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Does the stock market react to President Trump's tweets?

A study of the stock price reaction of the targeted companies in President Donald Trump's firm-specific tweets

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Abstract

Does President Donald J. Trump influence the stock market when posting company-specific tweets? In this study we explore the market efficiency theory and whether President Trump's influence a stock price reaction when targeting companies in his tweets. This is analyzed by conducting an event study to investigate whether there is any abnormality in stock prices surrounding an event and cross-sectional regression with explanatory variables to investigate possible predictors for abnormal return.

The main results of the study indicate that it is difficult to find clear significant effects of company-specific tweets on the targeted company's stock price. The results indicated that regardless of content we find a tendency to a decline in abnormal return, and that this effect is bigger for tweets containing negative content than positive content. When sorting data by sentiment, the results indicate negative effects of tweets containing teaser and threat. Further, out results indicates that mid cap companies can be more effected by negative tweets then larger companies and that there are some differences based on industries. Finally, we find tendencies of increased volatility regardless of content, and some differences in trading volume due to positive or negative content supporting our findings.

Key words: Market efficiency theory, President Trump, Twitter, microblogging effects, stock price reaction, abnormal return, trading volume, volatility, investor attention, event study.

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Index

List over tables

List over Appendices

1 Introduction

The use of social media and online communication has become a significant part of both private life and how businesses operate with more immediate communication and greater audience. Online investment forums are popular among investors and other financial professionals, and the social network service Twitter has been in the forefront of stock microblogging (Sprenger, Sandner, Tumasjan, & Welpe, 2010). But as Tafti, Zotti, and Jank (2016) states it is hard to capture the effects of the information released in social media outlets like Twitter.

Research regarding how Twitter and the stock market interact has revealed that the mood among the users on Twitter can be linked to changes in the financial market. And further, that individuals can influence the stock market with the use of Twitter, based on a great number of followers. E.g. when Kylie Jenner tweeted about Snapchat[1] in 2018, the market reaction sank the shares of Snapchats parent company 6.1 percent, leading to a $1.3 billion loss in market value (Gale, 2018).

This led us to believe that President Donald Trump, with more than twice as many of followers[2] and listed as the third most powerful person in the world[3] (Forbes, 2020), would have a significant impact when stating about publicly traded companies. In this study we want to investigate this relationship, and the main question of the study is:

> *How is a publicly traded company affected by being targeted in President Donald Trump company-specific tweets?*

President Trump is famous for his frequent use of tweets to share his opinion about whatever is on his mind. He uses his Twitter account both as a tool, a crutch and a cudgel, to praise his

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[1] Kylie Jenner tweeted from her account @KylieJenner the following: *«Sooo does anyone else not open Snapchat anymore? Or is it just me... ugh this is so sad»* (Feb 21, 2018) (KylieJenner, 2018)

[2] The account @KylieJenner have approximately 32.6 million followers on Twitter (Twitter, 2020a)

[3] #1 Xi Jinping (General Secretary, Communist Party China), #2 Vladimir Putin (President, Russia), #4 Angela Merkel (Chancellor, Germany)

supporters, to promote his presidential agenda, and to attack those he sees as being against him. With the number of followers on the @realDonaldTrump account, the companies targeted in his tweets will receive a great amount of attention, either the tweet is mentioning the company in a positive or negative sentiment. Since the majority of the firm-specific tweets are his *feelings* about the firm, they may not necessarily convey any novel info about the company (Brans & Scholtens, 2020). Therefore, the value-relevance is not self-evident and need to be tested further. The stock market's reaction helps detect whether the tweets are financially relevant or not. By studying the tweets targeting companies we investigate whether the information from his twitter account is of financial value and reflects market reactions, accordingly, putting the market efficiency theory to test.

To investigate the research question, we established more concrete hypotheses based on empirical evidence from research regarding the causal effects between microblogging on social media and the stock market. To test the hypotheses, we conduct an event study to investigate whether there is any abnormality in stock prices surrounding events and further used cross-sectional regression with explanatory variables to investigate possible predictors for abnormal return. The explanatory variables concern content of the tweet and firm characteristics of targeted companies. An additive analysis on stock volatility and trading volume is conducted to support findings in main analysis and highlight the impact of the tweets from multiple views.

Results from the study suggest that the President's tweets do not yield a significant response to the stock market. In fact, it seems that he tweets after unidentified company events have already affected the stock market. This will be discussed throughout the study. That said, when accounting for sentiment in tweets the results indicate that tweets with a strong negative sentiment like threats leads to a more negative response in the stock market. These results support other similar studies and confirms that investors are more sensitive to negative news. Based on the results we can also speculate on tendencies of different outcomes regarding firm characteristic. Smaller companies seem be associated with a greater affected by the tweets in comparison to larger companies. Further, the results indicate that when the tweets target industry manufactures, like car producers, positive tweets are associated with significantly no effect while negative tweets have a greater negative effect. The findings are supported by the additive analysis of volatility and trading volume.

Our study sheds a light on how a powerful person influence the stock market when using unfiltered social media platforms, like Twitter. It contributes to the existing research on Twitter and how posts influence the stock market by indicating the same tendencies. The study confirms and widen existing evidence from research on how President Donald Trump's tweets affect the stock market with a greater dataset, longer period of study and with more predictors. The results have to be seen as a combination of Trump as president and the tweet, as we cannot necessarily expand these results to other public figures. Supporting this, the task is not to consult other future presidents on the use of Twitter but simply contribute to a discussion and provide reflections around the actual function of the tweets made by one of the most influential individuals in the western world. Further, this paper contributes to financial literature with the discussion of news and efficient markets.

The paper is organized in five sections, where the first section is the introduction. Section 2 presents a literature review and hypothesis development. We define the theortical framework for the study, by describing market efficiency theory, market traders and asset pricing models. Previous research on both the general relationship between the media and stock market is presented, as well are more spesific research on Trump and Twitter. Section 3 describes the technical aspects of the study: methodology, sample and data. Section 4 presents the results from the analysis. We discuss the results connected to the hypotheses and previous research, and present an additive analysis on stock volatility and trading volume to highlight the impact of the tweets. Section 5 is the conclusion, presenting a summary of the results, contribution to research and suggestions for future research.

2 Literature review and hypotheses

The following chapter provides the background for the study, presents related research and hypotheses development.

2.1 Theories of capital markets and asset pricing

2.1.1 The Efficient Market Theory (EMT)

The essence of capital markets is the theory of market efficiency. When investors buy or sell stocks, they do so by contemplate the stock price, return and volatility. As Malkiel and Fama (1970) explains, the ideal is that prices provide accurate signal for resource allocation meaning that investors choose to invest and gain ownership in companies in which their activities are reflected in the stock prices. A market is *efficient* when the stock prices are fully reflected by all available information to the public.

However, there are nuances of efficiency with respect to what kind of information is absorbed in the prices. Weak form efficiency refers to only historical prices whereas semi-strong form of efficiency also includes other information that is publicly available, such as announcements of annual earnings, stock split and more. The strong form of market efficiency concerns the information that is typically obtained by corporate insiders and specialists. These groups of people have monopolistic access to information that is relevant for company activities and therefore the price of future valuation. According to Malkiel and Fama (1970), apart from only few exceptions with monopolistic information access, empirical research conclude that the efficient market model is valid, and it is a good approximation to reality. According to Neuhierl, Scherbina, and Schlusche (2013) press releases can make the level of informational asymmetry in the markets go down. Also, most types of announcements tend to increase return volatility and cause higher levels of valuation uncertainty because of the news element.

Seiler and Rom (1997) states that the market efficiency is put to the test when a study is performed to identify stock price reactions caused by events. These tests evaluate the efficiency at a certain point of time. From a macro perspective, the efficiency can be tested by watching whether the prices follow a random walk over a longer period. Predictions from financial theory claim that the security prices will fluctuate randomly in the short run if the EMT holds as it absorbs all publicly available information. Historical tests on stock markets have shown that stock returns change randomly and attempting to predict stock price movements fail. According to Seiler and Rom (1997) the best prediction of stock prices is to guess that the next period's price will be somewhat like last period.

2.1.2 The market traders

Hervé, Zouaoui, and Belvaux (2019) states that investors in capital markets are principally assumed to be Bayesian. Classical financial theory describes this behavior as the ability to have fully rational expectations about futures cash flow and investment risks. The theory also concedes that some investors are not able to be completely rational. These irrational traders, so-called noise traders, typically act on information that are mainly noise as exclusive information that they believe gives them an edge. The noise traders are said to hold random beliefs versus rational arbitrageur traders hold Bayesian beliefs (Tetlock, 2007).

According to Tetlock (2007) theoretical models that explore the effect of investor sentiment[4] on stock prices assume that both types of traders are risk averse meaning that they have a downward sloping demand for risky assets. The noise traders' random beliefs effect the stock prices in the market equilibrium, and in case of high pessimism, temporarily create increase in trading volume and downward pressure on prices. Since these shocks are assumed to be stationary, on average returns will rebound until there is a new belief shock (Tetlock, 2007). These results lead to a prediction that low sentiment will lead to downward pressure on prices and unusual high or low sentiment will generate high trading volume (De Long, Shleifer, Summers, & Waldmann, 1990).

Barber and Odean (2008) separate the traders in the market to be individuals and institutional investors and elaborate expectations according to theoretical models, where investors are risk averse and equally likely to sell stocks with negative signals as to buy when there are positive signals. Barber and Odean (2008) argue that *attention* is a major factor that affects a buy-or-sell decision which does not apply for institutional investors. Their research found evidence that individual investors display an attention-driven buying behavior which is similar for both

[4] The level of noise traders' beliefs *relative* to the Bayesian belief is referred to as *investor sentiment,* meaning that if noise traders have expectations below the rational traders, then the noise traders' beliefs are pessimistic. Further, it is assumed that the noise traders' perceptions are stationary which means that over time these beliefs do not stray arbitrarily far from the rational expectations (Tetlock, 2007).

small and large stock. Also, what utility an investor can get from a news event can also be affected by how many others choose to act on the news. Their choice to buy or sell is therefore likely bounded to personal preferences, whether the investor is a trend follower or a contrarian (Barber & Odean, 2008).

Institutions and individual investors differ significantly in their search problem. According to Barber and Odean (2008) institutional investors, as professionals, devote more time to do research than individuals before making a buy-or-sell choice, and they have tools like computers to narrow their search. Institutional investors can continuously monitor a wider range of stocks and can for instance use algorithms for purchase criteria or concentrating on a sector of stocks. On average individuals do so in a lesser extent (Barber & Odean, 2008).

2.1.3 Asset Pricing models

When the EMT is put into test, it's important to consider the context of the model that are used to calculate the expected return in the market. One must according to Fama and French (2004) first make up an opinion on how the market settles these prices regarding what is a risk factor and what characterizes the relationship between risk and return, when testing if prices are rational.

All models that has been developed are based on some simplifications of the reality and assumptions of investor behavior. The validity of these models has been tested and redeveloped as extensions or have created origin to different theories. Still, according to Fama and French (2004) there is arguably *no model* that perfectly represent the market and can explain the total variation of returns in assets, as researchers differ in their view of using proxies for market variables.

Capital Asset Pricing Model

The capital asset pricing model (CAPM), developed by William Sharpe (1964) and John Lintner (1965) (cited in Fama & French, 2004) is a start point of analyzing the required rate of return for companies with a certain level of risk compared to the market portfolio. CAPM is an extension of the model of portfolio choice by Markowitz (1959, cited in Fama & French, 2004) which assumes that investors are risk averse and that investors want to have a *mean-*

variance-efficient portfolio[5]. The CAPM adds two additional assumptions where all investors agree on the joint distribution of assets returns from t-1 to t, and all investor can unconditionally borrow and lend at the risk-free rate (Fama & French, 2004).

CAPM summarizes the relationship between a stock's return and the return of the market portfolio by the risk-free rate and asset return's sensitivity to the variation in the market return. Sensitivity is measured by beta which is the slope of the linear regression of the assets return on the market return. The intercept of the regression is the risk-free rate, which equals the expected returns on assets that are uncorrelated with the market return when there is risk-free borrowing and lending. Also, the beta premium is positive as we can expect a stock return that exceeds the risk-free return (Fama & French, 2004).

The assumption of unrestricted risk-free borrowing and lending in CAPM is an unrealistic assumption. Other versions have been made trying to substitute this assumption, like Black (1972) by allowing unrestricted short sales but the outcome remains the same. Nevertheless, CAPM is often used as introduction to the concepts of asset pricing and estimating the cost of equity capital. According to Fama & French (2004), evidence have shown that CAPM tend to describe a relationship that is too steep compared to the reality, when comparing historical average returns. As it turns out, the tradeoff between return and risk is flatter. This means that estimates for equity costs obtained by CAPM is too high (low) for high (low) beta stocks.

A proxy for the risk-free rate is typically the return of a one-month treasury bill, and the market premium is typically a portfolio of US common stocks minus the treasury bill rate. According to Fama & French (2004), cross-sectional regressions also find that the intercept is consistently greater than the risk-free rate. Research have shown that CAPM is not sensitive to expanding the market proxy beyond common stocks as the volatility of the stocks dominate the volatility of the expanded market returns (Fama & French, 2004).

[5] *Mean-variance-efficient portfolio:* a portfolio that given an expected return will minimize the variance of the portfolio return, and at the same time, given the variance of the portfolio will seek to maximize the expected return.

Multi-factor models

Logic of CAPM is continued in extended models like multifactor models (Fama & French, 2004). These models arise from empirical work that proved that much of the variation in the expected returns was not related to the market beta which means that there is a need for more complicated models. Fama and French (1993) argue that size and book-to-market (B/M) equity represent variables that produce undiversifiable risk in returns which is not captured by the market return in CAPM. Hence, these variables should be priced separately in the market. Supporting these arguments, Fama and French (2004) provided evidence that the returns of small companies covary more with each other than the returns of large companies, and also returns on value companies[6] covary more with each other, than growth companies[7]. Arising from these evidences is the three-factor model of Fama and French (1993) and Fama (1996) which explains the relations between the expected return of an asset, the risk-free rate and three different beta-measures for risk; the market beta, the SMB[8] beta and the HML[9] beta (Fama & French, 2004).

