THE EFFECT OF SOCIAL MEDIA ACTIVITY ON THE MARKET

–CASE ELON MUSK, EVIDENCE FROM THE US

Lappeenranta–Lahti University of Technology LUT

Business Administration, Bachelor's Thesis

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Examiner: Maija Hujala

ABSTRACT

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With the rise of Twitter almost all the known celebrities and big companies can be found there. One of the most followed CEOs on the platform is the founder of PayPal, Tesla and SpaceX, Elon Musk. The aim of this study is to provide an analysis on his twitter activity and to determine whether it has had any effect on the stock or crypto market. The full data of this study consists of Elon Musk's tweets from the period 1.1.2020 - 22.3.2021. This includes roughly 3000 tweets which were filtered according to event study guidelines.

This report uses event study methodology as a research method. Using this technique, an analysis on the average abnormal returns of the selected stocks and cryptocurrencies on the event date as well as the cumulative abnormal returns after the event was able to be formed. The event here being a tweet. This study also includes a regression analysis to examine how high interaction events have affected the selected stocks and cryptocurrencies as well. A high interaction event refers to a tweet that includes the following: a high number of likes, retweets, or comments. On average the AR on the event date is negative but the CAR ten days after the event is positive. The linear regression results however do not have statistical significance apart from one part and thus the value remains little.

TIIVISTELMÄ

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LUT-kauppakorkeakoulu

Kauppatieteet

Joni Kuokka

Elon Muskin sosiaalisen median käyttäytymisen vaikutus markkinoihin

Kauppatieteiden kandidaatin työ

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Avainsanat: Elon Musk, Twitter, krypto, Tesla

Twitterin nousun myötä lähes kaikki julkisuuden henkilöt ja suuret yrityksen löytyvät palvelusta. Yksi Twitterin seuratuimmista henkilöistä on mm. PayPalin, Tesla ja SpaceX:n perustaja, Elon Musk. Tämä tutkimuksen tarkoituksena on tuottaa analyysi Muskin twitteraktiivisuudestaan ja selvittää, onko tällä ollut vaikutusta osake- ja kryptomarkkinoihin. Tämän tutkimuksen data koostuu Elon Muskin twiiteistä ajalta 1.1.2020 – 22.3.2021. Tämä data sisältää yhteensä noin 3000 twiittiä, mutta tapahtumatutkimuksen oletuksien mukaan dataa on muokattu ja suodatettu.

Tässä raportissa tutkimusmenetelmänä toimii tapaustukimus. Tällä menetelmällä pystyn analysoimaan valittujen osakkeiden ja kryptovaluuttojen keskimääräiset epänormaalit tuotot tapahtumapäivänä sekä kumulatiiviset epänormaalit tuotot tapahtumapäivän jälkeen. Tapahtumalla tarkoitetaan twiittiä. Tämä tutkimus sisältää myös regressioanalyysin, jonka tarkoituksena on selvittää, kuinka korkean huomion tapahtumat ovat vaikuttaneet valittuihin osakkeisiin ja kryptovaluuttoihin. Korkean huomion tapahtumalla tarkoitetaan twiittiä, jossa on suuri määrä seuraavia: tykkäykset, retwiitit, kommentit. Keskimääräinen epänormaali tuotto tapahtumapäivänä oli negatiivinen, kumulatiivinen epänormaali tuotto muuttui kuitenkin positiiviseksi jokaisen arvopaperin osalta. Lineaarisen regression tuloksilla ei ole tilastollista merkitsevyyttä kuin yhdessä kohtaa, joten regression arvo jää varsin pieneksi.

LIST OF ABBREVIATIONS

CAPM	Capital asset pricing model
CEO	Chief executive officer
cDPM	continuous Dirichlet Process Mixture
CMRM	Constant Mean Return Model
EMH	Efficient market hypothesis
EOD	End-of-day
FSA	Financial Supervisory Authority of Finland
M & A	Mergers & acquisitions

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1. Introduction

Elon Musk's Twitter activity has been on the minds of many people as he is a very influential person. With his vast amounts of wealth and influence on the internet and social media in general, it is no wonder that people follow him closely on social media, especially on Twitter. Elon Musk's style as a big corporate CEO is very different from others as he does not seem to care what he says on social media. According to Twitter (2021a) Musk tweets at least once a day, often a lot more. Musk is a widely followed person on Twitter and at the time of writing this thesis, he has accumulated over 60 million followers.

The tone of Musk's Twitter activity is often formal, and he keeps his answers short. Musk also tends to participate in a variety of conversations. Musk appears to have been honest with his answers and comments and, for example, often said what he thinks of Tesla's new innovations even if his opinions have had a negative effect on the stock value or have been bad in some other way (Twitter 2021b).

In February 2021 a short study on Musk's Twitter activity (Ante 2021) was conducted. Ante (2021) focused mainly on the cryptocurrency side with his research and therefore it is logical for this study to expand further into the stock market side as well. The results of Ante's study found several abnormal trading patterns regarding cryptocurrencies after Musk's tweets. Ante's study also outlines the notion that many influential people can have a significant effect on the market without even attempting to do so. For example, on the 29th of January 2021 Musk changed his Twitter bio to *#bitcoin* which caused the cryptocurrency to surge by almost 30%. Musk's support of the message provider Signal (Musk 2021) by tweeting about it caused a massive purchase rush by investors, escalating the company's value from $55M to exceeding $3BN (DeCambre 2021).

1.1 Aim and research questions

Elon Musk's Twitter behavior has been researched before. The most recent case of this is a study by Ante (2021). However, Ante's study only focused on a couple of hand-picked tweets and the reactions caused by them. This study aims to explore what kinds of different effects a single person can have on stock and crypto rates through social media and what the main consequences of that are over a longer period or en masse. The main objective is to find out how the market, on average and at which speed, reacts to the tweets of a famous global CEO. How much power can social media really yield? Twitter is a worldwide media platform and thus hundreds of millions of people are subject to Musk's influence through this platform; be it directly or indirectly. Twitter has become the go-to platform for reaching out to many people quickly. Being able to type a quick 200-character message is popular even with world leaders and famous CEOs, such as Musk.

The main research question is as follows:

How has Elon Musk's Twitter activity affected the US stock and cryptocurrency market?

To aid this research, a few additional sub-research questions have also been formulated which help in concluding the abnormal returns of the market right after a tweet (sub 12 hours) and the cumulative abnormal returns after the tweet (10 days). It will also be seen whether reactions (likes, replies & retweets) have any kind of correlation with the abnormal returns. Therefore, the sub-questions for the research are as follows:

What has been the effect of Elon Musk's tweets on the abnormal returns of the US stock and cryptocurrency market?

What has been the effect of Elon Musk's tweets on the abnormal cumulative returns of the US stock and cryptocurrency market?

Has the number of reactions on a tweet resulted in a significant difference in the abnormal return of that day?

To receive a solid result from this thesis, the focus will be on the stocks of Tesla (TSLA), Bitcoin (BTC), and Dogecoin. The main point here is to see if Musk's posts about company tickers have had any significant effect on the company stock. A linear regression analysis will also take place to determine if Musk's posts with high interaction counts have had any effect on these stock or crypto returns as well.

As Tesla is Musk's own company and he often tweets about Tesla products and advancements it is logical to analyze Tesla's stock. Musk has also expressed a great interest in cryptocurrencies thus they are also accounted for as part of the analysis.

1.2 Limitations and structure

The data period spans from the beginning of January 2020 (1.1.2020) until the Spring of 2021 (21.3.2021). This period includes many other notable events such as the Covid-19 Pandemic and its effect on the stock market as well. This period was also chosen because in recent years Musk has been more active on social media and engaged in a discussion regarding different topics.

After the introduction, this thesis first highlights the theoretical framework which ties this thesis together. The concepts of efficient market hypothesis and market manipulation are covered. Following this, the thesis will go over literature that has studied these occurrences previously. Then the different research methods are covered, and the study data is presented as well. Lastly, the results and conclusions are presented.

2. Theoretical framework

The theoretical cornerstones of this thesis are formed by the efficient market hypothesis (EMH) and market manipulation. These are important concepts when analyzing the stock market and when one is trying to understand the effect people can have on the market, thus these concepts were chosen for the theory part of this thesis.

The theoretical framework revolves around understanding how the concepts of EMH and market manipulation connect with Elon Musk through Twitter. From here, one can start to piece together whether these phenomena have any effect on the stocks and cryptocurrencies seen in figure 1.

