and trade volumes and solely considers the closing values of Tesla, Bitcoin, and Dogecoin. More specific information might provide a more thorough understanding of the effect of Musk's tweets on the pricing of these assets.

As a final point, it is crucial to acknowledge the potential challenges in accounting for confounding factors that could impact the research outcomes. Confounding factors like market sentiment, macroeconomic conditions, or other related news events.

In conclusion, while this paper uses abnormal returns and cumulative abnormal returns to analyze the effects of Elon Musk's tweets on the prices of Tesla, Bitcoin, and Dogecoin, the previously mentioned limitations highlight the need for caution when interpreting the results and highlight the potential for further research in this area.

6.3 Further research recommendations

Based on the event study results shown in the tables 5.1 to 5.6, more research is needed in several areas to gain a better and more precise understanding of the connection between Musk’s tweets and its spillover effect on assets Tesla.

Future research can consider tweets and social media activity from other influential people, experts in the field, and financial influencers. This larger scope will provide a more thorough understanding of how influential personalities affect asset values collectively, revealing information about possible market-wide spillover effects.

To address the limitation of the t-test when dealing with complicated financial data, further research may choose non-parametric tests or advanced econometric models like panel data analysis or structural time series models as alternatives. These techniques will produce more reliable results and lessen biases that are present in traditional t-tests.

Furthermore, to account for confounding factors like market sentiment and macroeconomic conditions, further research can incorporate additional economic indicators and news sentiment analysis in their datasets. A more comprehensive approach will help recognize the relative significance of Musk's tweets compared to other factors influencing asset prices.

To improve the generalizability of this paper’s conclusion, expanding the dataset by including data from a more extended period or additional financial markets and cryptocurrencies will provide a broader analysis of spillover effects across diverse market conditions.

Finally, conducting sensitivity analyses and robustness checks will strengthen the study's credibility by assessing the influence of potential outliers or data anomalies.

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Appendix A Detailed overview tweets of Elon Musk

Tweet	Asset	Content	Date	Link
1	Tesla	*“Tesla made 0 cars in 2011, but will make around 500k in 2019”*	20/02/2019	https://twitter.com/elonmusk/status/1098013283372589056
2	Tesla	*"Tesla stock price is too high imo."*	01/05/2020	https://twitter.com/elonmusk/status/1256239815256797184
3	Tesla	*"Tesla will make fabulous short shorts in radiant red satin with gold trim."*	02/07/2020	https://twitter.com/elonmusk/status/1278760548188983296
4	Tesla	*“Strange that moved valuation, as Tesla is very much a production ramp problem, not a demand problem”*	25/10/2021	https://twitter.com/elonmusk/status/1452727731452588041
5	Tesla	*“Much is made lately of unrealized gains being a means of tax avoidance, so I propose selling 10% of my Tesla stock.”*	06/11/2021	https://twitter.com/elonmusk/status/1457064697782489088
6	Bitcoin	*“Bitcoin is my safe word”*	20/12/2020	https://twitter.com/elonmusk/status/1340573003579617280
7	Bitcoin	"*Tesla's action is not directly reflective of my opinion. Having some Bitcoin, which is simply a less dumb form of liquidity than cash, is adventurous enough for an S&P500 company.*"	19/02/2021	https://twitter.com/elonmusk/status/1362598034866118658
8	Bitcoin	"*You can now buy a Tesla with Bitcoin*"	24/03/2021	https://twitter.com/elonmusk/status/1374617643446063105
9	Bitcoin	"*Tesla & Bitcoin*"	13/05/2021	https://twitter.com/elonmusk/status/1392602041025843203
10	Bitcoin	"*To clarify speculation, Tesla has not sold any Bitcoin*"	17/05/2021	https://twitter.com/elonmusk/status/1394170030741413888
11	Dogecoin	"*Dogecoin might be my fav cryptocurrency. It's pretty cool.*"	02/04/2019	https://twitter.com/elonmusk/status/1113009339743100929
12	Dogecoin	"*Dogecoin is the people's crypto*"	04/02/2021	https://twitter.com/elonmusk/status/1357241340313141249
13	Dogecoin	"*Doge spelled backwards is Egod*"	06/03/2021	https://twitter.com/elonmusk/status/1368058884837928970

(Continues on next page)

Detailed overview tweets Elon Musk (continued)

Tweet	Asset	Content	Date	Link
14	Dogecoin	*"Doge Barking at the Moon"*	15/04/2021	https://twitter.com/elonmusk/status/1382552587099062272
15	Dogecoin	"*SpaceX launching satellite Doge-1 to the moon next year*"	10/05/2021	https://twitter.com/elonmusk/status/1391523807148527620