Using this extended asset pricing model, Fama and French (1993) and Fama (1996) found that the model captures more of the variation in expected returns, and the model is widely used in empirical research. Especially, the use of alpha in the time-series regression can reveal how quickly stock prices respond to new information.

One of the main shortcomings of this model is based on the motivation behind adding these factors to the model. These variables are not concerned with investor objectives whether they are rational or irrational. Instead, these variables try to capture patterns from research that have revealed how stock return seem to vary due to these factors. According to Fama and French (2004), if the objective is to study the stock response to new information, it is of interest to control for already known patterns in return and average returns for the period you

[6] *Value companies:* companies with high book-to-market

[7] *Growth companies:* companies with low book-to market

[8] "Small minus big" (SMB) is the difference between the returns of on diversified portfolios of small and big stocks

[9] "High minus low" (HML) is the difference in return between a diversified portfolio of high B/M and a diversified portfolio of low B/M

examine, whatever their source. Another shortcoming is related to the momentum effects, but Fama and French (2004) claim that these effects are short-lived therefore mostly irrelevant when models are used to estimate cost of equity capital

2.2 The stock market and the media

The relationship between the media and its effect on the stock market has developed as rapidly as the technological developments the last decades. In this section we present results from studies on financial website message boards, financial columns in a newspaper and other studies where Twitter is the information channel.

2.2.1 Message boards online as useful financial information

The communication on the Internet can be related to the stock market, like Antweiler and Frank (2004) found studying online stock message boards. They found a correlation for posting on message boards for prices, trading volume and volatility. Their main findings was that increased message board posting on one day seem to predict negative returns on the following day. They found results supporting that disagreements among the people who publish on the boards can induce trading activity, and both of these results are especially relevant for the trading volume of smaller-size trades. However, greater disagreements on one day predicts that the trades on the following day is *fewer* and not more.

According to Antweiler and Frank (2004), online stock message boards are useful to study insider trading and market efficiency because of the time-stamped messages and the content reflects the information that people acquire quickly.

2.2.2 Medias effect on the market when the information is not "new"

Tetlock (2007) has a different approach to the research on news coverage and stock prices. The study uses information in the newspaper column "Abreast of the Market" in the Wall Street Journal and investigate whether the comments in these columns can affect stock prices and volatility. An important aspect of this study is the fact that Tetlock (2007) assumes the information is not completely unknown for most market traders as the information is written after or shortly prior the closing bell on Wall Street, and therefore to be considered post-mortem of the market's life the prior day[10].

Tetlock (2007) found statistical evidence that the content in the news media can predict movements in the stock market activity, especially pessimistic cover. If the content is highly pessimistic it can predict downward pressure on stock prices. However, evidence show that there will be a reversion back to fundamentals. If the pessimistic cover is unusually high or low, it can forecast the level of *trading volume* of the stock. At the same time, Tetlock (2007) found that low market return can lead to high media pessimism. The results suggest that the absolute values of measures of pessimism have strong effect on the next day's trading volume on NYSE and even beyond their immediate impact on opening-hour volume. These results are also consistent with De Long et al. (1990).

The study did not provide statistical evidence that the media content has to provide any *new* information about financial asset values or that the information through media cover has no relation to the asset markets. These results are inconsistent with theories that claim that the media content can be a proxy for new fundamental asset value information, a proxy for market volatility or as a sideshow with no relation to asset markets (Tetlock, 2007).

Tetlock's (2007) findings are consistent with the theory of noise and liquidity traders. Media content can be seen as a proxy for investor sentiment or noninformational trading[11]. If the media cover reflects negative news about the future cash flows rather than investor sentiment, the correlation between the media pessimism and effects on returns in the short run will still be negative. In the long run, however, one would expect that the returns and volume would be reversed in the sentimental theory, whereas the information theory would predict that they will persist indefinitely. This discussion deals with extreme views that might appear in the newspaper as either pure noise or pure information. Tetlock (2007) also point out that traders might over- or underreact to information, even information that is not appeared to be big.

[10] The journalists behind the column viewed the content more as entertainment and they don't have a background as financial experts. The column explored yesterday's capital market activities measured by indices like the Dow Jones Industrial Average, and selected news from brokerage houses, stock analysts and other professionals' statements on why yesterday's activities happened and forecasts for today and the next days' activities.

[11] *Noninformational trading:* not based on arrival of new information to the marketplace

Further, if the media cover and pessimism appear as a proxy for information that is already incorporated into market prices, this type of theory predict that the cover should have no visible effect on future market activity.

According to Tetlock (2007) the effect of pessimism can be different for small stocks as they usually have the highest individual investor ownerships, and his study provides evidence that negative sentiment seems to have a longer lasting and larger impact on small stocks. That said, Tetlock (2007) encourage to be reasonable with these conclusion as it can be difficult to obtain the exact immediate response if investors read the news at different times, which is in line with conventional models that don't allow for existence of noise traders.

2.2.3 Can the public mood on Twitter affect the stock market?

Research projects based on Twitter investigate the mechanism of this microblogging forum as a source for stock return fluctuations in another dimension. As Zhang, Fuehres, and Gloor (2011) describes it: "The rising popularity of Twitter gives us a novel way of capturing the collective mind up to the last minute" (p. 56). A key concept of Twitter is the number of followers which is a measure of popularity, and consequently a way to influence many people and spread ideas and opinions (Zhang et al., 2011)

Two similar studies were done by Bollen, Mao, and Zeng (2010) and Zhang et al. (2011) where the main focus was to analyze the Twitter mood in the tweets for several users on the platform to capture the collective minds and investigate the effect on stock market indices like Dow Jones Industrial Average (DJIA), Nasdaq and S&P500. Their findings indicated a relationship between Twitter-activity and financial studies. Both studies based the content on whether the message was in a positive or negative form, and further systematized the content into subcategories.

Zhang et al. (2011) used mood words to systemize the tweets as emotional tags, like "fear", "worry", "hope", "happy" etc., and found that emotional outbursts on Twitter of any kind can predict how the stock market will be doing the next day. According to Zhang et al (2011) when the users express a lot of hope, fear and worry (high levels of emotional sharing on Twitter), they found that the DJIA goes down the next day, and opposite for less emotional sharing. This study indicates certain trends, especially related to tweets of hope and fear. That said, Zhang et al (2011) state that the results are preliminary, and more work is needed.

Bollen et al. (2010) divided the content into dimensions like Calm, Alert, Sure, Vital, Kind and Happy, and investigated whether the mood was correlated or could predict the value of the DJIA. According to this study, changes in the mood dimensions matched the shifts in the DJIA values, but in some delayed time frame (3-4 days later). Bollen et al. (2010) found that the calmness of the public mood is a better predictor of the DJIA rather than general levels of positive sentiment. This indicate that the prediction of the DJIA is better done with subcategories.

Sprenger, Sandner, Tumasjan, and Welpe (2014b) point out some limitation regarding the data collection in the studies done by Bollen et al. (2010) and Zhang et al. (2011). Both studies use randomized subsamples of all available tweets and according to Sprenger et al. (2014b) the majority of the content of all tweets may not be stock related, the conclusion cannot be certain that the stock specific information in the tweets are associated with the financial indicators. Further, we cannot draw assertions based on single stocks in these studies because they look at indices.

Sprenger et al. (2014b) suggests that there is more need for research focusing on stock-related tweets and how they are related to the market prices of these public companies. This argument is supported by Das and Chen’s (2007) findings of a stronger correlations between aggregated sentiment and index returns rather than individual stocks. Das and Chen (2007) further suggest development of message investigations because board messages are of different qualities and not standardized, which could complicate the process of extract sentiment from text. In their study they use digital computer programs to systematize the text in the message boards.

Sprenger et al. (2014b) investigate the effect of Twitter on individual stocks, comparing S&P500 stock prices and company specific news published on Twitter[12]. This study takes into account the structure of Twitter as a forum for social influence regarding the diffusion and processing of information, which is different from traditional message boards like Antweiler and Frank (2004) study. As to the mechanism behind Twitter, its ability to weigh information such that the attention is directed and generated to more valuable tweet, and that users receive more attention if they tweet above-average quality information (Sprenger et al., 2014b).

Results from Sprenger et al. (2014b) suggests that the message volume is less related to the stock returns compared to the quality and content (bullishness or sentiment) of the messages. According to Sprenger et al (2014b) if a user provides investment advice of high quality, he also receives more attention as previous argued. This means that the study can identify certain users in the microblogging community, but there is no simple rule to identify information of high value. To summarize, the study suggests that increased bullishness in the content of the messages can lead to an increase in stock prices as this is a proxy for positive investor sentiment.

In line with Sprenger, Sandner, Tumasjan, and Welpe (2014a) the return after news published on Twitter differs substantially to whether the news are good or bad. For negative news, the change in price happened largely on the actual event day, but positive news tend to leak and is already incorporate into the price before the information is officially announced by the company. Sprenger et al. (2014a) argue that this can suggest that positive news rarely comes as a surprise because of a tendency of a more widespread information leakage before positive news.

By using earnings announcements as benchmarks for news, Sprenger et al. (2014a) found that discussions on Twitter is a mirror to actual external news. The content of Twitter can

[12] The study analyzed 250,000 tweets on a daily basis using computational linguistics and study the relations between tweet sentiment and stock returns, message volume, trading volume, disagreement and volatility. The study considers the actual message content and sentiment, and not the message volume and word counts. Further, looking at explicit stock microblogging messages instead of all available messages on Twitter like prior studies, they mean that they can predict the validity of stock microblogs without noise.

therefore be used as a source for company specific news events that can be used in financial research.

2.2.4 Trump + Twitter

There are few studies that consider the effect of Donald Trump's company-specific tweets on the stock market. Born, Myers, and Clark (2017) studied in their working paper 15 company-specific tweets regarding 10 companies in his election period. The results indicated that both positive and negative tweets lead to abnormal return for the companies on the event date, and that the cumulative abnormal return disappeared after about three to five days.

Juma'h and Alnsour (2018) studied effect of tweets regarding immigration, employment, tax reform, finance, the economy and companies during Trump's campaign period and his first year of presidency. In the study 58 company-specific tweets were investigated, and they found that the tweets in the sample slightly moved the company's stock price. Brans and Scholtens (2020) investigated the sentiment from positive to negative according to SentiStrengt scores[13] on about 100 company-specific tweets on the event window (0,1) using the market model. Both studies found, in line with general studies of sentiment, that negative tweets have a greater response then the positive tweets.

2.3 Hypothesis development

Former general research of the relationship between (social) media and stock market reactions has focused the effect from several users on Twitter and how their communication can be seen in parallel to changes in the financial market. From these studies, the question of whether the same tendencies can be seen when one of the most famous and powerful user of Twitter tweets.

As mentioned in the previous section similar studies on Trump have been conducted, focusing on the effect of company-specific tweets and the following stock price reaction. Our study

[13] SentiStrengt is an automatic sentiment analysis of social web texts estimating the strength of positive and negative sentiment. -5 indicate extremely negative sentiment, 0 is neutral and +5 indicate extremely positive.

will have similarities with these studies but will investigate the relationship with a longer period of investigation and data.

There are established algorithms like the “Trump and Dump Bot” (T3, 2020), who short stock predictions by identify tweets when a publicly traded company is mentioned, analyzing the sentiment and decide to short the stocks of the company mentioned if the tweet demonstrate a negative sentiment. The algorithms operate in real-time and trade on the immediate effects. However, we are interested in the more “long term” effect because we will focus on the consequence for the targeted companies and investors, and not for active traders. With this background we form the hypotheses for this study. The main research question in this study is:

Research question: How is a publicly traded company affected by being targeted in President Donald Trump company-specific tweets?

The research question is based on knowledge that important financial information to be found in the media, and Twitter-communication can move the market accordingly to market efficiency (Antweiler & Frank, 2004; Bollen et al., 2010; Born et al., 2017; Sprenger et al., 2014a; Zhang et al., 2011). Using Twitter, Trump points the attention towards certain companies and according to Barber and Odean (2008) attention can affect investors and companies respectively.

It’s expected that financial outcomes react different to positive and negative news in markets where investors are risk averse (Barber & Odean, 2008; Sprenger et al., 2014a). Previous studies on Trump, Twitter and stock price reactions found different market reactions based on sentiment (Born et al., 2017; Brans & Scholtens, 2020; Juma’h & Alnsour, 2018). This leads to the study’s first hypotheses:

Hypothesis 1a: A positive tweet from President Donald Trump affects the company's stock price.

Hypothesis 1b: A negative tweet from President Donald Trump affects the company's stock price.

An extension to the assumption of risk averse investors and different financial outcomes, we make a statement for in which direction we expect to see an abnormal effect of positive and negative news, respectivly. These statements are based on previous research findings and make up the study's second hypothesis:

Hypothesis 2: The company's abnormal stock return is affected differently if the tweet is categorized as positive versus negative.

> **2a**: Positive tweets will have a positive effect on the abnormal return on the company's stock.
>
> **2b:** Negative tweets will have a negative effect on the abnormal return on the company's stock.

How the targeted companies are affected by the tweets is related to the message quality and content which supports a closer examination of what true meaning of what Trump expresses (Das & Chen, 2007; Sprenger et al., 2014b). In line with Bollen et al. (2010) and Zhang et al. (2011), we systematize the messages into subcategories of sentiment to investigate what kind of emotional outburst in Trump's tweets leads to a stock reaction. This is an extension previous research on the relationship. Based on previous findings with direction of abnormal return, the hypotheses also make statements of expected direction. The third hypothesis is:

Hypothesis 3: The company's abnormal stock return if affected according to categories on sentiment.

> **3a:** Tweets categorized as teaser will have positive effect on the abnormal return on the company's stock
>
> **3b:** Tweets categorized as threat will have negative effect on the abnormal return on the company's stock
>
> **3c:** Tweets categorized as positive private opinion will have positive effect abnormal return on the company's stock

3d: Tweets categorized as negative private opinion will have negative effect abnormal return on the company's stock
3e: Tweets categorized as positive public information will have positive effect abnormal return on the company's stock
3f: Tweets categorized as negative public information will have negative effect abnormal return on the company's stock

Research found that stocks can be affected differently after an event, based on company size and the share of individual investors (Tetlock, 2007) and that abnormal return could be explained differently by certain company characteristics (Kothari & Warner, 2007). Based on the lack of previous studies regarding Trump´s company-specific tweets and possible differences in stock price reaction based on the size of the company targeted, the studies fourth hypothesis is:

Hypothesis 4: The company's abnormal stock return is less affected as the company's market cap increases.