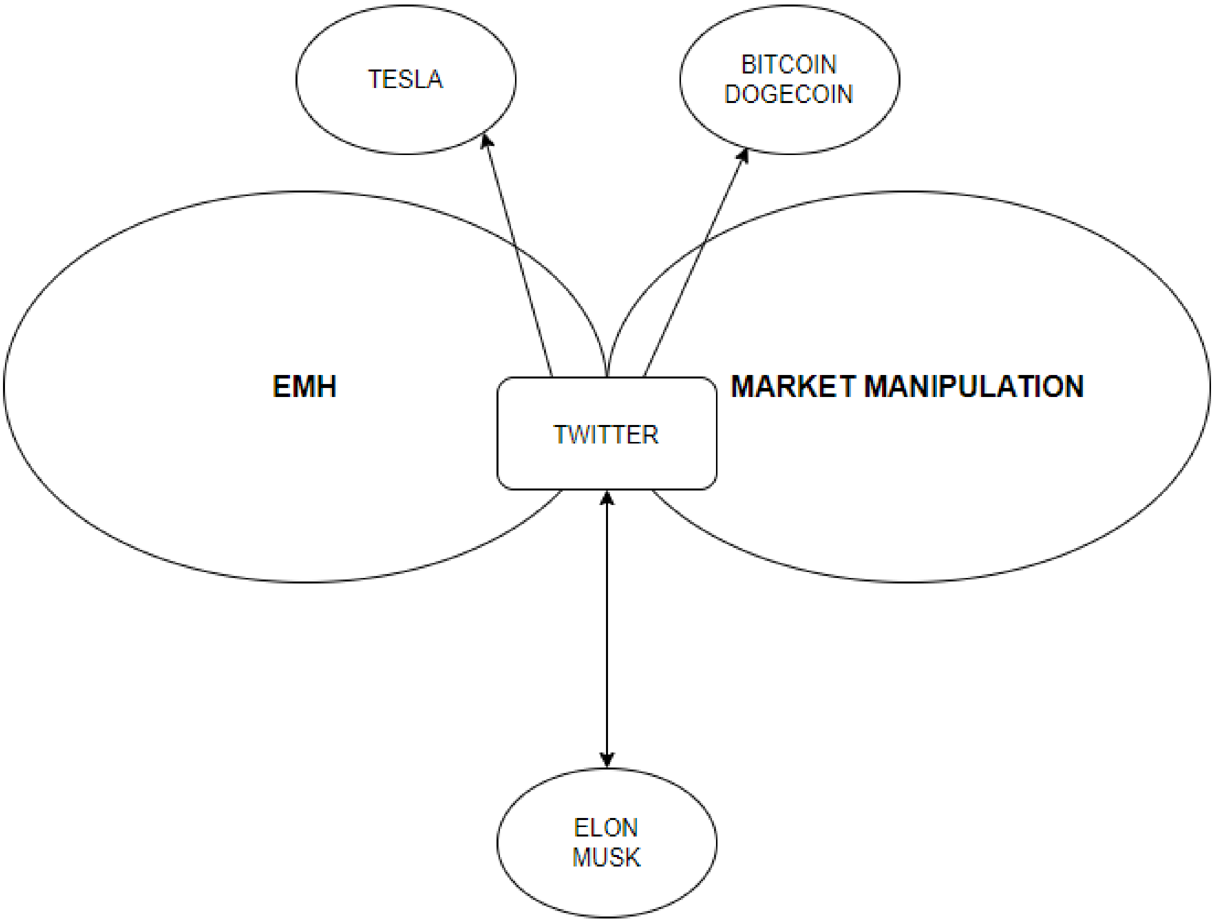

Figure 1. The theoretical framework

2.1 Efficient market hypothesis

Part of the theoretical framework for this study is the efficient market hypothesis EMH. Efficient markets have been a widely researched concept of financial markets and economics. An economist called Eugene Fama can be called the founder of this theory and after his findings, multiple other economists and researchers have further expanded on his studies. There are three levels of efficiency in the markets which are the following: strong, semi-strong, and weak (Tung & Mardsen 1998). The strong form assumes that all the information, both public and private is fully reflected in the stock price. This means that an investor cannot achieve oversized profits in any way because the stock is already priced efficiently. The semi-strong form assumed that all the public information is reflected in the stock price, but the private info is left out and thus investors can achieve oversized profits with insider trading. The weak form assumes that the stock price reflects all the historical data available. This leads to the investor being unable to achieve oversized profits based on the past (Tung & Mardsen 1998). The weak form is based on the mathematical phenomenon called *random walk* which depicts a variable the value of which cannot be determined beforehand. Based on this, efficient markets should follow this random walk phenomenon (Mishkin 2015, Knüpfer & Puttonen 2014, 167). Figure 2 presents the different levels of market efficiency in relation to the available information.

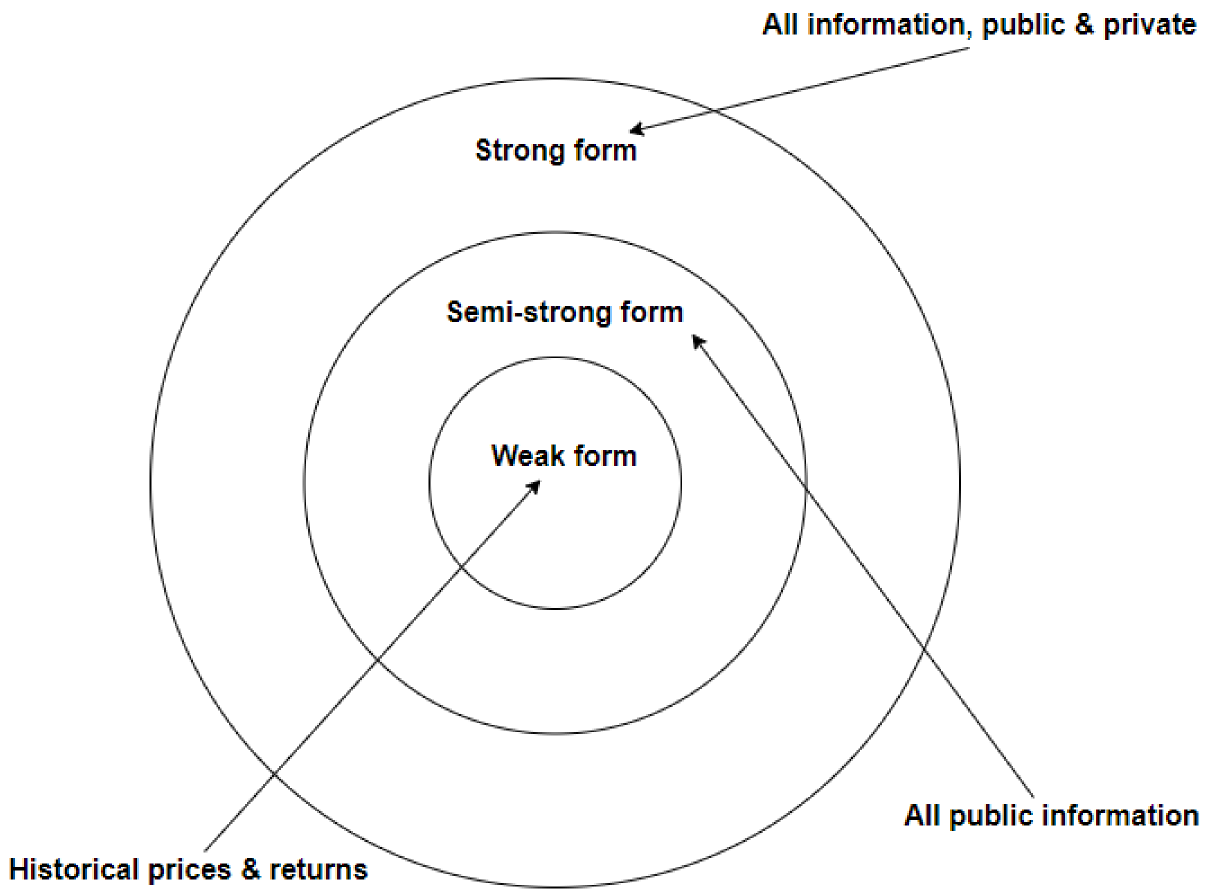

Figure 2. The Efficient Market Hypothesis different forms of information. Adaptation of Tung & Mardsen (1998)

Efficient markets are a widely used term in the financial analysis of the stock market. Efficiency in the markets, in short, means that all the available information has been included in the price of a security. (Fama 1970; Knüpfer & Puttonen 2014, 166). Informational market efficiency is the normal concept of market efficiency which most people consider when market efficiency is brought up.

Another form of efficiency in the markets is called operational efficiency which highlights the efficient use of resources, i.e., capital in the markets (Dimson 1998).

The core concept of the efficient market hypothesis is that every actor in the markets is acting rationally. Every investor or any other stakeholder always acts rationally and bases their actions on the full information available. The EMH is the financial market equivalent of the neoclassic ration choice theory. These bilateral theories have the same conclusion; the expectations of every financial stakeholder and predictions regarding the future are both guided by all the information available. (Mishkin 2015). However, efficient markets do not require every investor to act rationally all the time if the common consensus among the investors is rational behavior or acting. This means that stock prices are formed from the combined effort of every investor (Mishkin 2015; Knüpfer & Puttonen 2014, 171). Figure 3 displays the market reaction to positive company news in three different ways which are most common.

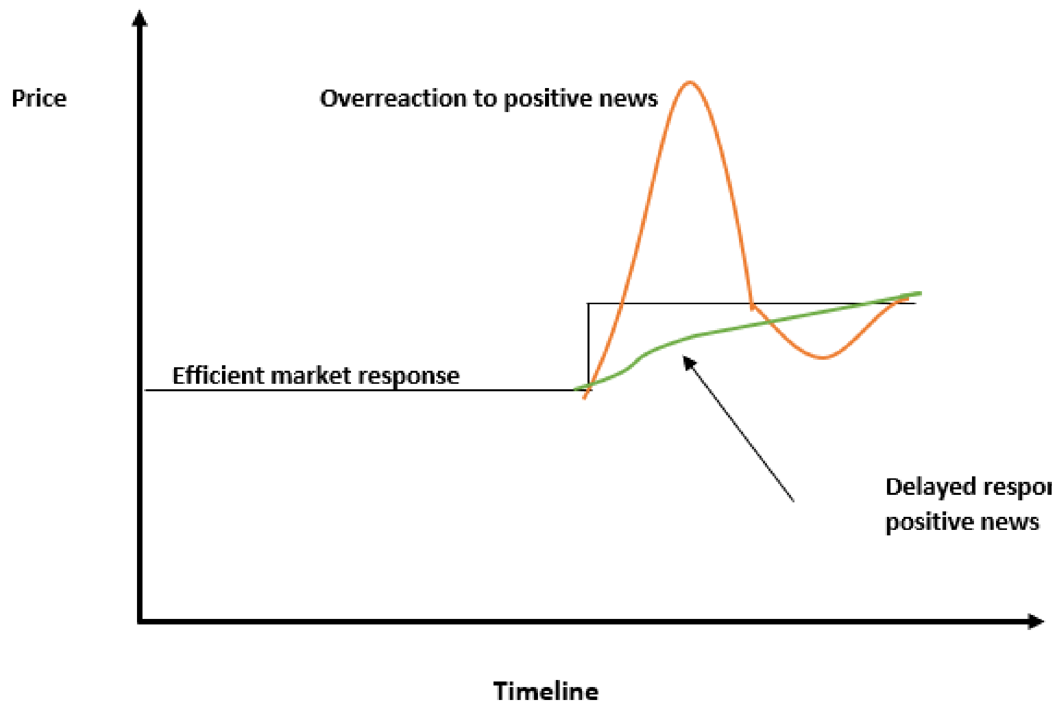

Figure 3. The Efficient Market Hypothesis different reactions. Adaptation of Smirnov (2021)

As this thesis focuses on the stock & crypto market the efficient market hypothesis is considered from this point of view. As stated previously the ideal market reflects all the information available and this information is immediately passed on to the investor. Therefore, the investor can make rational decisions based on the information. Available information means all the public information which is relevant when valuing a company. (Fama 1970; Mishkin 2015). According to Jensen (1978), the market is efficient at the knowledge level of ϑ_t when making a profit by selling overvalued or buying undervalued securities is impossible based on the same knowledge ϑ_t. Analyzing figure 3 one can see how the available information is instantly reflected in the efficient market response to "good news" these can be, for example, a better-than-expected Q2 result. The other reactions are depictions of inefficient markets.

The efficiency in the securities markets leads to fast adaptation in the market and thus no investor can take advantage of arbitrage on a regular basis. Arbitrage is the concept where an investor can make oversized profits by exploiting information that is not available to the entire market. When the information becomes available the arbitrage opportunity disappears (Kondor 2009; Mishkin 2015). Arbitrage in the market is considered an anomaly as they do not occur often and when they do, they vanish quickly (Dimson 1998). Knüpfer et al. (2014) have noted that an investment's market gap can vary both ways (negative & positive) due to anomalies, but these are completely random. Walczak (2001) theorized that due to the *random walk* phenomenon that is known on the stock market predicting stock price changes is impossible. This is because stock prices only change because of news and events that are relevant to the stock. Despite this *random walk* Schumaker and Chen (2009) managed to predict the direction of stock price movements with an accuracy of 56%.

The stock market will only react to information if it is both new and sudden. If a piece of news is new but it is already expected the information has therefore been available in the markets and the impact of the information is already included in the stock market prices (Knüpfer & Puttonen 2014, 167). The efficient market theory shows that the expected return of a security E_r is as large as the optimal forecast return, provided the forecast has been made using all the information available (Mishkin 2016). This leads to the assumption that stock prices shall not change if new information does not emerge.

2.2 Market manipulation

Market manipulation in short means misconduct in the financial market. There are many ways to manipulate the market and the two most common forms of market manipulation are insider trading and end-of-day manipulation (Aitken, Cumming & Zhan 2015). The motives for market manipulation can vary greatly. Manipulation can happen on the acquirer firm's side or on the target firm's side. The most common conspirator for intentional stock market manipulation is a well-informed trader. There are two main ways of stock manipulation. *Information-based manipulation*, where the trader affects the stock directly and does not disclose any information regarding it or *action-based manipulation* where the trader's actions cause changes in the stock price (Chakraborty & Yilmaz 2004). People only commit stock fraud if the benefits outweigh the cost. The cost here being incarceration and fines (Becker 1968).

2.2.1 End-of-day

The first form of manipulation to be covered is known as end-of-day (EOD) manipulation which in short means that trade is ramped up at the end of the day and therefore altering the stock price. It is not well known that this form of manipulation has massive incentives to do so. These EOD products are used to define different derivative values and directors' options so some people could benefit greatly from trading at high volumes at the end of the day (Aitken et al. 2015). EOD stock price movement is considered dislocated if it has been four or more standard deviations away from the mean price change during the previous hundred-day period and then in the subsequent morning when the market opens the stock price returns to mean price or close to it (Cumming, et al. 2020). EOD manipulation can also occur if two entities enter simultaneous buy or sell orders having arranged the scheme beforehand. These pre-arranged trades avoid the normal stock order queue and thus can cause fluctuation in the price of an asset. These forms of trading often gear towards EOD to manipulate the closing price of an asset (Aitken et al. 2015).

EOD manipulation has been researched conclusively in the M&A (mergers and acquisitions) sector. The manipulation of EOD stock price can happen for both the target and the acquiring firm. The acquiring firm may try to manipulate its own stock to save on acquisition costs while the target firm may manipulate its stock to boost valuation before the acquisition to gain a higher price (Cumming, et al. 2020). The effect of these kinds of manipulations has significant consequences due to the widespread use of closing prices (Comerton-Forde, Putninš 2011). EODs are often used to settle a specific deal in M&A and thus they are very closely monitored. This is, however not, what this thesis focuses on as there have not been any acquisitions by Tesla, -or any which have targeted Tesla or any other of Musk’s companies for that matter.

Another point people should consider is how EOD manipulation can make a stock less attractive. Firstly, EOD stock manipulation has a negative effect on the long-term value of a firm’s equity and lowers its liquidity. Secondly, EOD stock price manipulation makes firms’ share prices less informative. As known information is vital in the stock market (Marquardt & Zur 2014).

2.2.2 Insider trading

Insider trading refers to security trading by the stakeholders of a company also known as insiders. There are strict criteria to determine who is part of insiders within a business. This is because abusing insider information is illegal as this would give an unfair advantage to insiders. Insider trading means that part of the available information in the market is only available to a select few individuals who abuse it to create an arbitrage. This often damages a firm’s value in the long term and research has shown that restricting insider trading has a positive impact on innovation (Levine, Lin, & Wei 2017). Insider trading ties in with semi-strong market efficiency (seen in figure 1). If a market is in this situation, exploits with insider trading could happen. The motive for insider trading is simple, easy, and fast profits from securities. It is more common for corporate executives to receive stock options as a form of compensation, which they can cash out and pay capital gains taxes on, rather than taking the hit of higher income taxes (Packer 2014).

Insider trading cannot be understood without knowing what inside information is. Inside information is defined as being confidential information that is relevant and precise and that has not been made available to the market or public, but if released could substantially affect the value of the financial instrument related to the information (Häyrynen & Parkkonen 2006). This means that a corporate executive cannot use his/her upcoming knowledge of his/her company to buy the company stock before disclosing the important upcoming information.

Information is considered relevant when a rational investor would base their decision to invest on the specific piece of information and precise when it refers to circumstances that have already occurred, or which may reasonably be expected to come into existence or to occur (FSA 2021a). Examples of inside information include, for example, profit warnings, mergers, buyouts, and information regarding the financial statement.

Though it is well known that new information causes fluctuations in stock rates it is less known how new information moves amidst investors. One theory on this has been proposed by Shiller and Pound (1989) claiming that information spreads along the lines of diseases. However, Cujean (2015) has observed that the information transmission can also be direct between investors. In any case, the most important fact with information among investors is the information quality. Information quality can vary greatly. Information analysis by a stock analyst or by a normal day-trader can spread the same even if the quality of the information can be vastly different. Different types of information often have different consequences regarding financial outcomes and their implications (Ahern 2017).

2.2.3 Social media

With the increased use of the Internet and new relevant digital innovations, new ways to share information and to interact with people around the globe have risen. Information is most often shared on the Internet via social networks such as Twitter or forums such as Yahoo!. News sites such as The Wall Street Journal are very popular as well and most news sites have their own forums too. This enables every person to have access to information from investor to institution. The ability to predict stock prices is an essential issue with different valuation and business models. Creating a model to predict stock prices with good accuracy is one of the hardest tasks in finance (Piñeiro-Chousa et al. 2017; Derakhshan et al. 2019).

The main goal of this thesis is to analyze market manipulation through social media. The two aforementioned ways of market manipulation might be the most known ones, but social media's effect should not be underestimated. The Financial Supervisory Authority of Finland (FSA) (2021b) recommends being on guard regarding investment tips on the internet.

"Information about investment objects sold with baseless promises is spread via internet discussion boards and newsletters, for example. -- It is difficult to investigate the real background of an investment tip. What appears to be an unbiased analysis may be partial and based entirely on fabricated data."

Based on this one can often assume that most investment tips online should be avoided. Legislation regarding investment advice is very strict and only professionals are allowed to advise people but, on the internet, it is a different world. One can pretend to be anyone there. Due to the large number of messages on Twitter, it is a perfect breeding ground for fake news or attempts of manipulation.

Today social media is everywhere and a part of our daily lives. This requires people to understand how social media can affect the markets and most importantly, how it can affect investor behavior resulting in consequences that will undoubtedly reach the markets at all levels (Bissattini & Chrisodoulou 2013).

Sprenger, Tumasjan, Sandner, and Welpe (2014) found in their research that there is a correlation between message volume on Twitter regarding a specific stock and that stock's trading volume. Their study also found that there is no correlation between stock returns and message volume. Another study by Antweiler and Frank (2004) establishes that bullishness indices relate foreseeably to trading volume if the indices can be justified by computational linguistics. Another observation of theirs is that the relation is more present when viewed from trading volume to bullishness than from bullishness to trading volume. Combining these studies, a deduction can be made that there is a significant relationship between bullishness and returns (Piñeiro-Chousa et al. 2017). Zhang, Fuehres, & Gloor (2012) found that microblogging messages can behave as the collective economic opinion if all the retweets containing a specific work are counted. These words may be words like "*dollar*", "*job*", or "*business*". If tweets seem bullish or have a specific wording, they seem to be more likely to cause a reaction in the market.

Investors value their profile greatly. This means that information about the experience of different investors and their preferences about investing are more relevant if they have many followers on social media platforms. Social media networks influence investors in different ways, but this influence always leads to a variation of market risk (Piñeiro-Chousa et al. 2017).

Various studies in finance and psychology have shown that stock markets can be driven by the investors' mood states. This relationship has been observed in laboratory conditions as well and with many external factors such as weather, pollution, and sports results. All these factors influence the mood of people and therefore the stock market also (Kamstra et al. 2000). A study conducted by Bollen et al. (2010) has already demonstrated that tweet mood can predict stock market developments. The mood spreads rapidly on social media platforms as emotions are transmitted in text-based communication (Kramer et al 2014). The stock market nowadays is based quite heavily on feelings, be they negative or positive, the feelings are an essential indicator of the future value of that stock. Opinions about most companies are available online en masse and social media has dedicated groups for discussion about companies or the companies' futures. Sentiment information for stocks in addition to historical prices of them could help to predict the future price of stocks better (Derakhshan et al. 2019).

3. Literature review

Elon Musk has been one of the most successful people on the planet and his character has attracted quite a lot of research regardless of background. Musk's behavior is norm-breaking for a billionaire multi-CEO, and which sparked many discussions over whether he should change his behavior. In a Twitter conversation with BBC's James Clayton (2021a) Musk even stated that he would not like to continue as the CEO of Tesla but as of now, he is forced to due to investors. Musk's desire seems to lie in the design of products, and this "*being a leader with the spotlight"* thing does not seem to fit him. This chapter goes over social media's effect on the market and dives deeper into Ante's (2021) analysis of Musk's Twitter activity on the crypto market as well as having a touch on different analyses conducted on social media's effect on the market by various researchers.

The amount of literature about analyzing the stock market from the point of social media is relatively narrow. Although there has been some research made in this field. For example, to predict stock market prices using Twitter messages, authors of Si et al. (2013) applied a non-parametric topic model. This model was a continuous Dirichlet Process Mixture(cDPM) to learn daily topics which followed by a creation time series. Using a non-parametric model based on everyday topics automates this process which is its main advantage. The dataset used was small as it consisted of only three months.

According to Oh and Sheng (2011) stock microblog activity has predictive power for market returns; Ranco, Aleksovski, Caldarelli, Grčar, and Mozetič (2015) show that Twitter sentiment has a relation to the abnormal cumulative returns; and Rao and Srivastava (2012) elaborate how hedging trade signals from tweets can predict abnormal returns with high accuracy of 91%. These studies show that Twitter can have some sort of an effect on the market when viewed from the right angle. Another study was conducted into microblogging by Ruiz et al. (2012) who simulated investments and considered microblogging events such as the number of tweets and the number of different users who posted a tweet.

Musk has been stating for a while now that Bitcoin is on the verge of gaining widespread acceptance and that he is a supporter of Bitcoin. Musk has also stated that his tweets about Dogecoin are only jokes (BBC 2021b). In the study by Ante (2021) six different events by Musk were analyzed which all included either Dogecoin or Bitcoin in some way or another. These six events are listed in figure 4.