Furthermore, in line with Kothari and Warner (2007) argumentation regarding firm characteristics, it's reasonably to believe that some industries are more affected then others. We therefore look further into if any industries are more affected, or if there is possible to identify any trends. The fifth hypothesis therefor control for industry groups:

Hypothesis 5: The company's abnormal stock return is affected differently according to industry.

Finally, in line with other studies (Antweiler & Frank, 2004; De Long et al., 1990; Neuhierl et al., 2013; Sprenger et al., 2014b; Tetlock, 2007) we present an additive analysis on stock volatility and trading volume to highlight the impact of the tweets from multiple sides and give dept to our research question and support our findings.

3 Methodology and Data Collection

Event studies are typically applied to study reactions on the stock market and company value caused by an event and, hence, a natural approach to investigate this study' research question. Figure 3.1 visualize the timeline of the event study and provide an overview of what kind of decisions we have to make and what data to collect (MacKinlay, 1997).

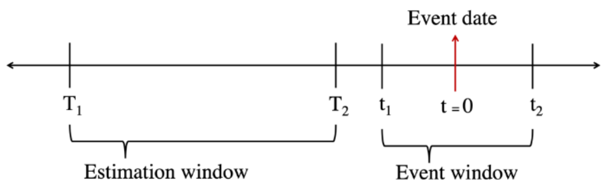

Figure 3.1: Timeline of an event study

First, we identify the event of interest. Second, we calculate the normal or expected stock return for the companies in the sample. Third, we calculate and analyze the abnormal returns and/ or the cumulative abnormal return around the event date (MacKinlay, 1997). It is also common to use a regression for a further analysis of the cumulative abnormal return. This chapter will provide an explanation of the methods and justification of choices that are made to proceed the research.

3.1 Data and sample

3.1.1 Twitter

Twitter is a many-to-many real-time unfiltered communication platform which covers a wide array of information and can serve the financial markets in multiple roles. The public timeline on Twitter is a comprehensive real-time information stream. It is a forum for discussion and a platform for sharing information and ideas' in which investors and other financial professionals can use for trading strategies (Sprenger et al., 2014b).

3.1.2 President Donald Trump

Donald John Trump (born June 14, 1946) is the 45th and current president of the United States of America. Before entering politics and being elected president, he was a television personality and businessman.

In the January 2017 inaugural speech Trump (2017) announced the economic strategy called "America First" and addressed: "Every decision on trade, on taxes, on immigration, on foreign affairs, will be made to benefit American workers and American families.". In the speech President Trump refered to the "American carnage" as "rusted-out factories scattered like tombstones across the landscape of our nation" and continued on saying: "One by one, the factories shuttered and left our shores, with not even a thought about the millions upon millions of American workers left behind" by a political "establishment" that "protected itself, but not the citizens of our country."

The President's economic strategy during his first three years (2017-2019) was boosting economic growth by tax cuts and additional spending, both with significantly increased federal budget deficits (CBO, 2020).

3.1.3 Presidents on Twitter

Barack Obama brought Twitter to the forefront of American politics during his 2008 presidential campaign, proving how it could be used effectively to communicate with likely voters (Sprenger et al., 2010). He was a pioneer using social media as a president, using Twitter to communicate rally location, donation options and positive messaging. However, Trumps content is the complete opposite.

Figure 3.2: Screenshot from tweet from the Presidents Twitter account (realDonaldTrump, 2017).

The President's Twitter career began before his presidency. Donald Trump´s Twitter account was opened in March 2009 and has since then sent almost 42,000 original tweets and retweeted about 6,000 tweets (Trump Twitter Archive, 2020). The tweets comment on a variety of topics, and one of the more frequent topics is people and companies that he believes are not doing what they should be, salute what likes and generally share his opinions about everything and everyone, especially companies in line with his political strategy "America

First”. He targets all kinds of companies, whether it´s aircraft manufactures like Boeing, drug manufactures like Pfizer, consumer cyclical companies like Walmart or car manufactures like Ford or General Motors.

In a television interview in November 2016, after winning the election, Trump stated that his use of social media would be “very restrained, if I use it at all” (Trump, 2016). Since Trump’s election in November 2016 the average has been of more than 10 tweets a day to his 68 million followers[14] (Newburger, 2019). As the President of the U.S. Trump has political influence and executive powers, and he has access to information not accessible to everyone. Therefore, it is reasonable to assume as Juma’h and Alnsour (2018) states in their research: “the information shared through the President’s Tweets can be used as a forecast to changes in the U.S. economy, financial markets, and targeted companies.” (p.101). As seen in figure 3.2 the number of followers increased during the candidacy period and increased even more rapidly after Nov 8, 2016 when he was announced president. During his presidency the number of followers has increased by 423 %.

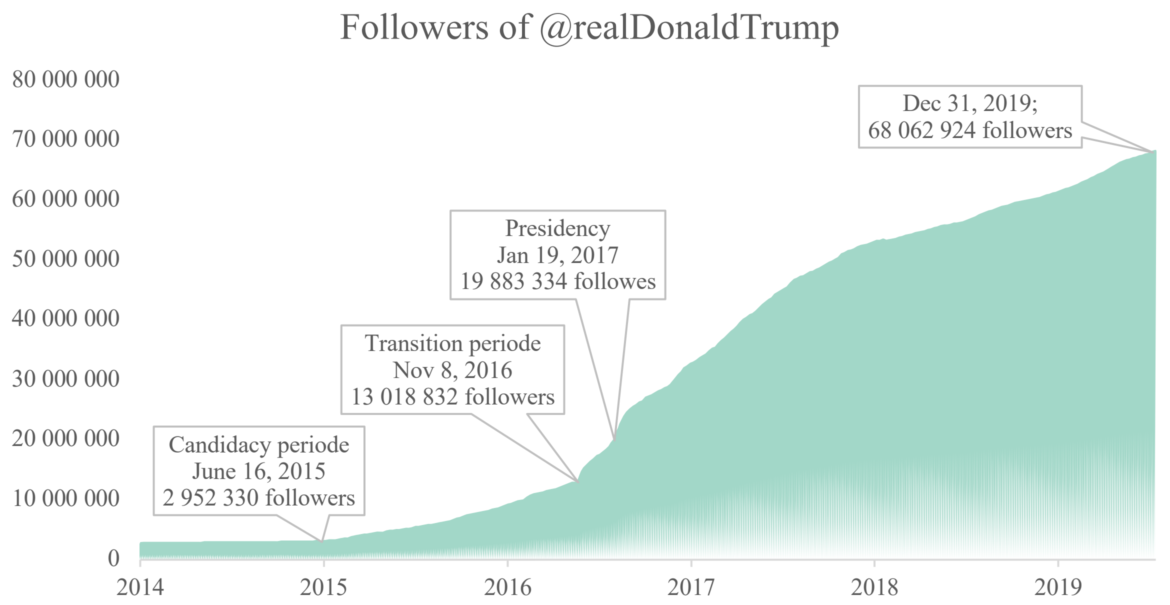

Figure 3.3: Visualization of number of followers of the account @realDonaldTrump on Twitter from 2014 to 2019. .
Source: Trackalytics (2020).

[14] Per Dec 31, 2019

3.1.4 Identify the events in the study

The events in this study is the tweets written and posted by President Donald Trump. The period of interest is from when he won the presidential election November 8, 2016 to December 31, 2019 when this study started. We collected the tweets from this period and extracted tweets mentioning publicly traded companies. We have identified the events of interest and the dates of these tweets are referred to as t=0 (MacKinlay, 1997). A more specific review of the Twitter data collection is presented in the next section.

Collection of Twitter data

The data consist of the tweets from the Twitter account *@realDonalTrump* within the period of interest that include the name of a publicly traded company. We used the search engine Trump Twitter Archive[15] to extract the tweets (Trump Twitter Archive, 2020).

First step of data collection was to extract and convert the 14,202 tweets and retweets from the Trump Twitter Archive to Microsoft Excel for processing (January 5, 2020). From the first sample we managed to extract 579 tweets mentioning publicly traded firms. All tweets mentioning non-publicly firms were excluded.

One of the most frequent topics of President Trumps tweets is his opinions about the press[16]. The impact of the tweets on the stock market is complicated by the President's general relationship with the media we therefore exclude media companies from the sample. After excluding the media companies, the sample contains 184 tweets.

At this point, the sample includes tweets mentioning publicly traded companies, excluding media companies. To prevent the sample from being biased and to capture the real effect of the tweet, we went through the 184 remaining tweets again. Securing an unbiased sample only

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[15] An archive with Trumps tweets updated hourly with number of retweets and likes. The archive also contains deleted tweets.

[16] Within our sample period Trump frequently mentions media, individual journalists, news outlets and journalistic sources. Examples of this is Washington Post mentioned 61 times, often referred to as "The Amazon Washington Post". CNN was mentioned 181 times, mostly referred to as "FAKE NEWS CNN". The New York times is mentioned 84 times, mostly referred to as "The Failing New York Times".

the most significant tweets were included, with either a strong positive or negative content. We excluded 53 neutral tweets, and the sample after this exclusion consists of 131 of President Trump's tweets.

The stock exchange is used to reduce the sample even further. Most of the companies included are on the NYSE or Nasdaq, which is why we use these as a basis for the sample. This led to four companies excluded and their tweets accordingly. These companies were Bayer AG, BMW, Mazda Motor Corporation and Softbank which are traded on other exchanges. The sample now consists of 124 tweets.

Because of the limitation of 140/280 characters per tweet, some of the tweets consist of 2-3 separate tweets that have been posted in direct continuation of the previous, as seen in the example mentioned below. Where, in most cases, the former tweet ended with three full stops (…) and the following tweets starts the same way. These sets of tweets will be compiled and presented together as one.

> *"Very disappointed with General Motors and their CEO Mary Barra for closing plants in Ohio Michigan and Maryland. Nothing being closed in Mexico & China. The U.S. saved General Motors and this is the THANKS we get! We are now looking at cutting all @GM subsidies including...."* (Nov 27, 2017)

> *".... for electric cars. General Motors made a big China bet years ago when they built plants there (and in Mexico) - don't think that bet is going to pay off. I am here to protect America's Workers!"* (Nov 27, 2017)

Also, tweets published within the same day targeting the same company will be compiled as one event. As we can read in the tweets the messages may also be connected and a response to his own tweets. After correcting this, the sample consist of 89 events, with 23 different companies. In appendix 1 there is a list of all companies within the study and in appendix 2 all events are listed[17].

[17] All tweets listed in full text in appendix 12.

Adjusting for time

The Trump Twitter Archive collects the metadata on each tweet via Tweepy and Twitter´s official API, which returns a timestamp date in Greenwich Mean Time (GMT). The Trump Twitter Archive site then translate the raw data (in GMT) to Eastern Standard Time (EST), which is 5 hours behind. The trading hours of New York Stock Exchange (NYSE) is from 9:30am to 4:00pm EST.

It is important to mention that not all the tweets come with location data and with Trump travelling through different time zones, not all the timestamps are accurate. Trump also posts tweets 24/7. Tweets posted outside trading hours and on non-business days are adjusted timewise so that we capture the effect on the correct trading day, as presented in table 3.1.

Table 3.1: Trading day adjustment

Day	Time interval	Corrected day of event
-1	4pm to 12pm	0
0	12pm to 9:30am	0
0	9:30am to 4pm	0
0	4pm to 12pm	+1

Note: If a tweet is posted after 4pm the date of event is corrected to the day after. For posts tweeted between 12pm and 4pm, the event day will be the same day. This is not a perfect system but will after consideration lead to the most precise results

We also corrected tweets posted on non-business days (Saturday, Sunday and holidays). Tweets posted on non-business days was corrected with event date next business day. In appendix 2 all events are adjusted for time, with correct trading day.

Content

As discussed in the previous section, the tweets were categorized in positive, negative and neutral. After removing the neutral, the finale sample of remaining 89 tweets and they are distributed as listed in table 3.2. To secure correct content category, the categorization was done twice. Examples of tweets in both content categories are listed below.

Table 3.2: Distribution of events based on content

Content in tweet	# of events
Positive	54
Negative	35

Example of positive tweet: *"Walmart a great indicator as to how the U.S. is doing just released outstanding numbers. Our Country unlike others is doing great! Don't let the Fake News convince you otherwise."* (Aug 15, 2019)

Example of negative tweet: *"What do I know about branding maybe nothing (but I did become President!) but if I were Boeing I would FIX the Boeing 737 MAX add some additional great features & REBRAND the plane with a new name. No product has suffered like this one. But again what the hell do I know?"* (Apr 15, 2019)

By doing the categorization, and later the sentiment categorization manually and not with digital analyzing tools we secure correct categorization. Because of the character limitation on Twitter Trump often skip commas which make tweets difficult to interoperate. He also writes using sarcasm and "slang" which analyze tools may not translate and therefor categorize correctly. We secured the loss of validity due to human mistakes by checking the classification multiple times. This way sorting the data differs from other studies where Twitter data are collected and categorized using digital tools (Bollen et al., 2010; Brans & Scholtens, 2020; Zhang et al., 2011)

Earnings announcements (confounding events)

To reduce the possibility that stock prices in the event window are affected by other announcements of information other than what we investigate, events with confounding earning announcements until five days prior to event date are excluded.

The use of earnings announcements as a control for confounding events is supported by Sprenger et al. (2014) who provided clear evidence that investors react to new information from earnings announcements. In our research we need to distinguish the investors' reaction to these types of announcements and the "announcements" from Donald Trump's tweets.

The dates for earning announcements was found on the companies' own press release information on their website for investors. We collected the earnings announcements from September 2016 to January 2020 for all companies represented in the sample. See appendix 3 for all dates. In table 3.3 events with confounding earning announcements is listed.