Event index	Date	Crypto in question	Content / activity on Twitter
1	29.1.2021	Bitcoin	1. Changed Twitter bio to *#bitcoin* 2. Tweeted: likely referring to the decision behind changing his Twitter bio
2	28.1.2021	Dogecoin	1. Posted a picture about Dogecoin, specifically the cover of magazine named *Dogue*
3	25.12.2020	Dogecoin	1. Tweeted: *Merry Christmas & happy holidays* and posted a picture which includes, among other things, the Dogecoin symbol
4	20.12.2020	Dogecoin	1. Tweeted: *One word: Doge* 2. Changed Twitter Bio to: *Former CEO of Dogecoin*
5	20.12.2020	Bitcoin	1. Tweeted: *Bitcoin is my safe word* 2. Posted a picture about Bitcoin, specifically how Bitcoin keeps a person from living a productive life 3. Tweeted: *Bitcoin is almost as bs as fiat money*
6	18.7.2020	Dogecoin	1. Tweeted: *Excuse me, I only sell Doge!* 2. Posted a picture about Dogecoin, specifically a could named *dogecoin standard* which is overrunning the global financial system

Figure 4: Events used by Ante (2021) in his study on Musk's Twitter activity.

In a previous study of theirs, Ante and Fiedler (2020) found that for cryptocurrency profit analysis the normal CAPM (Capital Asset Pricing Model) is not best and that the CMRM (Constant Mean Return Model) would fit better as this model calculates the profit over a period (Brown & Warner 1985).

Ante (2021) observed cumulative abnormal returns in 4 out 6 of these tweets which were picked for his study. This might seem high, but one must remember that these six tweets were hand-picked from a pool of thousands of tweets and for a more conclusive result one would need to have more data. These events however illustrate the significant impact Elon Musk's Twitter activity can have on cryptocurrency markets. Musk changing his Twitter bio to display the Bitcoin text might have been a deliberate action to make a statement. The case about Dogecoin was a joke as Musk admitted to that later himself (Krishnan et al., 2021). If one person can cause such big shifts in the crypto market with one tweet, it makes one think how much power some influential people have. It is good to remember that behavior like this can also have negative effects on financial returns (Brans and Scholtens 2020; Ge et al. 2019). This is also perceivable for cryptocurrency markets. The presented results show that individual tweets can have a significant influence on returns and trading volumes of cryptocurrencies and can thus be a basis for a great deal of further research, just what this thesis focuses on. As an example, for further research are these so-called pump-and-dump schemes, in which the prices of cryptocurrencies are artificially driven up, often by coordinated manipulation (Mirtaheri et al. 2019; Pacheco et al. 2020).

Gomez-Carrasco and Michelon (2017) found in their study that consumer associations and trade unions can utilize Twitter and microblogging services to great effect when trying to influence investor and consumer behaviour. This study found that abnormal trading volume when these entities were Tweeting about a specific company security varied between 133% to 626% with the mean of course being zero. From this data, the conclusion can be reached that these entities have a great influence on people's decisions. The research of Jin (2016) also supports this. He found that the trading volume of Chinese stocks increases significantly, and their volatility drops after the company in question has created a profile and started using Sina Weibo for microblogging. However, the expected return is less than assumed from which the conclusion can be made that sales outweigh purchases.

Another famous person whose Twitter activity has been researched in an event study is former US President Donald Trump. His Twitter activity was scrutinized by Brans and Scholtens (2020). This study focused on Trump's tweets during his presidency. Trump's vocal opinions and his behavior on Twitter was often covered in media as well. His behavior was unheard of for a president. Brans and Scholtens focused mainly on AR and CAR in their study which ties in well with this study on Elon Musk. The study on Trump found that overall, the tweets did not cause any significant change in stock returns but after conducting a sentiment analysis as well the results were a bit different; tweets by Trump with negative sentiment about a publicly listed company very often caused a negative response by the investors to that company.

4. Methods

This chapter goes over the methods used in this thesis. In the first subchapter, a review is given on the data which was used in this event study. After that, the basic concept of an event study is described. The research method and the theoretical background connected to it will also be covered.

4.1 Data

The data of this study consists of Elon Musk's tweets from the beginning of January 2020 until the middle of March 2021. The tweet data was acquired by scraping Twitter with a scrapper tool which allowed the tweets to be handled in csv format. The stock data was gathered from the Refinitiv Eikon database as well as Yahoo Finance. The Twitter tweet data contains the basic info regarding each tweet, for example, number of likes, retweets & replies. The data collection and analysis was conducted between 15.11.2021 – 22.11.2021. The data was also manipulated to highlight tweets that contained keywords that could be linked to the stocks or cryptocurrencies in the research. These included, for example, *"Tesla", "model", "Doge" & "crypto"*. The stock data includes basic data regarding the stock such as opening and closing value.

To get a clear picture of the data, keywords were used to mark the most important tweets to analyze AR and CAR. Another modification that was made to the data was combining all the tweets per day to one as one of the assumptions of an event study is that other variables do not affect the results.

4.2 Event study and its steps

Event study has no pre-determined structure, but the methods used can be seen in many studies which have been conducted already. At first, the researcher chooses the event or events which they want to analyze and identifies the period linked to the companies or stocks in the study. This entire period is called the event window. This event window includes at least one event day and one day after the event which makes it possible to analyze events which have occurred after the stock exchange has closed on day one. In addition to the event window, another term, an estimation window, is also defined which allows the study to find normal profits to which the event has not affected (MacKinlay 1997). In figure 5 the difference between the estimation window and the event window can be seen visually.

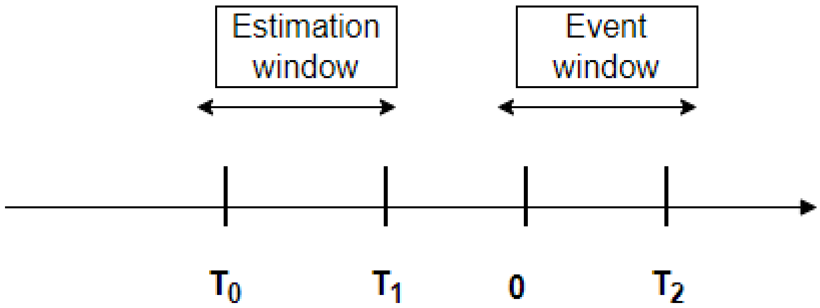

Figure 5. The timeline of an event study. Adaptation of MacKinlay (1997).

The criteria on what grounds a specific business is chosen for the study should also be defined. A criterion can be for example available information or geographical location (MacKinley 1997). Sorescu (2017) has summarized a six-step guide for event studies:

1. Event definition and sampling
2. Treatment of confounding effects due to concurrent or overlapping events
3. Selection of an appropriate asset pricing model
4. Tests of significance and their power
5. Common determinants of abnormal returns
6. Controls for sample selection bias

To conduct the study, the abnormal returns of the dependent variables need to be determined. Abnormal return is defined as the part of the return of an asset that cannot be explained by the changes in the market. It can be viewed as part of the asset return which deviates from the so-called normal return. Normal return can be calculated in many ways, and it is often expressed as the expected return of an asset, often abbreviated E_r (Bodie et al. 2002, 353). When investors have a positive reaction to an event an assumption can be made that abnormal returns are positive as well. On the other hand, if the reaction is vice versa abnormal return can be assumed to be negative as well (Chen & Siems 2004). If a security is defined as *i* and the event day is defined as *t* the formula for abnormal return can be written out as:

$$AR_{it} = R_{it} - E(R_{it} | X_t) \qquad (1)$$

Where AR_{it} is the abnormal return, R_{it} is the actualized return and $E(R_{it}|X_t)$ is the normal return at period t (MacKinlay 1997).

MacKinlay (1997) has presented two methods for measuring normal performance. The first method is called the *constant mean return model* and the other is called the *market model.* However, MacKinlay also states that there are other accepted ways for measuring normal performance, one of which is called the *factor model*.

The constant mean return model as the name states that mean returns are always constant regardless of time. The formulas for this model can be viewed below.

$$R_{it} = \mu_i + \zeta_{it} \qquad (2)$$

$$E(\zeta_{it}) = 0 \qquad var(\zeta_{it}) = \sigma^2_{\zeta i}$$

Where μ_i is the mean return for the security *i,* $R_{it,}$ is the period-t realized return for the same security, and ζ_{it} is the period-t disturbance term security *i* with an expectation of zero and variance $\sigma^2_{\zeta i}$ (MacKinlay 1997).

The market model relates the security return to the market portfolio return. This model is often considered the more common model when measuring abnormal returns. This model assumes a linear relationship between the returns. Therefore, it can be specified as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \qquad (3)$$

$$E(\epsilon_{it}) = 0 \qquad var(\epsilon_{it}) = \sigma^2_{\epsilon t}$$

Where R_{it} is the security return during period t, R_{mt} is the market portfolio return during period t and ϵ_{it} is the zero-mean disturbance term. α_i, β_i and $\sigma^2{}_{\epsilon t}$ are the parameters of the market model. In this model as well, the expectation is zero and variance is the market variance $\sigma^2{}_{\epsilon t}$. The market model is a potential improvement over the constant mean return model as it removes the portion of the return which is connected to the variation in the market's return. This reduces the abnormal return variance which leads to a higher chance of detecting event consequences. The market terms in this model are derived from the R^2 of the market regression (MacKinlay 1997).

Using the market model specify abnormal returns in the market the following formula can be derived:

$$AR_{it} = R_{it} - \alpha_i - \beta_i R_{mt} \tag{4}$$

Where AR_{it} is the abnormal return (Vaihekoski 2004, 232; MacKinlay 1997). Deriving this formula further the mean abnormal returns can be measured. The formula for that is as follows:

$$AR_{\mathrm{t}} = \sum_{i=1}^{N}(AR_{it}) \tag{5}$$

Where *N* is the number of events in the study, AR_{it} is the abnormal return of the events and AR_{t} is the mean abnormal returns of period *t* (Vaihekoski 2004, 232, MacKinlay 1997).

When measuring the behavior of returns during a specific period it is often beneficial to examine daily returns as well. To do this, the returns must be aggregated over time (MacKinlay 1997). The cumulative abnormal return model, (CAR), can be expressed as follows.

$$CAR_i\,(t_1, t_2) = \sum_{t=t1}^{\mathrm{t2}}(AR_{it}) \tag{6}$$

Vaihekoski (2004) describes the mean cumulative abnormal return as follows:

$$CAR\,(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1, t_2) \tag{7}$$

4.2.1 Statistical significance

In event studies, standardized t-tests are often used to determine statistical significance. These tests assume that the abnormal cumulative returns are normally distributed (Sorescu 2017). Henderson (1990) found that a parametrical t-test works better in this context than non-parametrical tests. The null hypothesis states that the event has had no effect on the security price. This can be determined using the measure *t* (Vaihekoski 2004, 233).

$$t_{AR_t} = \frac{AR_t}{\sqrt{\sigma^2_{AR_t}}} \sim t(N) \tag{8}$$

The core assumption of this test is the normal distribution of abnormal returns. The denominator describes the standard deviation of abnormal returns, and the numerator describes the mean abnormal returns during period *t* (Graham & Ramiah 2011).