Table 3.3: Events with confounding effects

Ticker	Event number	Event date	Earning announcement
TM	28	08.04.2017	08.04.2017
NOVN	45	07.19.2018	07.18.2018
F	47	07.26.2018	07.25.2018
HOG	64	04.23.2019	04.23.2019
TWTR	65	04.24.2019	04.23.2019
GOOGL	69	07.26.2019	07.25.2019
WMT	74	08.16.2019	08.15.2019
FCA	83	10.31.2019	10.31.2019
GM	84	10.31.2019	10.29.2019
GM	86	11.01.2019	10.29.2019
WMT	87	11.14.2019	11.14.2019

After removing these events from the sample, the sample consists of 78 events.

Adjusting the sample for cross-sectional independence

According to Brown and Warner's (1985) assumptions for event study we need to secure that the sample is cross-sectional independent. Cross-sectional dependence caused by common events for single industries or common time periods (MacKinlay, 1997) are not applicable to our case, however we observe that Trump tweets about companies more than once. This could lead to an issue of cluster effects in our study with overlap of event windows. If these tweets are close together, we must assume dependence between these events because it can be difficult to separate effects of one tweet from the other. Brown and Warner (1985) and MacKinlay (1997) recommend evaluating the severity and the degree of cluster to see if actions should be made.

We found that cluster effects are problematic for several events where they appear one or two days consecutively. We observe that if a company is targeted two days consecutively, then both tweets are negative, or both are positive. Following MacKinlay's (1997) advice to not aggregate the cumulative abnormal returns in the analysis in case of total clustering or make a portfolio of cluster events, we propose a middle ground with an analysis without the problematic events. To secure unbiased results and isolate the effect of a tweet we remove latter events from our sample which leads to an additional reduction in sample size by 10 observations[18]. Table 3.4 lists the latter events with overlapping event window which is removed from the sample.

Table 3.4: Events with cluster events

Event num	Ticker	Event date
4	UTX	12.01.16
8	XOM	12.13.16
30	MRK	08.15.17
37	AMZN	04.02.18
41	HOG	06.27.18
44	PFE	07.11.18
52	NKE	09.07.18
55	GM	11.29.18
59	TM	03.18.19
86	GM	11.01.19
89	AAPL	11.25.19

The sample now consists of 68 events.

3.2 Event study methodology

3.2.1 Calculation of the normal stock return

In this study we use T_1 = -250 days and T_2= -10 days as estimation window and makes the basis for the financial data collection. Our decision is based on several sources, as we found that the length of the window varies from different studies. However, the essence of the length is to have enough data on the stock to make a good estimate of the normal return. Brown and

[18] Event 86 is both affected by cluster effects and confounding effects.

Warner (1985) suggests that for each stock in the sample, we must have 30 daily returns at a minimum for the entire period of 250 days, and no missing data in the last 20 days. Also, the length of the estimation window provides independent data which is further explained under the market model in this section (MacKinlay, 1997).

We have chosen T_2= -10 days to prevent the data that we use to calculate normal return to be influenced by a potential effect of the actual event. This can happen if there is no gap between the estimation window and event window (MacKinlay, 1997). In that way, we prevent that both the normal and abnormal return will capture the impact of event and create bias estimates.

The event window is identified as the period over which the stock prices *may be affected* by the event. Data collected from this period will be examined and compared to the normal return estimated in the estimation window (MacKinlay, 1997). Deciding the event window is one of the final things we did using the collected data. We return with the assessments we took regarding length of event window in section 3.2.4 “Event window”.

Calculation of return

We retrieved the financial data from Yahoo! Finance, consisting of daily stock prices for the respective companies, from November 15. 2015 to January 30. 2020. With this time period we secure that we have sufficient data for the estimation window and post event date. To secure accurate calculated returns we use the adjusted closing price[19] for each stock (Reese & Robins, 2017)

We calculated the stock returns using the following formula 3.1 where we transform the prices into natural logarithm returns and obtain the continuously compounded daily returns.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

[19] Adjusting closing prices accurately reflect the stock's value after accounting for any corporate actions (Reese & Robins, 2017)

The observed price is label P, t is referring to time, P_t is the current stock price, and P_{t-1} is the previous stock price the day before t.

Model approaches

The normal return is the stock return in case no event happening (MacKinlay, 1997) and is calculated using theoretical models. For the rest of the study we will refer to *benchmark models*, which is different approach for the calculation of normal stock return.

As Fama and French (2004) explains all models are simplifications of reality and some models can capture the variation in the stock price and return better than others or capture other parts of the variation. Since it can be difficult to claim the models are wrong, but can capture different relationships, we decide to use several benchmark models in this study even if MacKinlay (1997) and Brown and Warner (1985) typically are in favor of the statistical model, market model, as a powerful methodology and a well-specified model under a wide variety of conditions.

We believe, that using different models can be a quality insurance, hence we will use both statistical and economic models. This way to monitor the results is supported by Kothari and Warner (2007) in how to prevent the Type I and Type II errors in test statistics in event studies. These guidelines have been essential to our study as we want to draw a conclusion based on our sample that should be correctly representing the population. The risk of making the errors are based on significance level but also assumptions of the sample and the tests we will use. This refers to the actual ability to detect abnormal performance when it is present, and assumption of well-specified statistical tests also connected to benchmark models.

The market model was used as the starting point to calculate normal return, and we followed up by using Capital Asset Pricing model (CAPM) and Fama-French three-factor model (FF3M) as two other benchmark models. CAPM and FF3M are *economic model*s that are not solely based on statistical assumptions but also concern assumptions based on investors' behavior as explained in section 2.1.3.

In the next sections we elaborate how to calculate normal and abnormal return for each benchmark model. However, explaining the cumulative abnormal return (CAR) will be done in general as there is no distinct difference in the approaches at this point.

Market model

The market model is built up to explain the relationship between the return of the company *i* at time *t* as a function of the market portfolio as a stable linear relationship (MacKinlay, 1997).

Formula 3.2 display the return for a specific company *i*:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3.2}$$

R_{it} and R_{mt} are the returns of stock *i* and the market portfolio respectively, in period t. Alpha, denoted α_i, represents the intercept and beta, denoted β_i, represents the slope parameter. The zero mean disturbance term is defined as ε_{it}, and the assumptions follows as:

$$E(\varepsilon_{it} = 0)$$
$$var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$$

The model is built on statistical assumptions that the stock returns are jointly multivariate normal and independently and identically distributed through time. These assumptions are strong, but according to MacKinlay (1997) is empirically reasonable in practice.

The market portfolio is represented by a broad-based stock index. We collect the market prices of the index for the same period as the length of the estimation period for the individual stocks in the sample (MacKinlay, 1997) and transform the prices into returns using equation 3.1. Further, to prevent the OLS estimated parameters to be bias and inconsistent, we use the same trading intervals (daily returns) for the stock returns and the index return (Brown & Warner, 1985).

When applying the market model, we run a simple regression based on each stock return and the index return to estimate of the model parameters. The normal benchmark stock return at time *t* is what we get from equation 3.3.

$$E(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i R_{mt} \tag{3.3}$$

Second, we obtain the abnormal return, denoted AR_{it}, for company *i* and the time *t*, by subtracting the benchmark return ($E(R_{it})$) from the realized stock return observed in the market at time t (R_{it}) as explained by formula 3.4 (MacKinlay, 1997):

$$AR_{it} = R_{it} - E(R_{it}) \tag{3.4}$$

Assumed under the null hypothesis, is that conditional on the event window market return, the abnormal returns will be jointly normally distributed with a zero conditional mean and a conditional variance $\sigma^2(AR_{it})$, where:

$$\sigma^2(AR_{it}) = \sigma_{\varepsilon_i}^2 + \frac{1}{L}\left[1 + \frac{(R_{mt} - \hat{\mu}_m)^2}{\hat{\sigma}_m^2}\right] \tag{3.5}$$

The length of the estimation window is denoted L, R_{mt} is the return of the market at time t, $\hat{\mu}_m$ is the true value of the mean market return, and $\hat{\sigma}_m^2$ is the variance of the market (MacKinlay, 1997). The second term of the variance represent the sampling error in alpha (α_i) and beta (β_i), which is common for all the event window observations and leads to serial correlation of the abnormal returns, even though the true disturbances are independent through time. This sampling error will vanish when the length of the estimation window is long and the term will approach zero, leaving the variance of the abnormal return as $\sigma_{\varepsilon_i}^2$, and further the abnormal return observations will be independent through time (MacKinlay, 1997). This supports our choice of estimation window.

The distribution of the sample abnormal return of a given observation in the event window is

$$AR_{it} \sim N\left(0, \sigma^2(AR_{it})\right)$$

This means that when we make statistical inferences, we will use the normal distribution table to find the critical values.

The choice of index as a proxy for market return

Following this benchmark model is the choice of index to represent the market return. In the United States the S&P 500[20], DJIA[21], Russell 1000/2000/3000[22] and Nasdaq Composite[23] are the most broadly followed indices. In addition to these indices there are about 5,000 others that make up the U.S equity market (Bloomberg News, 2017).

When choosing what index to include in the market model, we include the index representing the movement of the companies represented in the sample. Since one of the requirements of the companies is that the stocks are traded at either NYSE or NASDAQ, the index chosen needs to be representable for the movement in the U.S stock market.

There are many similarities between the DJIA and S&P 500, both are much used as American stock market indices. The main difference between them is the number of companies included and the weighting methodology. Since the companies in our sample are all companies with a great market cap, the Russell 3000 is not representable since it includes both the large-, mid-

[20] *The Standard & Poor 500* (S&P 500) is a stock market index based primarily on market capitalizations of the 500 largest publicly traded companies in the United States (the U.S), but a constituent committee also consider other factors including liquidity, public float, sector classification, financial viability, and trading history. The S&P 500 index is one of the most commonly followed equity indices and is considered to be one of the best representations of the stock market in the U.S. (Bloomberg, 2020d).

[21] *The Dow Jones industrial Average* (DJIA) is a price-weighted average of 30 largest publicly traded companies in the U.S stock market (Bloomberg, 2020a).

[22] *The Russell 3000* index is a market index composed of 3,000 large U.S companies, based on the market capitalization. The index represents approximately 98 % of the investable U.S equity market (Bloomberg, 2020c). The Russel 2000 index measures the performance of the smallest 2,000 companies in the Russell 3000 index, representing about 8 % of the Russell 3,000 total market capitalization (Bloomberg, 2020b) and the Russell 1000 includes the biggest 1,000 companies in the Russell 3000 index.

[23] The Nasdaq Composite Index is the market capitalization-weighted index of over 3,300 common equities listed on the Nasdaq stock exchange. The Nasdaq Composite index is composed of about 50 % technology companies (Chen, 2019).

and small cap stock. The Nasdaq Composite is not representable of the data included in this study because the index is dominated with technology companies.

The majority of companies in the sample are included on the S&P 500 and based on the composition of the index we choose to use the S&P 500 as reference index in the market model.

Capital Asset Pricing model

In CAPM the expected return of a stock is determined by its covariance with the market portfolio, and defines the normal return of a stock for company i, as

$$R_i = r_f + \beta_i(r_m - r_f) \tag{3.6}$$

Where r_f represents the risk-free rate, beta β_i is the slope and represents the sensitivity of stock i. The market risk premium, denoted $(r_m - r_f)$, where r_m represents the market return.

To make an estimate on the beta coefficient, the asset price relationship is rearranged to where the dependent variable is the *excess* return as the equation 3.7 explains:

$$E(R_i - r_f) = \hat{\beta}_i * (r_m - r_f) \tag{3.7}$$

In CAPM the assets excess return is completely explained by the risk premium and beta which implies that the intercept in a time-series regression will be zero for all assets. This intercept is Jensen's alpha, denoted α_i (Fama & French, 2004).

$$E\left(R_{it} - r_{ft}\right) = \alpha_i + \hat{\beta}_i * \left(r_m - r_f\right) + \varepsilon_{it} \tag{3.8}$$

The excess is because CAPM requires the return of the asset to be above the risk-free rate which is based on the level of the risk of the asset compared to the market portfolio (which has a beta coefficient of 1). As this follows, a difference between the statistical and the economic models is that we look at abnormal return and excess abnormal return, respectively.

The excess abnormal return is calculated by subtracting the expected benchmark excess return from the realized excess return observed in the market as the equation 3.9:

$$AR_{it} = (R_{it} - r_f) - E(R_i - r_f) \tag{3.9}$$

Data collection for CAPM

We collected the data of risk-free rate and market premium from Kenneth French Data Library (French, 2020a) for the estimation period, where there is an updated list of daily returns on US. Research returns listed back to the July 1, 1926[24].

Fama-French Three-Factor model

Since the FF3M is an extension of CAPM, the first part of the equation of pricing relationship is similar. In addition to the market risk premium, the model also contains the independent variables Small-minus-Big, denoted SMB_t and High-minus-Low , denoted HML_t, at time t. The FF3M is explained by equation 3.10:

$$R_{it} = r_f + \beta_{i1}(r_m - r_f) + \beta_{i2} * SMB_t + \beta_{i3} * HML_t \tag{3.10}$$

To estimate the excess return, we run a multiple regression on this rearranged relationship and obtain estimates of three beta coefficients.

$$E(R_{it} - r_f) = \hat{\beta}_{i1}(r_m - r_f) + \hat{\beta}_{i2} * SMB_t + \hat{\beta}_{i3} * HML_t \tag{3.11}$$

The same for the time-series regression of excess return in FF3M is that the intercept is also zero for all assets, which follow this regression (Fama & French, 2004):

$$E(R_{it} - r_{ft}) = \alpha_i + \hat{\beta}_{i1}(r_{mt} - r_{ft}) + \hat{\beta}_{i2} * SMB_t + \hat{\beta}_{i3} * HML_t + \varepsilon_{it} \tag{3.12}$$

[24] The risk-free rate is the one-month treasury bill rate (from Ibbotson Associates). The market return (r_m) is the value-weight return of all CRSP firm incorporated in the USA and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares and price the beginning of t, and good return data for t (French, 2020a).

The excess abnormal return is obtained by subtracting the benchmark excess return from the actual excess return observed in the market at time t:

$$AR_{it} = (R_{it} - r_f) - E(R_i - r_f) \tag{3.13}$$

Data collection for FF3M

We collected the return data on the addition variables SMB and HML at Kenneth French' data library for the estimation period as well as the data for market return and risk-free rate (French, 2020b). The explanation of SMB and HML can be found under multifactor models in section 2.1.3.

3.2.2 Calculation of the cumulative abnormal returns

In order to draw overall inferences for Trump's tweets, the abnormal returns are aggregated both through *time* and *across securities* (Brown & Warner, 1985; MacKinlay, 1997). The formula for aggregating the cumulative abnormal return (CAR) through time is seen in equation 3.14.

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it} \tag{3.14}$$

CAR is defined as the sum of the abnormal returns for stock *i* from t_1 to t_2 AR_{it}, denoted $CAR_i(t_1, t_2)$, which results in an individual CAR for each event in the sample with the length of event window. The variance of the CAR is given in equation 3.15.

$$\sigma_i^2(t_1, t_2) = (t_2 - t_1 + 1)\sigma_{\varepsilon_i}^2 \tag{3.15}$$

The horizon length, denoted $(t_2 - t_1 + 1)$ is the length of the event window and the total number of days (including day 0 which is the event day) (MacKinlay, 1997). Under the null hypothesis the distribution of CAR is as followed

$$CAR_i(t_1, t_2) \sim N(0, \sigma_i^2(t_1, t_2))$$

Further, since testing only single tweets is not meaningful in our study, we want to aggregate across events as well as test the average effect of the tweets. We aggregate CARs (across securities) by using the formula 3.16:

$$\overline{CAR}(t_1, t_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i\,(t_1, t_2) \tag{3.16}$$

When we include the cross-section aggregation with the time series $CAR_i(t_1, t_2)$ for each individual stock, we obtain the average cumulative abnormal return, $\overline{CAR}$, for the sample, N.

In equation 3.17 the variance of the $\overline{CAR}$ is shown, and the covariance terms are set to zero based on the assumption that the event windows of the N stocks in the sample do not overlap, as displayed in section 3.1.4 when the sample was adjusted for cross-sectional dependence.

$$var(\overline{CAR}(t_1, t_2)) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_i^2(t_1, t_2) \tag{3.17}$$

Further, the statistical inferences can be drawn of $\overline{CAR}$ using

$$\overline{CAR}(t_1, t_2) \sim N[0, var(\overline{CAR}(t_1, t_2))]$$

3.2.3 Significance tests

Finally, we make a statement for our overall effect of the tweets and we use both parametric and non-parametric test for this part of the analysis as it leads to a greater confidence in the results (Kolari & Pynnonen, 2011). The use of non-parametric tests can support our findings in the study if the assumptions in the parametric tests are somewhat not valid.

In the t-test the $\overline{CAR}$ is tested. We test the null hypothesis that the value of the average cumulative abnormal return is zero and the alternative hypothesis that the return is different from zero (MacKinlay, 1997).

$$H0: \overline{CAR} = 0$$
$$HA: \overline{CAR} \neq 0$$

The One sample Wilcoxon Signed Rank test is like the t-test but is based on the median instead of the mean.

$$H0: \widetilde{CAR} = 0$$
$$HA: \widetilde{CAR} \neq 0$$

If the null hypothesis is rejected, we find statistical evidence that the value is different from zero and that the tweets have an effect.

3.2.4 Event window

To identify the event window, no set rules were found in literature. MacKinlay (1997) explains that is common to use multiple days in this window, meaning that the window is larger than the actual period of interest, not just the event date. The length that we choose can affect the test results of the study and a short window is preferable. Brown and Warner (1985) states that the test statistics in event studies continues to be generally well-specified with an event window over more than one day but that the power of the tests decreases if the abnormal performance occurs over a longer interval.

As Brans and Scholtens (2020) states, the tweets often are statements of his feelings about the targeted company. So, after adjusting the sample for companies own earnings announcements, it is reasonable to believe that the content in the tweets are mostly noise and events will consequently have, if any, a short-term effect. To capture this effect the event window has to be short. Our expectation of a relatively quick response in the markets after event is supported by the sentimental theory by Tetlock (2007) and that news travel fast especially when studying the mechanism behind Twitter as a communication forum (Seiler & Rom, 1997; Sprenger et al., 2014b). On the other hand, if he contributes with exclusive and/or new information, we could expect to see more long-term and/or larger effects. We investigate this by presenting the aggregated CAR graphically and look for abnormal fluctuations in the return around event date, according to the EMT (Malkiel & Fama, 1970; Tetlock, 2007).

Figure 3.3 and 3.4 show the cumulative abnormal returns for each benchmark model for positive and negative events, respectively, from ten days prior the events and ten days after the events. Using these graphs, we are interested in seeing any patterns around event day.

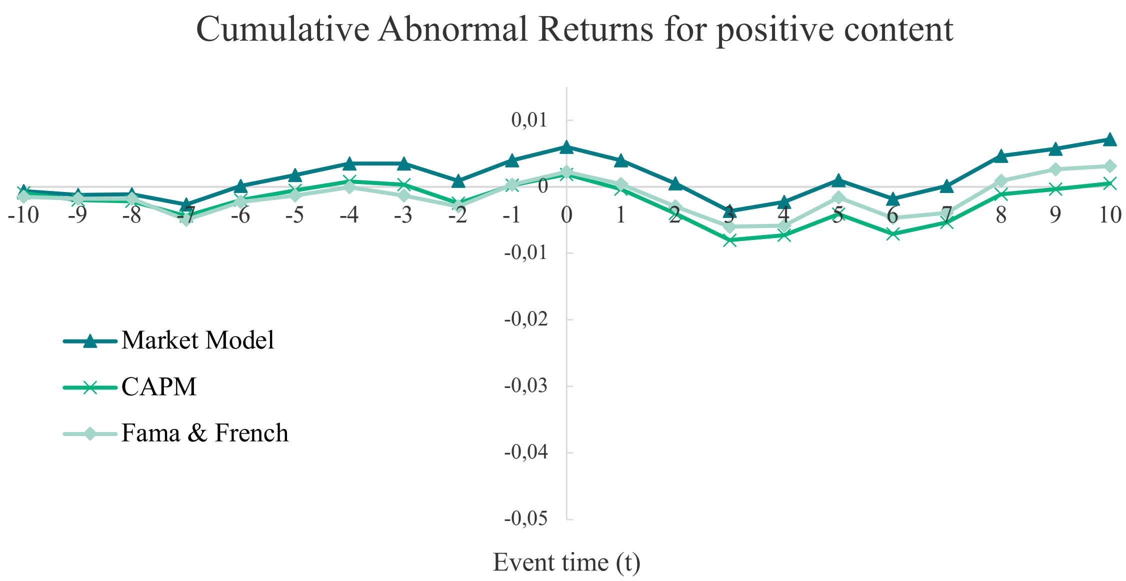

Figure 3.4: CAR for positive events from t_{-10} to t_{+10}. The different lines indicate all three benchmark models, n=40.

First observation of figure 3.3 and 3.4, we see that each benchmark model follow approximately the same patterns and we can agree that these models detect similar abnormal returns. CAPM and FF3M capture only excess abnormal return (Fama & French, 2004).

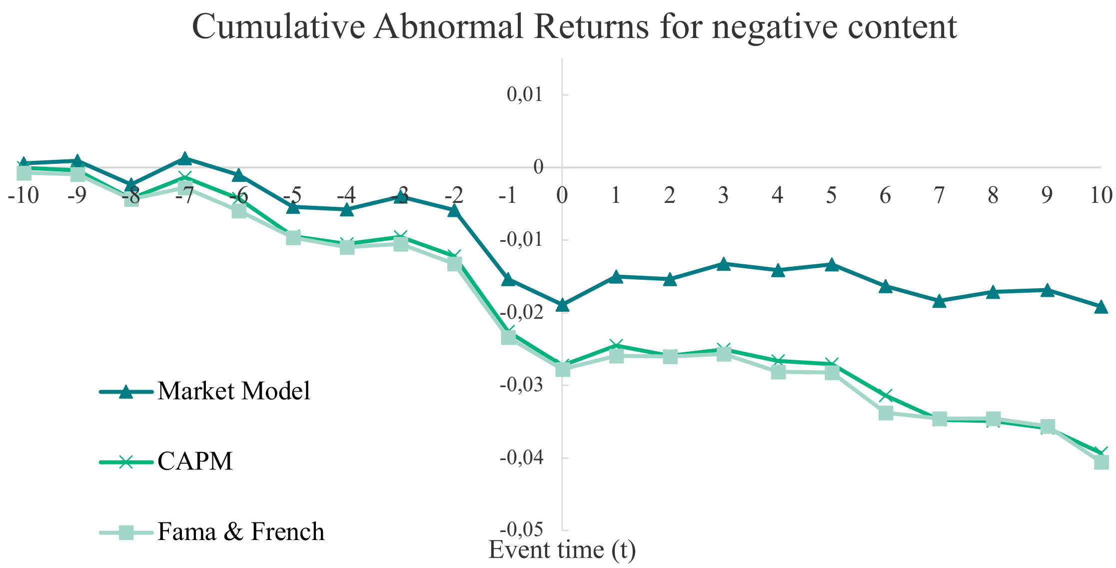

Figure 3.5: CAR for negative events from t-10 to t+10. The different lines indicate all three benchmark models, n=28.

For both positive and negative sample, we can verify the tendency of random walk in daily stock price fluctuations which is line with market efficiency, and a best guess of next day's stock price (or return) is a *close guess* to the previous day (Seiler & Rom, 1997), which is relevant for the positive subsample in figure 3.3. We observe a slight increase in aggregated CAR two days prior day zero, a small change in direction on day zero and a decline after that, but the changes are smooth and not steep. This could indicate that we see no effects for the positive tweets. Figure 3.3 based on positive subsample do not indicate any clear choice of event window.

For the negative subsample, in figure 3.4, we see more dramatic curves. However, the clearest effect happens before the actual event day in our study. We observe a decrease steeper between -2 and -1, before it slightly flattens out between -1 and 0, and change direction after day zero. This could indicate that Trump tweets after something happens in the market, even if we have controlled for earnings announcements in the sample. To prevent other potential news from interrupting our results we do not include -2 in our event window. As mentioned in section 3.1.4 when adjusting for time, the reaction from -1 to 0 may arise because of difference in time translation from GMT time when the tweets come without location data. Based on these figures it's difficult to conclude if the fluctuating in return is because of this or if the fluctuation is following a random walk.

We investigate this further by testing significance for several short windows within the period -2 to +2, and these results are presented in table 3.5. In appendix 4 the results from the normality and significance test of CAR for all benchmark models are listed.

Table 3.5: Normality and significance test of different event windows

		Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
		z-value	p-value	z-value	p-value	t-value	p-value
Total	(-1,1)	2.973	0.001***	-1.790	0.073**	-1.191	0.238
	(-1,2)	3.567	0.000***	-2.102	0.036**	-1.676	0.098*
	(0)	3.022	0.001***	-1.082	0.279	-0.594	0.554
	(0,1)	1.534	0.063**	-1.082	0.278	-0.767	0.446
	(0,2)	-0.108	0.543	-1.546	0.122	-1.450	0.152
Positive	(-1,1)	3.722	0.000***	0.027	0.979	0.689	0.495
	(-1,2)	3.963	0.000***	-0.699	0.485	-0.084	0.934
	(0)	2.787	0.003***	0.605	0.545	0.652	0.519
	(0,1)	-0.362	0.641	-0.470	0.638	-0.180	0.858
	(0,2)	1.756	0.040**	-1.505	0.132	-1.189	0.242
Negativ	(-1,1)	0.397	0.346	-2.550	0.011**	-2.413	0.023**
	(-1,2)	0.835	0.202	-2.505	0.012**	-2.566	0.016**
	(0)	2.018	0.022**	-2.186	0.029**	-1.609	0.119
	(0,1)	2.259	0.012**	-1.116	0.265	-0.873	0.390
	(0,2)	-0.017	0.507	-0.592	0.554	-0.845	0.406

Note: Test results from Shapiro-Wilk W test for normality and rank test and t-test for significance on CAR for different event window using FF3M for the total sample and the two subsamples. See appendix 4 for all benchmark models.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

The Shapiro-Wilk W test[25] is used to decide if we use the One Sample Wilcoxon Signed-rank test (signed-rank test) or the standard t-test. For the total sample both window (-1,1) and (-1,2) are statistically significant, with window (-1,2) having the lowest p-value. For the negative subsample we find statistically significant result for the three first windows using signed-rank test, and since the two first windows are normally distributed, we can find similar results for t-

[25] The Shapiro and Wilk (1965) test analyze the variance and detect normality (Coin, 2008). In the Shapiro Wilk W test, the null hypothesis is that there is normal distribution in the sample. Initially, we want to obtain normal distributions which means that we are interested in a large p-value of this test, hence we do not want to reject H0.

test as well. When testing the positive subsample, the results reveal no statistically significant effect of the tweets on the CAR in any length. The results are the same using the market model and CAPM.

Based on figure 3.3 and 3.4 and table 3.5 and discussion we argue the use of an event window of –1 day prior the event and 2 days after, which seem to capture abnormal performance around day zero. That said, it could be debatable whether there is a causal relationship between the tweet and the abnormal return due to the discussion above.

3.2.5 Robust analysis of the event window

After selecting the window of interest, we further investigate the robustness of the data in the sample by creating a plot for positive and negative events in figures 3.5 and 3.6. The sensitivity to the presence of outliers in the sample can pose a problem and should be consider when analyzing normality (Stock & Watson, 2015).