After measuring the cumulative abnormal return, the next step is to test the null hypothesis which assumes that the event has no effect on the value of the examined security. The assumption states that the events which are examined are not correlating with each other (Vaihekoski 2004, 233). The following formulas are used for the examination:

$$J_1 = \frac{CAR(t_1, t_2)}{\sqrt{\sigma^2(t_1, t_2)}} \sim N(0,1) \tag{9}$$

The denominator variance is calculated using the following formula (Vaihekoski 2004, 233):

$$\sigma^2(t_1, t_2) = \frac{1}{n^2} \sum_{i=1}^{n} (t_2 - t_1 + 1)\sigma_i^2(t_1, t_2) \tag{10}$$

4.2.2 Critique

Event studies, just like other methods, are not immune from criticism. There are many facts regarding this research method that have come under scrutiny. According to Wells (2004), most of the existing critique is aimed at the theoretical structures and their applications in event studies. For example, using beta β in the market model is problematic as the model assumes that the beta which is derived from historical returns is expected to remain unchanged in the future as well. Many studies have however shown that the market beta changes.

Another flaw in this method is the so-called white noise filtering issue which is relevant when handling large datasets. Analyzing these datasets, the non-relevant factors should be filtered so they do not skew the results or hinder the analysis. This causes many problems when in some cases these white noise factors cannot be filtered and thus the results may be skewed, and misleading or outright wrong conclusions can be made.

4.3 Linear regression analysis

Regression analysis is a research method that seeks to clarify causal relationships between variables. It studies the effect of dependent variables on the independent variable. The aim of the regression analysis is to find out how big the causal effect between the variables is. The linear regression model is one of the most used and practical models in econometrics (Hill et al. 2018, 47-49):

$$y_t = \beta_1 + \beta_2 x_{t_2} + \beta_3 x_{t_3} + \cdots + \beta_K x_{tK} + \varepsilon \tag{11}$$

Where y_t is the dependent variable, β_1 is the constant term, $\beta_2, \beta_3, \beta_K$ are the unknown parameters, x_{t_2}, x_{t_3}, x_{tK} are the independent variables and ε is the error term.

The regression model holds many assumptions as well. According to Hill et al. (2018) the multiple regression analysis which is used in this thesis has six assumptions concerning the equation components:

1. All data pairs of (y_t, x_t) are collected from a population which satisfies the following rule:
   $y_t = \beta_1 + \beta_2 x_{t_2} + \beta_3 x_{t_3} + \cdots + \beta_K x_{tK} + \varepsilon$ $\qquad t = 1,2 \ldots, N$
2. The error term ε expected value E (ε) is conditionally zero with all observations
3. The error term ε variance is constant, $var(\epsilon) = \sigma^2$ conditional homoskedasticity

4. The covariance of any different error terms equals zero. $\mathrm{cov}\,(\varepsilon_i, \varepsilon_j) = 0$, $i \neq j$. Auto correlation may not exist among residuals.
5. There is no exact linear relationship between the different independent variables, the variables must take at least to different values.
6. The residuals in the model are normally distributed (optional)

The most common way to estimate the parameters of the regression model is called the OLS or *ordinary least squares*. This method attempts to minimize the squared distance of different observation points from the regression line. Squaring the values prevents large positive distances from canceling out due to large negative distances. This rule is arbitrary but found to be very effective and is simply one way to describe a line that runs through the entire dataset. The vertical distances themselves are called the *least squares residuals* (Hill et al 2018, 61).

4.4 Data handling

When analysing stocks, it is good to remember that the stock market is not open all the time. Due to this, in the case of Tesla, tweets from weekends had to be combined with the next day when the stock market would be open. Usually, this means that Monday events were in fact (Saturday+Sunday+Monday) events. The same logic was applied regarding holidays during which the stock market was closed such as the 4th of July or Thanksgiving. For cryptocurrencies, this was not a problem as the crypto market is always open.

The expected return of Tesla and cryptocurrencies were calculated according to the market model (equation 3). For Bitcoin, the assumption of $\beta = 0$ had to be made as Bitcoin is viewed as the "standard" crypto and is not really a security in the same way as stocks are. The β of normal currency is 0 so therefore it was logical to make this assumption. It could also be assumed that the β of Doge would also be zero but in this thesis, it was calculated by basing it on BTC reactions. The risk-free interest rate was calculated from the 10-year US Government Treasury Bond. The excess return of each asset was calculated by subtracting the expected return from each daily return. The daily return in this thesis was calculated using the logarithmic return as follows:

$$Daily\ return\ \% = \ln\left(\frac{Daily\ value}{Value\ the\ day\ before}\right) \quad (12)$$

The alpha and beta were calculated using *slope* and *intercept* functions in Excel except for BTC. The number of events of Tesla was 307 and for BTC and Doge 447 since weekends were combined in the case of Tesla. After this, the abnormal returns and cumulative abnormal returns could be calculated as well in accordance with event study methodology which was described in formulas 1-10.

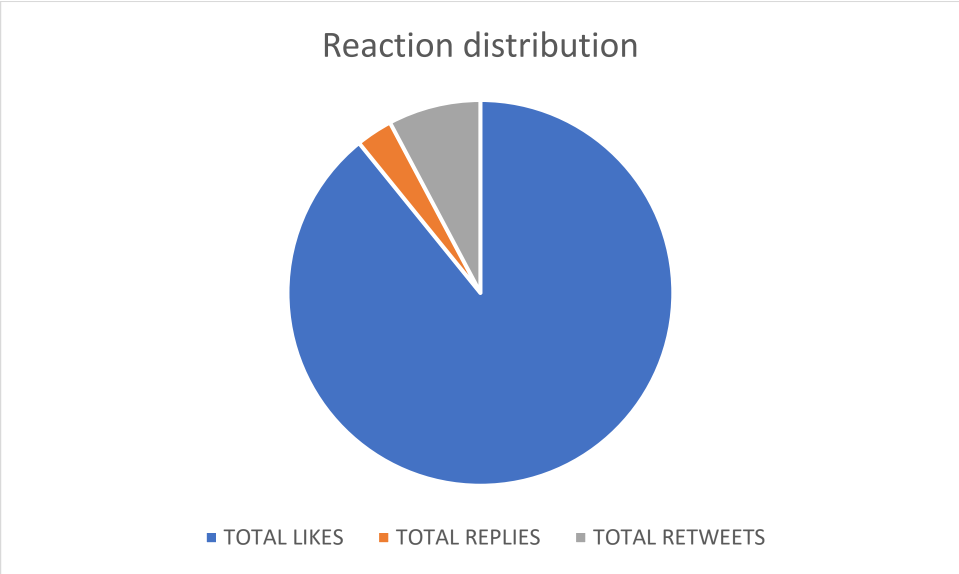

Figure 6: The distribution of likes, replies, and retweets during the event period

As seen in figure 6, likes are by far the most dominant reaction type to Musk's tweets. Due to this the LIKES variable was used as the factor when assessing high reaction tweets.

5. Results and discussion

This section will display the results of this event study. The first sub-section will go over the abnormal returns (AR) and cumulative abnormal returns (CAR) after which the results of the regression analysis are displayed.

5.1 AR and CAR

Using the methods which were mentioned previously the following results were formulated. Tables 1-3 display the average abnormal returns of a high reaction (> 1M) Elon Musk tweet with a word or words related to the specific asset. In the tables, the AR column stands for the abnormal return. I the tables the t-values and statistical significances can also be seen. The event day (index = 0) is highlighted for easier visibility.

Table 1. High reaction tweet effect on Tesla stock:

	AR	t	p
-10	1.78 %	2.024	**0.044**
-9	1.27 %	1.440	0.151
-8	-3.77 %	-4.290	**0.000**
-7	0.35 %	0.398	0.691
-6	0.70 %	0.800	0.424
-5	2.74 %	3.119	**0.002**
-4	-0.05 %	-0.061	0.952
-3	3.27 %	3.722	**0.000**
-2	1.37 %	1.558	0.120
-1	2.05 %	2.331	**0.020**
0	-1.33 %	-1.516	0.131
1	2.26 %	2.566	**0.011**
2	-2.92 %	-3.320	**0.001**
3	1.77 %	2.009	**0.045**
4	-0.86 %	-0.974	0.331
5	3.26 %	3.707	**0.000**
6	-1.26 %	-1.436	0.152
7	1.09 %	1.239	0.216
8	-0.79 %	-0.898	0.370
9	3.58 %	4.074	**0.000**
10	-1.31 %	-1.486	0.138

The Tesla table was formed by taking the average AR from three high reaction events which occurred on 26th of June 2020, 7th of January 2021, and 28th of January 2021 respectively. These events were among the highest reaction events during the observation period. The highest return for the Tesla stock was on average nine days after the event, the lowest was eight days before the event. Roughly half of the events are statistically significant at 5%.

Table 2. High reaction tweet effect on BTC value:

	AR	t	p
-10	2.39 %	1.552	0.121
-9	-0.50 %	-0.325	0.746
-8	1.14 %	0.740	0.460
-7	3.07 %	1.991	**0.047**
-6	-0.10 %	-0.067	0.947
-5	0.97 %	0.632	0.528
-4	3.16 %	2.052	**0.041**
-3	0.79 %	0.511	0.610
-2	1.76 %	1.145	0.253
-1	0.83 %	0.541	0.589
0	1.63 %	1.056	0.291
1	0.32 %	0.206	0.837
2	1.61 %	1.045	0.296
3	-3.67 %	-2.385	**0.017**
4	-0.74 %	-0.480	0.631
5	2.55 %	1.654	0.099
6	-1.97 %	-1.279	0.202
7	0.24 %	0.156	0.876
8	1.35 %	0.877	0.381
9	-1.58 %	-1.028	0.304
10	4.90 %	3.179	**0.002**

The BTC table was formed from the average AR events which took place on the 20th of December 2020, 10th of January 2021, and 19th of February 2021 respectively. The highest BTC return can be seen on average ten days after the event whereas the lowest three days after the event. These numbers tell the story of randomness. Most of the AR values aren't statistically significant at 5%. The relevant values are highlighted. An important note which cannot be seen from the observations is that tweets regarding Bitcoin had the lowest number of reactions during the observation period.

Table 3. High reaction tweet effect on Dogecoin value:

	AR	t	p
-10	1.98 %	1.286	0.199
-9	-1.44 %	-0.933	0.351
-8	-3.84 %	-2.496	**0.013**
-7	3.54 %	2.301	**0.022**
-6	-3.03 %	-1.967	**0.050**
-5	-5.07 %	-3.290	**0.001**
-4	1.96 %	1.275	0.203
-3	-6.68 %	-4.340	**0.000**
-2	-1.84 %	-1.193	0.234
-1	2.07 %	1.342	0.180
0	-2.71 %	-1.760	0.079
1	0.74 %	0.478	0.633
2	-1.38 %	-0.896	0.371
3	-1.01 %	-0.654	0.514
4	0.44 %	0.284	0.777
5	0.72 %	0.468	0.640
6	2.10 %	1.361	0.174
7	0.73 %	0.476	0.634
8	-0.70 %	-0.457	0.648
9	2.31 %	1.502	0.134
10	3.10 %	2.011	**0.045**

The Dogecoin table is an interesting twist to the mix as the events which were combined overlap with each other. Musk's Twitter activity regarding Dogecoin was confined into a small window between the 4th of December 2020 – 7th of December 2020. During this time Musk released many tweets with tickers such as "*Doge*". The reactions on these tweets were also extremely high. The highest AR for Doge came on average 7 days before the event and the lowest three days before the event. Most of the AR values before the event are statistically significant, but after the event, the significance is not there anymore.