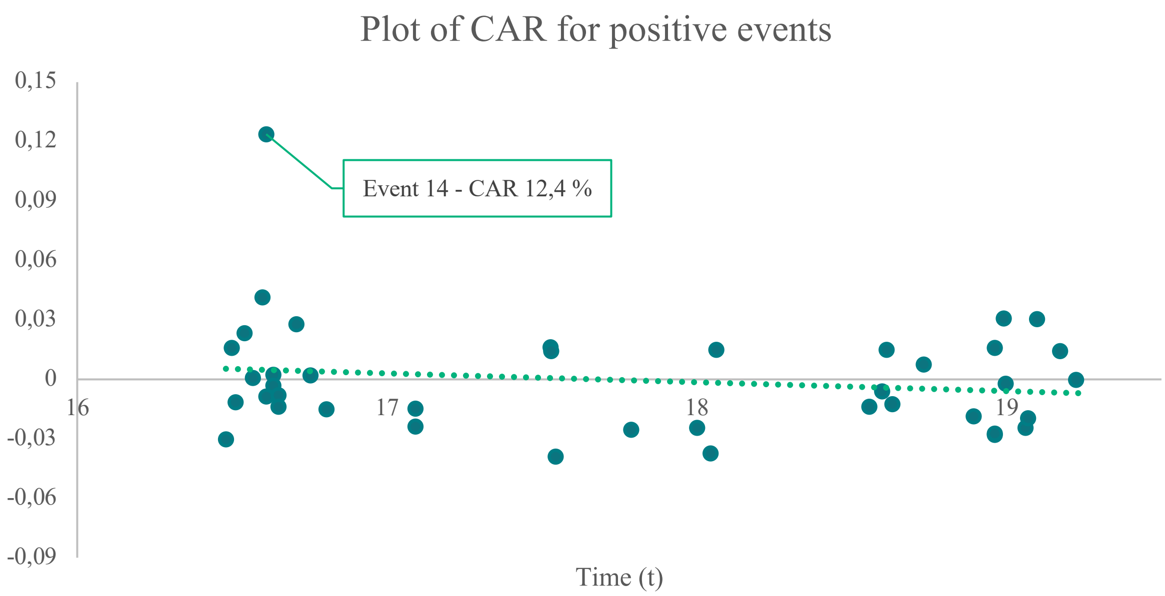

Figure 3.6: Plot of CAR for positive events using FF3M for event window (-1,2).

In figure 3.5 the plot of CAR for positive events with a trendline is displayed. We see here that the data points are more centered around zero, distributed relatively evenly above and below. The only observation that stands out is the event number 14, highlighted in the figure. The trendline indicated a decline in CAR, from above zero in the beginning of the in the period of study when he was elected president to below zero in the end of the period in 2019.

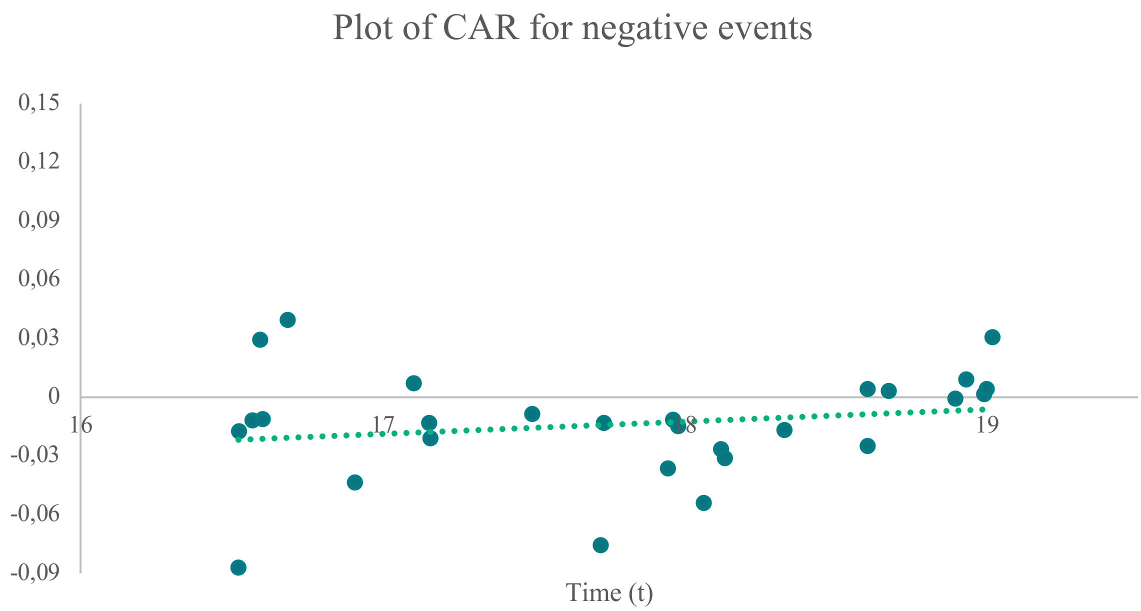

Figure 3.7: Plot of CAR for negative events using FF3M for event window (-1,2).

In figure 3.6 we see the plot of CAR for negative tweets. The trendline is slight upward sloping towards zero, indicating that the tweets may have less of a negative cumulative abnormal effect in the end of our sample period then in the beginning. Based on figure 3.6 we do not clearly identify any outliers, as we do in figure 3.5 for positive subsample.

As Coin (2008) enlightens, single extreme observations can lead to misleading results and possibly Type I and Type II errors as this point may not be representative for the main effect on the data. We must decide on whether this extreme observation represent a problem to obtain correct estimates in our study.

Distribution

Both histograms and normality tests are used to investigate the distribution of the total sample and the two subsamples.

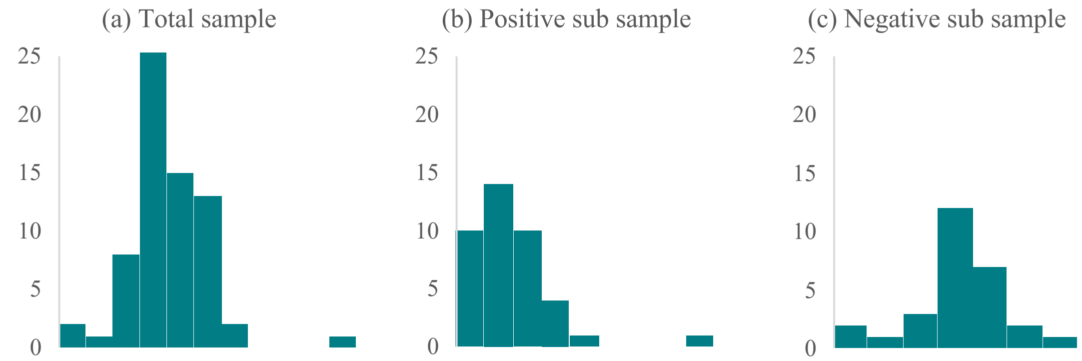

Figure 3.8: Histogram of distribution of CAR using FF3M for (a) the total sample n=68, (b) the positive subsample n=40 and (c) the negative sub sample n=28.

The distribution for the total sample and the positive and negative subsample is visualized in figure 3.7, supported by Shapiro Wilk W test for normality in table 3.6. For normality tests results using the other benchmark models see appendix group 10 regarding statistical inference (10.1 for the total sample, 10.2 for the positive subsample and 10.3 for the negative subsample).

Table 3.6: Normality test for all samples

	z-value	p-value
Total sample	3.567	0.000***
Positive subsample	3.963	0.000***
Negative subsample	0.835	0.202

Note: Results from normality tests using Shapiro Wilk W-test for event window (-1,2) using FF3M. Total sample (a) n=68, positive subsample (b) n=40 and negative subsample (c) n=28. See appendices 10 for all benchmark models.
** p < 0.10, ** p < 0.05, *** p < 0.*

The histogram for the total sample in figure 3.7 reveals long tails which indicates a non-normal sample and presence of outliers supported by the test results in the normality test.

A sample size of 68 CARs is not very large but could be large enough to show a tendency of the true distribution of the sample. According to Krithikadatta (2014) there is evidence that a sample of 30 can have a form of a normal tendency. When increasing the sample to 120 the normal distribution will not change drastically if the data is normal by nature and the mean will stay approximately the same, but the standard deviation will be slightly different (Krithikadatta, 2014).

We could claim that the data is approximately normally distributed as the negative subsample is normality distributed and that the existing of outliers could affect the larger sample normality results. Figure 3.7 (c) show the histogram for the negative subsample and the results are more alike a normal distribution but still heavy tails. The normality test results in table 3.6 reveal the same results, that the subsample is normally distributed.

Other problems arise with smaller sample sizes as it can be difficult to see the correct dispersion of the data (Krithikadatta, 2014), and that sample size represents the ability to make good estimates for the population. According to Kothari and Warner (2007) small samples can lead to difficulties regarding the OLS estimates[26] where you necessarily cannot rely on the central limit theorem or asymptotic results. Further, Brown and Warner (1985) enlightens the problems about skewness and kurtosis in smaller samples. For the positive subsample, displayed in figure 3.7 (b), the histogram stands out as skewed to the left. Both the histogram for the total sample and the positive subsample indicate at least one extreme observation.

Outliers

We used Excel as a tool to calculate the statistical definition of outliers based on the median and quartiles for each benchmark model[27]. See appendix 5 for the limits for inner and outer fences for the event window. The identified mild and severe outliers is listed in table 3.7. CAPM and the market model identified the same outliers, see appendix 6.

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[26] Ordinary Least Square (OLS) assumptions apply for linear regression models and is the basis of how to estimate the parameters in the model. These assumptions for statistical models are (1) linearity in the parameters (2) there is random sampling of observations (3) The conditional mean is zero (4) no multi-collinearity (or perfect collinearity) (5) there is homoscedasticity and no autocorrelation (6) Error terms should be normally distributed (Stock & Watson, 2015).

[27] For each benchmark model we found the median, the lower quartile which is the 25 percent of the lowest data sorted by size from low to high, and upper quartile which is 75 percent of the data. The range between these two quartiles is the interquartile range. Then we identify the fences for extreme observations. The inner fence is the interquartile range multiplied by 1,5 and the outer fence is the interquartile range multiplied by 3. We find the inner fence as lower or upper inner fences if we take the value of the respective quartiles minus the inner fence, and likewise for the lower and upper outer fences. Extreme outliers are defined as observations that are beyond the upper or lower outer fence, while mild outliers are beyond the upper or lower inner fence.

Table 3.7: Identification of outliers

Mild outliers	Ticker	Event	Content	Sentiment	Market Cap	Industry	FF3M
	RXN	5	Negative	Public	Mid cap	Industry manuf.	-0.087
	AMZN	36	Negative	Private	Mega cap	Consumer cycl.	-0.076

Severe outliers	Ticker	Event	Content				FF3M
	FCAU	14	Positive	Public	Large cap	Industry manuf.	0.124

Note: The other benchmark models identify the same outliers, see appendix 6.

The effects of the total sample removing only what is defined as sever outliers is shown in figure 3.9 (a), whereas removing both severe and mild outliers as visualized in figure 3.9 (b) and (c).

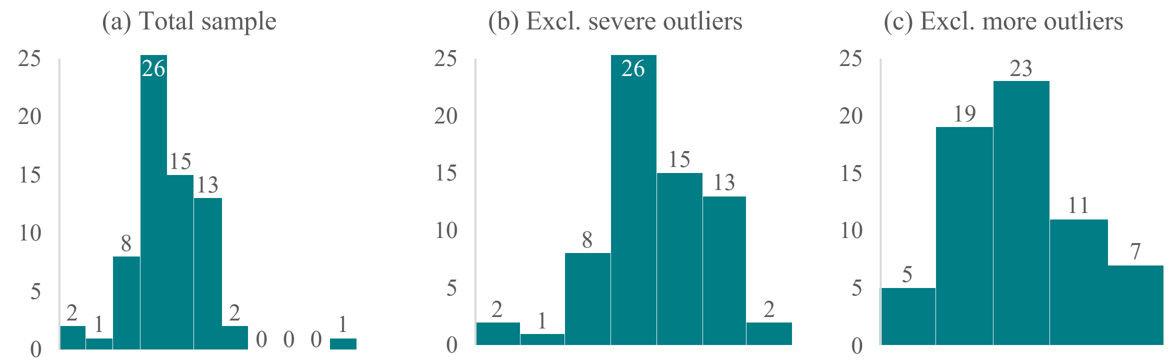

Figure 3.9: Histogram of distribution of CAR when using FF3M in event window (-1,2) for the total sample. (a) the total sample n=68, (b) total sample excluding only severe outlier n=67 and (c) total sample excluding both mild and severe outliers n=65.

When we remove the one extreme outlier from the total sample (including both positive and negative events), we can clearly see an effect on the normal distribution. When removing both mild and severe outliers the sample is normally distributed, supported by both visualization and test results in table 3.8. The results are the same with the other benchmark models, listed in appendix 10.1.

Table 3.8: Normality test for total sample when removing outliers

	z-value	p-value
Full sample	3.567	0.000***
Removing severe outliers	1.363	0.087*
Removing both mild and severe outliers	-0.148	0.559

*Note: Results from normality tests using the Shapiro Wilk W-test for event window (-1,2) using FF3M for the total sample n=68, total sample excluding severe outliers n=67 and total sample removed both mild and severe outlier. n=65. All benchmark models are listed in appendix 10.1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

As Coin (2008) suggests that some severe observations can make the result go from statistically significant to become insignificant, and the other way around. As McWilliams and Siegel (1997) recommend, it is crucial to assess whether the results are driven by outliers, and handling of them should be done carefully. Especially since we have a fairly small sample.

These observations can be part of a natural variation, but there can also be other underlying reasons like measurement errors or other events (Frecka & Hopwood, 1983). Since Trump is a powerful man, and his decisions have enormous impact on lots of people, it's not unlikely that some of his tweets have a great impact. The following tweets are identified as severe and mild outliers:

> **Event 14 (severe outlier):** *"It's finally happening - Fiat Chrysler just announced plans to invest $1BILLION in Michigan and Ohio plants adding 2000 jobs. This after Ford said last week that it will expand in Michigan and U.S. instead of building a BILLION dollar plant in Mexico. Thank you Ford & Fiat C!"* (Jan 9, 2017)
>
> **Event 5 (mild outlier):** *"Rexnord of Indiana is moving to Mexico and rather viciously firing all of its 300 workers. This is happening all over our country. No more!"* (Dec 3, 2016)
>
> **Event 36 (mild outlier):** *"I have stated my concerns with Amazon long before the Election. Unlike others they pay little or no taxes to state & local governments use our*

Postal System as their Delivery Boy (causing tremendous loss to the U.S.) and are putting many thousands of retailers out of business!" (Mar 29, 2018)

Based on the content of these outliers, we cannot exclude these tweets from the sample easily. McWilliams and Siegel (1997) found in their research of event study quality that researchers simply eliminate outliers from their sample, assuming these data points reflects noise or measurements error. That said, we see that two of the three tweets contain information assumable to be already known public information. This support the discussion in section 3.2.4 "Event window" regarding Trump commenting/replicate information already known to the market. But since the outliers do not interfere with the confounding events identified in the study, we argue that we cannot simply remove them. The analysis is proceeded with different samples where we both include and exclude outliers and make an overall interpretation of the results and to secure reliability and validity of the study. Our handling of outliers are in line with suggestions from Professor Foster (1980) who presents several ways to control for outliers.

It's important to discuss the possibility to completely isolate the effects of one single event as stated by Fama and French (2004) and the fact that the market reacts to all kinds of factors simultaneously.

3.2.6 Summary of dependent variable

In figure 3.9 we present a summary of the dependent variable CAR for the event window in the different samples. The samples are total sample with and without outliers, positive subsample with and without outliers and negative subsample with and without outliers. The dependent is a quantitative continuous variable. For the summary using all benchmark models see appendix group 9 (9.1 for the total sample, 9.2 for the positive subsample and 9.3 for the negative subsample).

Table 3.9: Summarizing samples

		Severe outliers	Mild outliers	Mean	Median	Min	Max	n
Total sample	Full			-0.59 %	-0.98 %	-8.68 %	12.37 %	68
	Excl. outliers	X		-0.78 %	-1.09 %	-8.68 %	4.13 %	67
	Excl. more outliers	X	X	-0.56 %	-0.87 %	-5.38 %	4.13 %	65
Positive subsample	Full			-0.04 %	-0.47 %	-3.89 %	12.37 %	40
	Excl. outliers	X		-0.36 %	-0.61 %	-3.89 %	4.13 %	39
	Excl. more outliers	X	X	-0.36 %	-0.61 %	-3.89 %	4.13 %	39
Negative subsample	Full			-1.38 %	-1.23 %	-8.68 %	3.97 %	28
	Excl. outliers	X		-1.38 %	-1.23 %	-8.68 %	3.97 %	28
	Excl. more outliers	X	X	-0.86 %	-1.15 %	-5.38 %	3.97 %	26

Note: Summarization of total sample, positive subsample and negative subsample, with the mean, median, min and max values and the number of observations of CAR for the three samples using FF3M. See appendix group 9 for market model and CAPM.

3.3 Regression analysis methodology

To achieve a more complete picture of event, it is preferable to use cross-sectional tests. In this section we explain how the data was prepared for regression analysis. We make control variables based on sentiment and different firm characteristics.

3.3.1 Preparing the data – making control variables

Sentiment

To investigate the effect of Trump's tweets on a more complex level and separate his personal opinions from other public known information, a closer analysis of sentiment is conducted (Bollen et al., 2010; Sprenger et al., 2014a, 2014b; Zhang et al., 2011).

The tweets are placed in the following categories:

Private opinion: Trump's private preferences. Opinion sharing about companies that doesn't necessary is the truth about the company's values or business operation.

Example 1 (positive): *"Thank you to Novartis for not increasing your prices on prescription drugs. Likewise to Pfizer. We are making a big push to actually reduce the prices maybe substantially on prescription drugs."* (Jul 19, 2018)

Example 2 (negative): *"My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person -- always pushing me to do the right thing! Terrible!"* (Feb 8, 2017)

Teaser: Promising words about a possible future business operation, meeting or teasing future news without revealing actual content.

Example: *"Had a very good phone call with @EmmanuelMacron President of France. Discussed various subjects in particular Security and Trade. Many other calls and conversations today. Looking forward to dinner tonight with Tim Cook of Apple. He is investing big dollars in U.S.A."* (Aug 10, 2018)

Public information: Tweets commenting on assumed to be already known information in the market regarding business operations. This information may possible be known for securities traders other than noise traders.

Example (positive): *"More great news as a result of historical Tax Cuts and Reform: Fiat Chrysler announces plan to invest more than $1 BILLION in Michigan plant relocating their heavy-truck production from Mexico to Michigan adding 2500 new jobs and paying $2000 bonus to U.S. employees! https://t.co/47azKD0l9B"* (Jan 1, 2018)

Example (negative): *"Rexnord of Indiana is moving to Mexico and rather viciously firing all of its 300 workers. This is happening all over our country. No more!"* (Dec 3, 2016)

Treat: Tweets about possible future "punishment" for companies based on company decision, especially those in conflict Trump's political strategy "America first".

Example: *"Apple will not be given Tariff waiver or relief for Mac Pro parts that are made in China. Make them in the USA no Tariffs!"* (Jul 26, 2019)

Table 3.10: Distribution of events based on sentiment

Content in tweet	Positive	Negative	Tot # of events
Threat	-	7	7
Public	16	2	18
Private	11	19	30
Teaser	13	-	13
Total	40	28	68

Company size based on market cap

We collected the market capitalization of the companies in the sample from Yahoo! Finance and sorted the companies into different groups based on the conventional classification scale from Financial Engines (2018). Market cap is the company's outstanding shares multiplied by the stock price per share. The categories are Mega Cap (>$200bn); Large Cap ($10-200bn); Mid Cap ($2-10bn); and Small Cap (<$2bn) (Financial Engines, 2018).

Table 3.11: Distribution of events based on size

Market Cap	Positive	Negative	# of events
Mega Cap	14	12	26
Large Cap	26	10	36
Mid Cap	0	6	6
Small Cap	0	0	0
Total	40	28	68

Categorizing of industry and sector

Sector and industry information for all companies in the sample were retrieved from Yahoo! Finance. To narrow the companies into less groups the companies was categorized according to similarities and sorted into four main industries: "Internet content and information", "Industry Manufacturer", "Drug Manufactures" and "Consumer Cyclical".

Table 3.12: Distribution of events based on industry

Industry	Positive	Negative	# of events
Industry Manufacturer	28	14	42
Consumer Cyclical	7	9	16
Drug Manufacturers	3	2	5
Internet Content and Information	2	3	5
Total	40	28	68

In appendix 1 the market cap and industry group of each company is listed, and in appendix 2 all events are listed with content and sentiment categorization.

3.3.2 Summary of control variables used in the regression analysis

Table 3.13 provides an overview of the predictors we use in the regression analysis for the dependent variable CAR.

Table 3.13: Overview of independent variables

Name of variable	Type of data	Type of variable	Explanation
Content	Categorical	Nominal with two categories	Positive/negative
Negative	Categorical	Binary	1 if negative, 0 if not negative
Positive	Categorical	Binary	1 if positive, 0 if not positive
Sentiment	Categorical	Nominal with 4 categories	Private / Threat / Teaser / Public
Private	Categorical	Binary	1 if private, 0 if not private
Threat	Categorical	Binary	1 if threat, 0 if not threat
Teaser	Categorical	Binary	1 if teaser, 0 if not teaser
Public	Categorical	Binary	1 if public, 0 if not public
Market Cap (M)	Quantitative	Continuous	Market Capitalization in billions
Market Cap	Categorical	Ordinal with 4 groups	Small Cap (0) / Mid Cap (1) / Large Cap (2) / Mega Cap (3)
Small Cap	Categorical	Binary	1 if small cap, 0 if not small cap
Medium Cap	Categorical	Binary	1 if mid cap, 0 if not mid cap
Large Cap	Categorical	Binary	1 if large cap, 0 if not large cap
Mega Cap	Categorical	Binary	1 if mega cap, 0 if not mega cap

Industry/group	Categorical	Nominal with 4 categories	Industry manuf. / Consumer / Drug / Internet
Industry Manuf.	Categorical	Binary	1 if industrial, 0 if not industrial
Consumer	Categorical	Binary	1 if consumer, 0 if not consumer
Drug Manuf.	Categorical	Binary	1 if drug manuf., 0 if not drug manuf.
Internet Serv.	Categorical	Binary	1 if internet serv., 0 if not internet serv.

3.4 Validation of results

A prerequisite for studying the impact of the tweets considers whether the event study has been used and implemented correctly, whether the results have been reported clearly and that the interpretation of the results is correct. These problems are connected to both reliability and validity of the study (Golafshani, 2003).

According to Brown and Warner (1985) and McWilliams and Siegel (1997) the following assumptions must be valid for results to be reliable: (1) markets are efficient, (2) the event was unanticipated and (3) that there were no confounding effects during the event window. For the first assumption we must believe that the markets during the test period were efficient, and on average reflecting all available information. We include several different companies, over a wide spread of industries. An assumption is that an event is anything that results in new relevant information. Many of the tweets is categorized at all ready public information, but here we try to identify if it has any effect when Trump (with his 68 million followers) can add any new information which lead to a change in the market price.

The second assumption we feel is satisfied because Trump tweets whenever he feels like it, and we never know when he will tweet. On the other hand, Trump tweet much of the same content and often directed to the same companies. This indicate that the tweet may be anticipated, and the market starts moving before the formal announcement.

For the third and most critical assumption we have during the study taken into care by removing events with confounding effects with recent publication of earnings announcements and controlling for cluster effect by removing latter events when there was an overlap in event window with tweets regarding the same company. We have not excluded cluster events regards to different companies within the same event window, because he often tweets about multiple companies within the same tweet, which can raise some concern regarding isolating the impact of one particular event. Other confound events can also include announcement of new products, declaration of dividends, announcement of mergers and so on. In this study, not other confounding effects have been controlled for. We still feel this assumption is satisfied due to the variation of companies and event times.

For further research as McWilliams and Siegel (1997) strongly recommend we "report firm names and event dates in data appendix" (p. 652). See the list of events in appendix 12. This allows for transparent information not only for replication, but also as extension of the reported findings.

4 Results

In this section the results from the different analyses are presented. The results when using FF3M will be displayed in text, while the results using the two other benchmark models will be found in appendix.

To support the main research question in this study we investigate whether there is presence of abnormal return related to the company-specific tweets. We find statistically significant results that there is presence of abnormality in stock return in the event window (-1,2) for the total sample using both parametric and non-parametric tests.

Table 4.1: Test results for the total sample

	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	3.567	0.000***	-2.102	0.036**	-1.676	0.098*
Excl. outliers	1.363	0.087*	-2.361	0.018**	-2.624	0.011**
Excl. more outliers	-0.148	0.559	-2.036	0.042**	-2.140	0.036**

*Note: Normality test using Shapiro-Wilk W test and signed-rank test and t-test for significance for event window (-1,2) using FF3M for the total sample n=68, total sample excluding severe outliers n=67 and total sample excluding both mild and severe outliers n=65. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

From the normality test in table 4.1 the results indicate an improvement in normality when severe outliers are excluded. When both mild and severe outliers are excluded the total sample is normally distributed. For all three versions of the sample, both the signed-rank test and t-test have significant p-values, which means that the average CAR in samples are significantly different from zero. We argue that we do no "harm" by removing extreme observations. The results are the same using market model and CAPM, as seen in appendix 10.1.

Based on the results in table 4.1 we find evidence indicating that tweets are associated with abnormal return, even before we consider the content. However, to test our hypotheses and in line with empirical findings we investigate the sample further by separating positive and negative events.

4.1 Content analysis

The content analysis is divided into two hypotheses. The first hypothesis is whether there is an abnormal return for the company when being tweeted about by Trump, studying the positive and negative tweets separately. With the second hypothesis we try to identify the direction of the abnormal return. Are positive (negative) tweets associated with positive (negative) abnormal return?

Hypothesis 1 is divided into 1a and 1b. Hypothesis 1a is regarding how a positive tweet affects the company's stock price. To test this hypothesis, we perform a signed-rank test and t-test of the positive subsample to see if we find statistically significant result that the value of the average CAR is different from zero. We test the sample with and without adjusting for outliers. The results from the tests are displayed in table 4.2.

Table 4.2: Test results for the positive subsample

	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	3.963	0.000***	-0.699	0.485	-0.084	0.934
Excl. outliers	0.316	0.376	-1.005	0.315	-1.087	0.284
Excl. more outliers	0.316	0.376	-1.005	0.315	-1.087	0.284

*Note: Normality test using Shapiro-Wilk W test and rank test and t-test for significance for event window (-1,2) using FF3M for the positive subsample n=40, positive subsample excluding severe outliers n=39 and positive subsample excluding both mild and severe outliers n=39. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

The test for normality indicates that the positive subsample is normally distributed when adjusted for the one outlier[28]. The results are not statistically significant in neither of the significance tests. When using the market model and CAPM the results are the same, as seen in appendix 10.2. This imply that we reject hypothesis 1a that a positive tweet from President Donald Trump affects the company's stock price.

The results that positive tweets have no significant effect on CAR is not surprising, as discussed in section 3.2.4 “Event window”. Since we cannot claim any abnormal stock return when investigating the positive subsample as a whole, the results can without further investigation indicate that the tweets do not contribute with any new information that either rational or irrational investors react to.

Literature have detected that emotional outbursts on social media can create abnormality in the stock market. According to the theoretical models explained by Barber and Odean (2008), we would expect positive news to have positive effects, which we do not find in our study. The results from the study of Zhang et al. (2011) also suggests that both positive and negative emotional outburst on Twitter influence stock markets, which is inconsistent with our findings. However, it’s important to notice is that these studies are not completely equivalent.

That said, as Tetlock (2007) explains, the media should not be a sideshow with absolutely no relations to the marketplace. This indicate that Trump mainly refers to what could be considered as “old news” for investors. When we fail to lend support to hypothesis 1a, it means that we cannot claim that the fluctuation is stock return is caused by Trump’s positive tweets and not white noise. The variation can simply be random fluctuation in stock prices as Seiler and Rom (1997) mentions, which is consistent with market efficiency in the short run. These findings are supported by the graph of aggregated CAR for the positive subsample in figure 3.3 in the previous section.