After examining all the tables thoroughly, all the tables have some significant events at 5%. Also, an observation can be seen that Tesla has the highest amounts of statistically significant events. This is logical as Musk is the CEO of Tesla and should have a bigger influence on the company than on some cryptocurrencies. Compared to Ante (2021) and his study, he found many events which had a great impact on the crypto rates. The most likely reason for this is that this thesis has focused on a larger dataset and not just on a few specific tweets. If one goes further into examining Musk's tweets some of them will have a statistical significance regarding stock or crypto rates but not all. On a larger level, this seems to be the case a little less.

In tables 4-6 the cumulative abnormal returns (CAR) can be seen by period. The cumulative returns offer another point of view to events as most events have longer-lasting effects compared to just one day. The tables also display the corresponding variance, J-variable, and the statistical significance of each period.

Table 4. Tesla CAR

Tesla high reaction event CAR				
t1, t2	**CAR**	**var**	**J1**	**p**
[-10, -1]	9.71 %	0.00077	3.49	**0.000**
[-5, -1]	9.38 %	0.00039	4.77	**0.000**
[-1, +1]	2.97 %	0.00023	1.95	**0.025**
[0, 0]	-1.33 %	0.00008	-1.52	0.065
[0, +1]	0.92 %	0.00015	0.74	0.229
[+1, +5]	3.51 %	0.00039	1.78	**0.037**
[+1, +10]	4.82 %	0.00077	1.73	**0.042**

In the case of Tesla, most of the periods are statistically significant at 5%. The CAR is largest [-10, -1] before the event and lowest on the day of the tweet [0, 0]. It is intriguing to see that the CAR values increase the farther away from the event they are. According to these results, Musk's tweets cause a delayed reaction to Tesla's stock value which contradicts the EMH. A reason for this could be that most investors tend to wait after some good news is released and thus the positive reaction comes a bit later. For example, if Musk tweets about a new Tesla invention, investors might not instantly make decisions about buying/selling and therefore the reaction is delayed.

Table 5. BTC CAR

BTC high reaction event CAR				
t1, t2	**CAR**	**var**	**J1**	**p**
[-10, -1]	13.51 %	0.002371852	2.77	**0.003**
[-5, -1]	7.52 %	0.001185926	2.18	**0.015**
[-1, +1]	2.78 %	0.000237185	1.80	**0.036**
[0, 0]	1.63 %	0.000237185	1.06	0.145
[0, +1]	1.94 %	0.00047437	0.89	0.186
[+1, +5]	0.06 %	0.001185926	0.02	0.493
[+1, +10]	2.99 %	0.002371852	0.61	0.269

With Bitcoin all the CAR values are positive and as with Tesla, the highest value is at [-10, -1]. The lowest value is reached at [+1, +5]. Only values before the event are statistically significant and this tells a story of randomness. According to this result, Musk does not really seem to influence the cumulative abnormal returns of BTC.

Table 6. Dogecoin CAR

DOGE high reaction event CAR				
t1, t2	**CAR**	**var**	**J1**	**p**
[-10, -1]	-12.34 %	0.002371852	-2.53	**0.006**
[-5, -1]	-9.56 %	0.001185926	-2.78	**0.003**
[-1, +1]	0.09 %	0.000237185	0.06	0.476
[0, 0]	-2.71 %	0.000237185	-1.76	**0.039**
[0, +1]	-1.97 %	0.00047437	-0.91	0.182
[+1, +5]	-0.49 %	0.001185926	-0.14	0.443
[+1, +10]	7.04 %	0.002371852	1.45	0.074

Dogecoin is very similar to Bitcoin in the sense of having the statistically significant events in the beginning. Despite this, a trend of increasing CAR can be seen as the lowest value is at [-10, -1] and the highest at [+1, +10]. This however might just be random as the statistical significance cannot verify it in the end.

The CAR values of every security are statistically significant before the event apart from Tesla which remains statistically significant after the event as well. For each asset, the same trend of increasing

CAR after [0, 0] can be seen. This is interesting when viewed from the point of view of the EMH as it states that efficient markets should instantly react to new information which is not happening in this case. One could also assume that if a tweet has intriguing new information about a stock such as Tesla, people would instantly jump in and invest. These results disagree with that hypothesis, and with Tesla, the average CAR at [0,0] is even negative at a 10% significance level. One could think that high reaction Musk's tweets often decrease Tesla stock value (maybe because more people sell and expect the receive quick profits) and then with time the stock recovers and increases in value as well.

It should also be kept in mind that some of the CAR events of Tesla include days during which the stock market was closed. This could also affect the results as Musk's tweets during weekends might not have such an impact compared to during the week.

Another important factor regarding event studies is the assumption that the changes in asset value are only caused by the event in question. There is always more than one reason which affects market rates. There is also no certainty that white noise can be completely filtered away. Most likely some white noise remains. Regarding the Beta values in the study, an assumption of constancy for the entire event period was made when the betas were calculated. In reality, this is not really the case. An assumption of Beta = 0 for BTC was made as BTC can be regarded as a currency as well as a security.

5.2 Regression analyses

The multiple linear regression was formed to view the effect of the number of reactions to the returns on Musk's tweets and to answer the third research question. The regression was formed for Tesla, BTC, and Dogecoin separately. The dependent variable is the abnormal stock return during the period. The independent variables are the number of reactions per tweet. The correlation matrices can be found in appendices 1-2. This regression analyses the Tweets' effect from the entire period 1/2020 – 3/2021. The regression analysis was formulated using the *ordinary least squares* method or OLS. The confidence interval is 95%.

The assumptions regarding the regressions can be seen in appendices 3-9. The residuals are expected to be normally distributed. The model is also assumed to be homoscedastic, and that multicollinearity does not exist.

After formulating the multiple regression analysis and calculating VIF values, clear multicollinearity can be seen. Due to this, the regression was changed to a simple regression model in which the LIKES, REPLIES, and RETWEETS variables were combined into one. Due to this, there is only one independent variable REACTIONS.

In table 7 the simple regression results can be viewed. The table shows the parameters, the standard errors, t-value, statistical significance, the R^2 value, the adjusted R^2 value, and the F-value. Regarding the multicollinear model, the results for that can be seen in appendix 7.

Table 7: The simple regression results

TSLA_RETURN	Coefficent	Standard error	t-value	PR >|t|
REACTIONS	-4.13E-09	4.59E-09	-0.9	0.368
CONSTANT	0.0101448	0.0037768	2.69	0.008
	R²	**Adjusted R²**	**F-value**	**Pr>F**
	0.0027	-0.0006	0.81	0.3684
BTC_RETURN	**Coefficent**	**Standard error**	**t-value**	**PR >|t|**
REACTIONS	4.36E-09	3.8E-09	1.15	0.251
CONSTANT	0.0039755	0.0023251	1.71	0.088
	R²	**Adjusted R²**	**F-value**	**Pr>F**
	0.003	0.0007	1.32	0.2515
DOGE_RETURN	**Coefficent**	**Standard error (robust)**	**t-value**	**PR >|t|**
REACTIONS	**4.38E-08**	**1.56E-08**	**2.81**	**0.005**
CONSTANT	-0.0065615	0.0050589	-1.3	0.195
	R²	**Adjusted R²**	**F-value**	**Pr>F**
	0.0538	0.0517	7.90	0.0052

The regression values are highly interesting. When comparing these to the previous AR and CAR values, the regression tells a different story. According to the regression, only 0.27% of Tesla's excess return can be explained by Musk's tweets. Regarding Bitcoin, that number is 0.3% and for Dogecoin it is 5.38%.

All these values end up being relatively low in the end, especially Tesla and Bitcoin. Only values in the Dogecoin regression have statistical significance at 5%. It was also interesting to find out that regarding Doge, this model was heteroskedastic but for Tesla and Bitcoin it was not. These results can be seen in appendix 4.

In regression, the assumption is made that other factors have been managed to be filtered out apart from the event which is being studied in the regression**.** The R^2 value depicts how much Musk's Twitter activity accounts for the excess returns of these specific assets. A low value for R^2 means that the filtering of other variables failed, and the model's goal is questionable as other reasons account for most of the change in the asset values.

The results of this study account for a low amount of asset excess returns. This seems logical in the end. If one man on Twitter could have a bigger impact on asset returns the EMH would have been scrapped a long time ago. The regressions considered all Musk's tweets so it would not be logical for them to have a large a R^2 value. Some tweets by Musk for sure have larger impacts on market rates as he is the CEO of Tesla in the end and can release very vital information regarding the company. This is in contradiction to what Ante (2021) found in his study that some actions by Musk have great effects on the crypto market (and why not on the stock market as well) but most of them have little or no effect.

6. Conclusions

This study aimed to find out if Elon Musk's Twitter activity has had any significant effect on the rates of Tesla, Bitcoin, and Dogecoin. This was tested using an event study, with which the abnormal returns AR and cumulative abnormal returns CAR were calculated. Another part of this study was a multiple linear regression analysis with which the effect of tweet reactions of excess returns was studied. Due to multicollinearity, the multiple regression had to be converted into a simple regression for accurate results. The underlying concept which this study is based on was the efficient market hypothesis EMH and market manipulation in its many forms. One cannot positively say if Musk's Twitter activity has ever meant to be manipulation but from time to time it has ticked all the boxes related to social media market manipulation. Next are the answers to the research questions:

How has Elon Musk's Twitter activity affected the US stock and cryptocurrency market?

According to the results of this study, Elon Musk's tweets do not have a massive impact on the specific asset values in the study. None of the AR values for the high reaction tweet day in this study are statistically significant so one cannot say with precision how much the real effect would be. High reaction Musk tweets seemed to have a trend among the assets of causing increasingly positive cumulative returns. On the other hand, these were only statistically significant in the case of Tesla. It however seems that Musk may have some delayed effect on stocks and cryptocurrencies. It is also good to keep in mind that the assumptions made in this study have most certainly influenced the results and future studies' results regarding this topic may vary. Cryptocurrencies are such a new concept and research related to them is relatively new, so some assumptions are bound to be made.

What has been the effect of Elon Musk's tweets on the abnormal returns of the US stock and cryptocurrency market?

The different AR values for the asset are not statistically significant on the event day but especially in the case of Tesla roughly half of the AR events are statistically significant so some correlation can be observed. For the cryptocurrencies this is not really the case.

What has been the effect of Elon Musk's tweets on the abnormal cumulative returns of the US stock and cryptocurrency market?

The different CAR values remain interesting across the board, the most interesting are Tesla and Dogecoin. In the case of Tesla, the CAR values even seem to contradict the EMH as the statistically significant values are only occurring further away from the event which indicates a delayed investor reaction. An investor should instantly react to new information, but this does not seem to be the case. Maybe many of the investors wait for a few days and assess the market on their own before making decisions. Regarding Dogecoin its CAR at [0,0] is statistically significant but the value is negative which seems odd and counterproductive.

Has the number of reactions on a tweet resulted in a significant difference in the abnormal return of that day?

The regression analysis in this study is mostly statistically insignificant which in turn means that high reaction twitter posts do not influence the excess return of Tesla, Bitcoin or Dogecoin. As stated previously, some of Musk's tweets may have an impact on asset values but on a larger level there is no data to prove it. The simple regression that is free of multicollinearity is statistically significant regarding Dogecoin. Doge also has the highest R^2 value, over 5%. For Tesla and Bitcoin nothing valuable can be gathered from the regression. The linear regression results depict that only a tiny percentage of the excess returns have been caused by high reaction tweets.

For future research regarding this topic, an idea for a study would be to analyze Musk's tweets monthly. Maybe some months have a high statistical significance and some a lot lower. Another option would be to further filter tweets with more advanced filters and not just specific words as this study did. Another improvement that could be made is using dummy variables for the regression. These dummies should be carefully planned out and maybe created from some of the tweet data as well. All in all, the results of this study follow the lines of Brans and Scholtens (2020) that abnormalities are hard to find from a large, over a year spanning dataset, of tweets.

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APPENDICES

Appendix 1. TESLA Correlation Matrix; multicollinear and fixed values

	TSLA_RETURN	LIKES	REPLIES	RETWEETS
TSLA_RETURN	1.0000			
LIKES	-0.0490	1.0000		
REPLIES	-0.0729	0.9002	1.0000	
RETWEETS	-0.0635	0.9554	0.8365	1.0000

	TSLA_RETURN	REACTIONS
TSLA_RETURN	1.0000	
REACTIONS	-0.0515	1.0000

Appendix 2. BTC and DOGE Correlation Matrix; multicollinear and fixed values

	BTC_RETURN	DOGE_RETURN	LIKES	REPLIES	RETWEETS
BTC_RETURN	1.0000				
DOGE_RETURN	0.3498	1.0000			
LIKES	0.0518	0.2309	1.0000		
REPLIES	0.1210	0.2100	0.8840	1.0000	
RETWEETS	0.0520	0.2317	0.9595	0.8244	1.0000

	BTC_RETURN	DOGE_RETURN	REACTIONS
BTC_RETURN	1.0000		
DOGE_RETURN	0.3498	1.0000	
REACTIONS	0.0544	0.232	1.0000

Appendix 3. TESLA, BTC and DOGE RAMSAY RESET TEST values

Test	P-value
RAMSEY RESET test	0.7031

Test	P-value
RAMSEY RESET test	0.7114

Test	P-value
RAMSEY RESET test	0.0003

Appendix 4. TESLA, BTC and DOGE BREUSCH-PAGAN test for heteroscedasticity

Breusch-Pagan test for heteroskedasticy	
chi2	2.84
Prob > chi2	0.0922

Breusch-Pagan test for heteroskedasticy	
chi2	0.44
Prob > chi2	0.5056

Breusch-Pagan test for heteroskedasticy	
chi2	136.04
Prob > chi2	0.0000

Appendix 5. VIF values for the multicollinear multiple regression

Variable	VIF	1/VIF
LIKES	18.77	0.053289
RETWEETS	11.85	0.084379
REPLIES	5.46	0.183311

Variable	VIF	1/VIF
LIKES	19.07	0.05245
RETWEETS	13.01	0.076846
REPLIES	4.73	0.211546

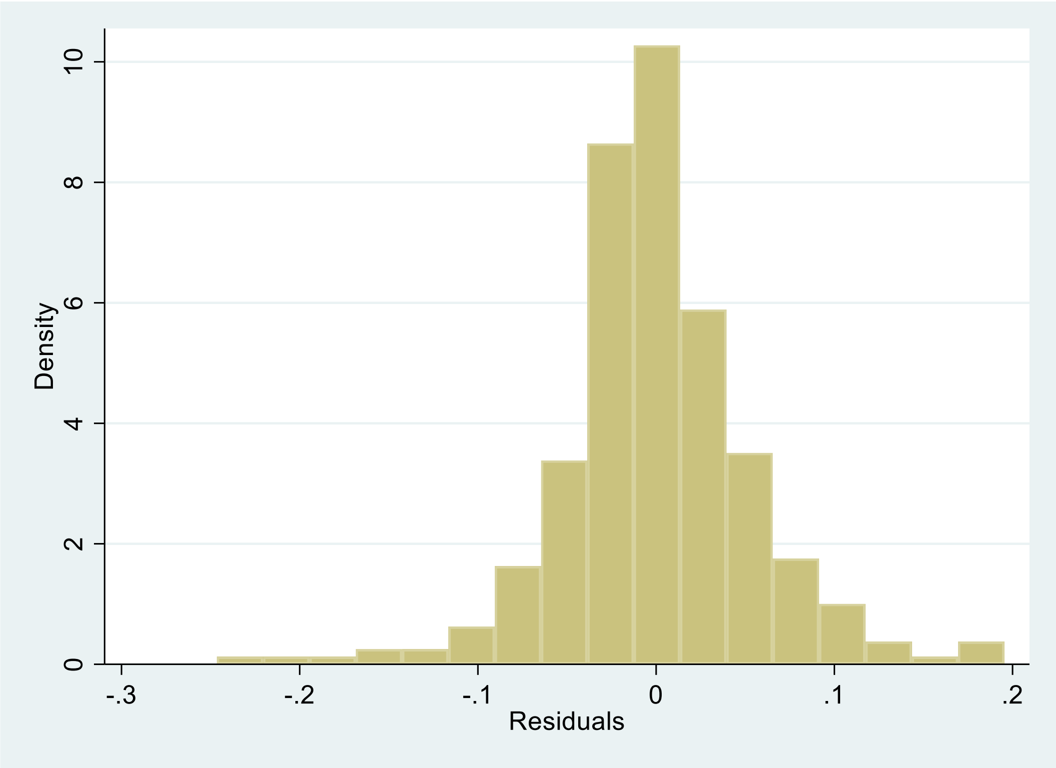
Appendix 6. Shapiro-Wilk W test for normal data

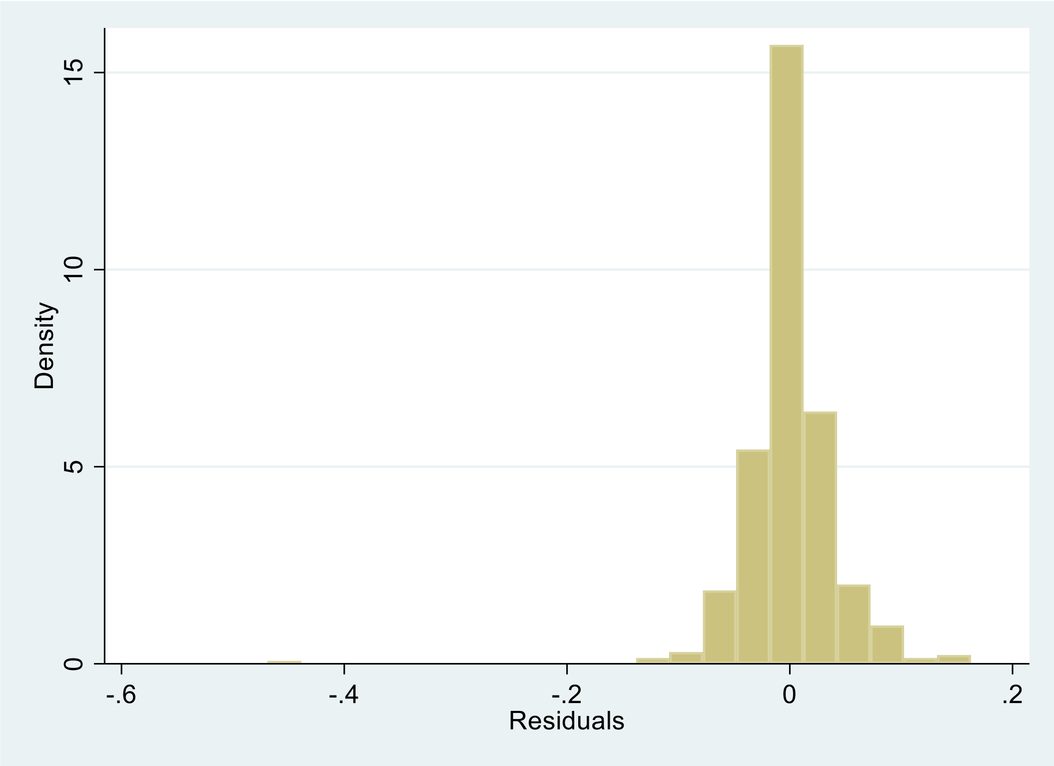
Shapiro-Wilk W test for normal data					
Variable	Obs	W	V	z	Prob > z
resid1 (Tesla)	307	0.95814	9.103	5.19	0.00000
resid2 (BTC)	447	0.80646	58.862	9.746	0.00000
resid3 (Doge)	447	0.56433	132.504	11.687	0.00000

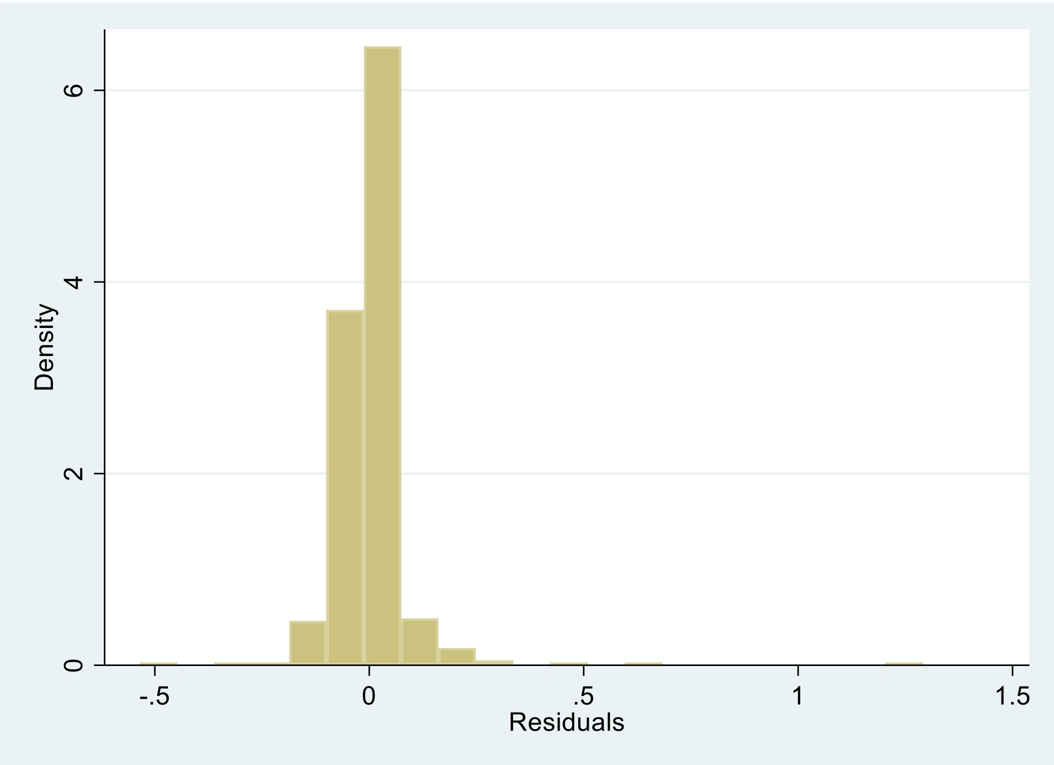
Appendix 7. The multicollinear multiple regression results

TSLA_RETURN	Coefficent	Standard error	t-value	PR >|t|
LIKES	3.13E-08	2.26E-08	1.39	0.167
REPLIES	-4.57E-07	0.000000333	-1.36	0.175
RETWEETS	-2.02E-07	0.000000166	-1.22	0.225
CONSTANT	0.0090223	0.003937	2.29	0.023
	R^2	Adjusted R^2	F-value	Pr>F
	0.0116	0.0018	1.19	0.3182
BTC_RETURN	Coefficent	Standard error (robust)	t-value	PR >|t|
LIKES	-3.63E-08	0.000000021	-1.73	0.085
REPLIES	0.00000092	0.00000035	2.62	0.009
RETWEETS	0.000000113	0.000000129	0.87	0.383
CONSTANT	0.003919	0.002574	1.52	0.129
	R^2	Adjusted R^2	F-value	Pr>F
	0.0300	0.0235	2.44	0.0637
DOGE_RETURN	Coefficent	Standard error (robust)	t-value	PR >|t|
LIKES	1.24E-08	5.19E-08	0.24	0.812
REPLIES	0.000000255	0.00000065	0.39	0.695
RETWEETS	0.000000274	0.000000382	0.72	0.474
CONSTANT	-0.0054016	0.0051975	-10.4	0.299
	R^2	Adjusted R^2	F-value	Pr>F
	0.0550	0.0486	3.59	0.0000

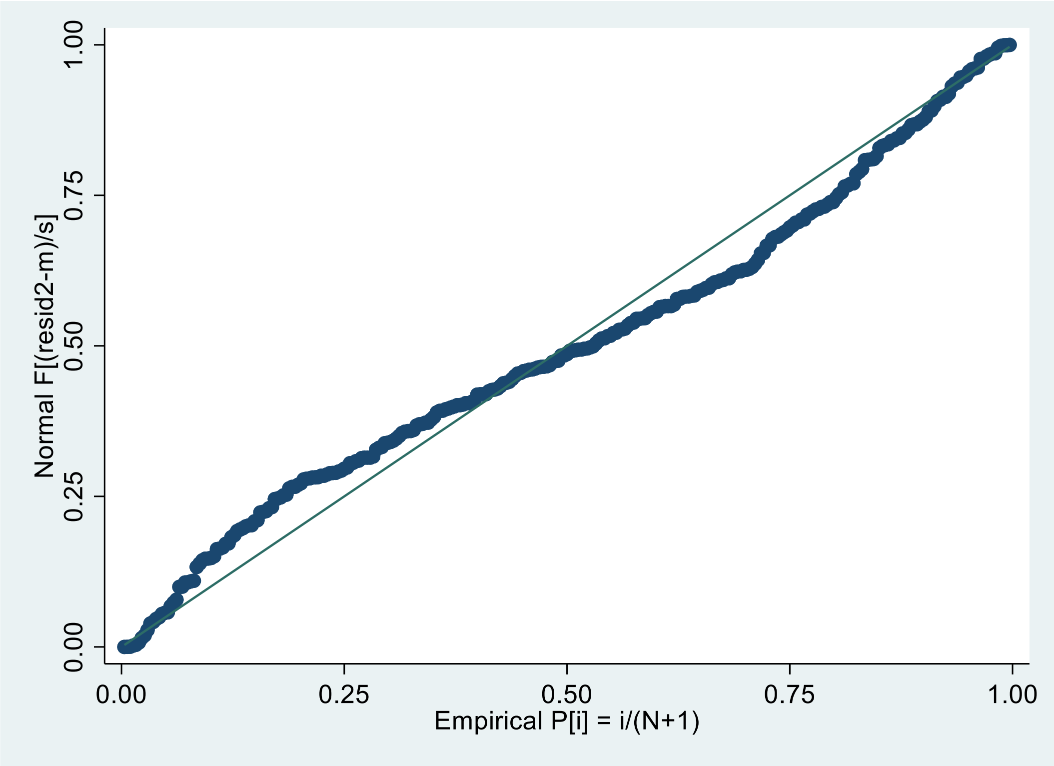
Appendix 8. Residual histograms

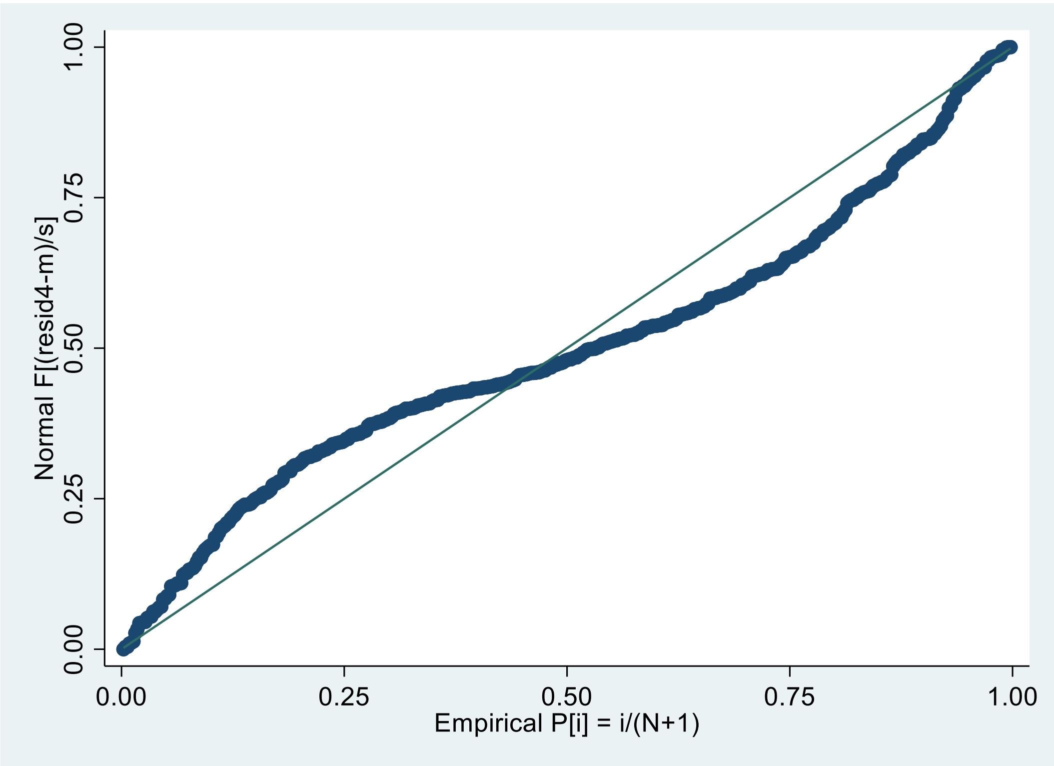


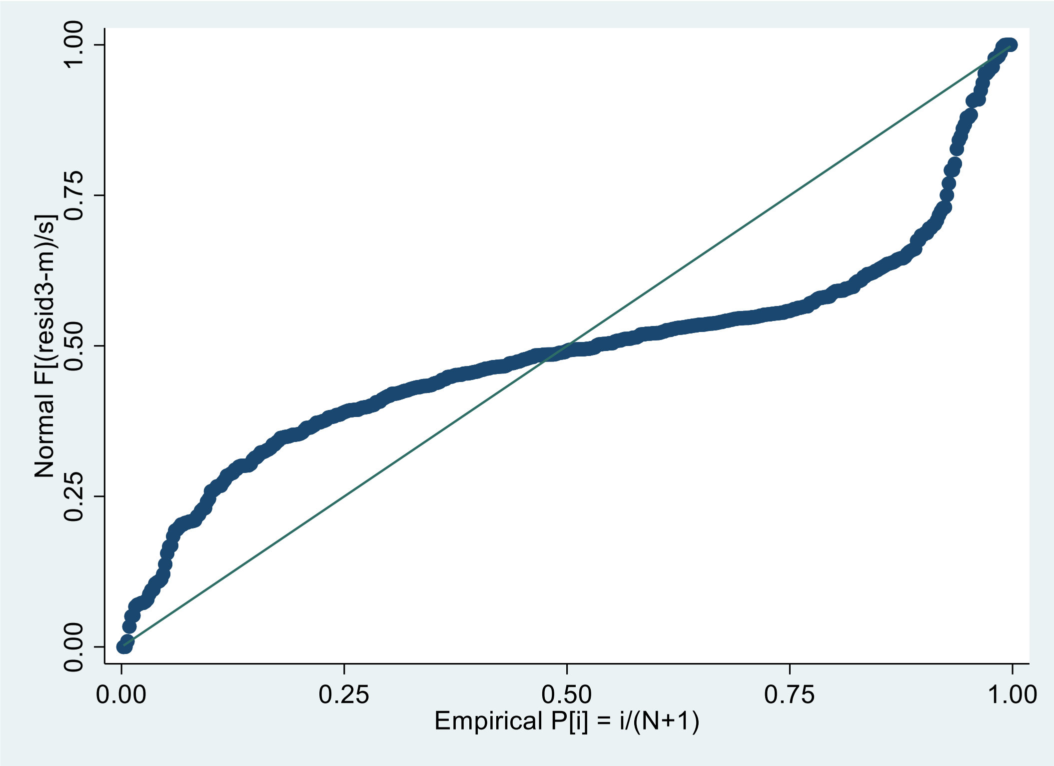

Density
0
5
10
15
-.6
-.4
-.2
0
.2
Residuals


Density
0
2
4
6
-.5
0
.5
1
1.5
Residuals

Appendix 9. Residual Pnorm figures






Normal F[(resid3-m)/s]
0.00
0.25
0.50
0.75
1.00
Empirical P[i] = i/(N+1)
0.00
0.25
0.50
0.75
1.00