The second part of the first hypothesis, hypothesis 1b is regarding if negative tweets affects the company’s stock price. We test this hypothesis in the same way performing a signed-rank

[28] The results are identical when excluding only severe and when excluding both mild and severe outliers because there is only one positive outlier and its categorized as severe.

test and t-test for the average CAR of negative subsample with and without adjusting for outliers. Table 4.3. presents the results from these tests.

Table 4.3: Test results for the negative subsample

	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	0.835	0.202	-2.505	0.012**	-2.566	0.016**
Excl. outliers	0.835	0.202	-2.505	0.012**	-2.566	0.016**
Excl. more outliers	-0.148	0.559	-2.036	0.042**	-2.140	0.036**

*Note: Normality test using Shapiro-Wilk W test and rank test and t-test for significance for event window (-1,2) using FF3M for the negative subsample n=28, negative subsample excluding severe outliers n=28 and negative subsample excluding both mild and severe outliers n=26. * p < 0.10, ** p < 0.05, *** p < 0.01*

The results from the normality test indicate that the negative subsample is normally distributed both with and without the two mild outliers. Nevertheless, the samples are statistically significant both with the signed-rank test and the t-test.

The results are the same when using the CAPM, as seen in appendix 10.3. But, when using the market model, the results are less statistically significant. However, we want to look at the overall effects even if there are differences between the benchmark models regarding significant results. This is line with Fama and French' (2004) discussion of model simplifications of reality and underlying assumptions. It is reasonable to believe that the models catch some different risk-return relationships in the financial markets and that in this case the market model stands out as less significant than the two other models.

Overall, the findings from table 4.3 lend support to hypothesis 1b that negative tweet from President Donald Trump is associated with an effect on the company's stock price. These results are consistent with Tetlock (2007) and Sprenger et al. (2014a) that negative news posted on Twitter have an effect of the respective stock prices. The results are also supported by other studies on the link between Trump and Twitter, further discussed in section 3.2.4 when identifying the event window for the negative subsample.

According to literature presented in this study, we can support that there is a difference between positive and negative news in the sense of tweet-content. A possible explanation for this could be, like Sprenger et al. (2014a) discussed, that positive news could already be incorporated into the market prices before the actual tweet date due to leakages. For instance, the number of tweets that we have categorized as already known public information is a total of 16 positive tweets, which means that we can assume that these tweets have approximately zero effect on stock price due to leakage, which also supports the graphical view of the positive tweets where we see no clear effects. Both findings can therefore be supported by market efficiency as the prices reflects what investors already know or see as valuable information.

Identification of the direction of abnormal return

From the first hypothesis we have results that indicate the presence of an abnormal stock reaction when tweets are published. The second hypothesis is related to the direction of the potential effect and we investigate if a positive (negative) tweet is estimated to have a positive (negative) effect. To test the second hypothesis, we run a simple regression model with a binary variable for negative content. The regression results are shown in table 4.4 for the total sample. We investigate the results both with and without outliers.

Table 4.4: Regression results from Model 1

	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.010	-0.007	-0.002
	(0.007)	(0.006)	(0.005)
Constant	-0.000	-0.003	-0.003
	(0.004)	(0.003)	(0.003)
Observations	68	67	65
Adjusted R^2	0.019	0.009	-0.013
F	2.284	1.389	0.151
p	0.135	0.243	0.699

Note: Regression results from Model 1 content analysis using FF3M for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. For all benchmark models see appendix 11.1.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

The results in table 4.4 do not provide statistically significant results. However, they indicate that tweets categorized as positive is associated with a small negative close to zero effect on CAR and that negative events are associated with a negative effect on CAR. The effect of negative events is greater, but still insignificant. When running the regression using data from CAPM, the predictor negative is statistically significant in the total sample and F-test also reveal significant results, as seen in appendix 11.1. To ensure the statistical results and the assumptions underlying the t-test for this regression model, we find strong p-values for the robustness analysis[29] included in appendix 11.1. For both total sample and sample excluding all outliers, the result indicate that the residuals from the regression is homoscedastic.

We fail to lend support to hypothesis 2a that positive tweets are associated with a positive effect. The results lend some support to hypothesis 2b that negative tweets will have a negative effect on the abnormal return when using CAPM. But since these results are not valid throughout all benchmark models, we find no overall statistically significant support to the hypothesis. This means that there is insufficient evidence to conclude that this is an actual effect at the population level.

Overall, our findings can substantiate the discussion regarding the study's first hypotheses. With the negative events we find results consistent with theoretical models and that investors are risk averse. These assumptions are based on the rational investors, and not the noise traders who make random decisions (Barber & Odean, 2008). What we observe from table 4.4, is that regardless of the signals in the market we obtain a downward pressure on the prices. Our results can be supported by similar findings done by Zhang et al. (2011) which found that regardless of content of outburst on Twitter they found a decline in the Dow Jones the following day.

[29] In the robustness analysis for each regression we ensure homoscedasticity using the Breusch-Pegan test and the Cameron-Trivedi decomposition of Whites test. In presence of heteroscedasticity, the estimates will be less precise according to the true population value. The latter test also displays the results from a test for skew and kurtosis which is related to the distribution of the sample. The desired result is small chi-square values and big p-values which means skew and kurtosis is not a problem in our data. Also, we use robust command when running regressions which adds a less strict assumption to the sample allowing for robust standard errors. In regressions with several predictors we test for multi-collinearity using the variance inflation factor (VIF) where values above five indicates highly correlated independent variables and poor estimates, making the p-values questionable (Stock & Watson, 2015).

Our findings are different from what Sprenger et al. (2014b) found, which was that investors react to a positive content in Twitter messages which leads to an increase in stock prices. The predictor Negative reveals an associated decline in CAR on average, which is also consistent with Tetlock's (2007) results of pessimistic content. However, when controlling for outliers we obtain a smaller difference between positive and negative tweets. When removing the outliers, the causal relationship between tweets and abnormal return in the total sample can arguable be caused by other underlying company events. The positive and negative are closing up on each other meaning we see smaller differences in content relevance.

The results from the content analysis points in the same direction as previous research on Trump and Twitter and that investors seem to react more to the negative outburst on the twitter account. Regardless of whether we can claim a causal effect, for companies and investor in general we support that negative publicity can seem undesirable. On this subject we cannot claim to find new significant results, but we support other research. In the next section we analyze the content further, but in a different approach.

4.2 Sentiment analysis

The study's third hypothesis is related to the sentiment in the tweets and states that the abnormal return is affected according to subcategories of sentiment. We investigate whether CAR is affected differently according to sentiment categories, like Bollen et al. (2011) and Zhang et al. (2011) as they saw the need for more specific measures of Twitter mood indicators.

To test the third hypothesis, we perform a regression analysis using the subcategories as control variables and we run the regression using the sample with and without adjusting for outliers. The sample consists of tweets that contain either a private (positive/negative) opinion, a (negative) threat, a (positive) teaser or already known (positive/negative) public information, resulting in six predictors for sentiment. We supplement the total sample regression with regression on subsamples as well.

The regression results for total sample is shown in table 4.5.

Table 4.5: Regression results from model 2

	Full	Excl. outliers	Excl. more outliers
Teaser	0.018	0.018	0.018
	(0.011)	(0.011)	(0.011)
Private Neg	0.011	0.011	0.015
	(0.010)	(0.010)	(0.010)
Private Pos	0.012	0.012	0.012
	(0.010)	(0.010)	(0.010)
Public Neg	-0.008	-0.008	0.050***
	(0.044)	(0.044)	(0.009)
Public Pos	0.028**	0.020**	0.020**
	(0.013)	(0.010)	(0.010)
Constant	-0.021**	-0.021**	-0.021**
	(0.009)	(0.009)	(0.009)
Observations	68	67	65
Adjusted R^2	0.031	0.006	0.046
F	1.166	1.003	
p	0.336	0.424	

*Note: Regression results from Model 2 sentiment analysis using FF3M for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. For all benchmark models see appendix 11.2. The omitted variable is threat. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Using FF3M in sentiment regression we obtain less statistically significant results compared to market model and CAPM, however we find results that point in the same direction, see appendix 11.2 In these respective models we find all variables statistically significant in the sample where we exclude all outliers, except for the predictor private positive. Market model reveals joint significant result from the F-test for all sample sizes. However, as mentioned in the content analysis, we should be careful to draw a conclusion based on only single models as they all can include some truth about the population (Fama & French, 2004).

We support the results by running a robustness analysis as displayed in appendix 11.2, which indicates moderate but not severe correlation between the independent variables and residual homoscedasticity for full sample and sample excluding all outliers.

Using categorical variables based on sentiment seem to better describe the changes in CAR in addition to positive and negative content, which supports studies by Bollen et al. (2010) and Zhang et al. (2011). We see more statistically significant results in regression model 2, and also a joint significance in market model means that all variables together can contribute to valuable information about abnormal return, which means that these predictors can be a better model for describing effects of the CAR in comparison to only positive and negative content.

The added categorizes considers the way Trump formulates and express himself and what kind of message the tweet contains, supporting the importance of quality and sentiment in tweets (Sprenger et al., 2014b). We observe greater R-squared for this regression model compared to model 1 and the sample excluding all outliers provides a larger R-squared which is desirable. However, R-squared is still a small value which indicated that there is a lot more to the change in CAR to be explained by the sentiment of Trumps tweets.

Since the intercept in full sample regression in model 2, reveal a strongly negative associated change in CAR on tweets that contain a threating message, even positive estimates in this model must be seen up against this control group. The results indicate a tendency that all sentiment categories are on average associated with a decrease in CAR. The results are supported by regression analysis of the subsamples in table 4.6.

Table 4.6: Regression results from model 2a and 2b

	2a: Positive subsample			2b: Negative subsample		
	Full	**Excl. outliers**	**Excl. more outliers**	**Full**	**Excl. outliers**	**Excl. more outliers**
Public	0.016	0.008	0.008	-0.019	-0.019	0.036***
	(0.011)	(0.008)	(0.008)	(0.044)	(0.044)	(0.005)
Teaser	0.005	0.005	0.005			
	(0.008)	(0.008)	(0.008)			
Threat				-0.011	-0.011	-0.015
				(0.010)	(0.010)	(0.010)
Constant	-0.008	-0.008	-0.008	-0.010	-0.010	-0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
Observations	40	39	39	28	28	26
Adjusted R^2	0.005	-0.028	-0.028	-0.026	-0.026	0.148
F	1.080	0.556	0.556	0.629	0.629	3.170
p	0.350	0.578	0.578	0.541	0.541	0.061

Note: Regression results from model 2a and 2b sentiment analysis of subsamples using FF3M. Model 2a include positive subsample n=40, positive subsample excluding severe outliers n=39 and positive subsample excluding mild and severe outliers n=39. Model 2b include negative subsample n=28, negative subsample excluding severe outliers n=28 and negative subsample excluding mild and severe outliers n=26 For all benchmark models see appendix 11.3 and 11.4.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

In this sentiment analysis we have formulated a hypothesis regarding each predictor in the model with an expected direction of return. Based on the regression results from all three models we make a statement on the following hypotheses.

Teasers

The results from the regression in model 2 reveal that tweets categorized as teasers are associated with a decline or close to zero change in CAR on average, which is not statistically significant in the total sample using FF3M, but statistically significant using the two other benchmark models included in appendix 11.3. Since two out of three models provide statistically significant result, we believe we have evidence that are valid for rejecting the hypothesis 3a which states that Teaser is associated with a positive effect on the abnormal return. This is also supported by results in subsample regression in model 2a, however this is not statistically significant but points in the same direction. See appendix 11.3.

Threats

The results indicate that tweets categorized as threats are associated with a decline in the CAR on average. In the model 2 the results are statistically significant throughout all benchmark models which we believe indicate strong evidence on this predictor. In model 2b using subsamples, we support that our results, and we find statistically significant when controlling for outliers in market model and CAPM. Based on the overall results our findings lend support to hypothesis 3b that tweets categorized as threats will have a negative effect on the abnormal return.

Private (positive)

Model 2 further indicate that positive private opinions is associated with a negative effect on the CAR, however not statistically significant in any benchmark model. The results are supported by subsample regression in model 2a, which also suggests a decline in CAR which is statistically significant in market model and CAPM. Overall our findings lend support for rejecting hypothesis 3c that positive private opinions will have a positive effect.

Private (negative)

All benchmark models reveal the same tendencies, that a private negative tweet is associated a decline in CAR. When the sample is controlled for outliers, we see that the associated change in CAR is weaker, meaning the effect of the tweet decreases. We can therefore identify the effect of the one mild outlier we categorized as private negative opinion. This means that when we include the outlier we observe a larger effect on the predictor then without it. However, the remaining results is still small negative close to zero, and the predictor is statistically significant in sample where outlier is excluded in market model and CAPM. Overall, the results lend some support to hypothesis 3d that Private negative tweets are associated with a negative change.

Public (positive)

For both regression model 2 and 2a we find tendencies for a decline in CAR when controlling for outliers. In model 2 the predictor moves from positive to less positive, and in CAPM and FF3M it moves from positive to negative/close to zero but is statistically significant using all benchmark models. The change is betas can be explained by the removal of event 14, which was identified as a severe outlier, and which confirmed by Coin (2008). The results are supported by the subsample analysis in model 2a. Based on these observations we believe that we have results indicating that the outlier can affect the result substantially where we conclude that we have data that support a rejection of hypothesis 3e because we find close to zero/ negative effect after adjusting for outliers.

Public (negative)

Based on the results form regression model 2 we obtain different results when we include or exclude outliers. One of the mild outliers identified are an event categorized as public negative. When not excluding the outliers, we obtain support for the hypothesis that there is an associated decline in CAR with this predictor. However, excluding the one outlier the results support rejecting the hypothesis because of strong significant results in all benchmark models for an associated *positive* change for the predictor. These results are supported by the subsample regression revealing the same tendencies and similar significant result for when controlling the sample for without outliers.

These results could indicate that when Trump replicate what we assume the public already knows and what he considers to be negative, the market reacts in the opposite way. An implication of this could be that Trump provide new information to his followers, which he presents as negative, but the markets sees this as positive news, e.g. when companies are moving their production outside America. In that way, we fail to find support for hypothesis 3f that tweets categorized as public negative is associated with negative effect on CAR.

This analyze contributes to the study by further investigating the content of the tweets, and if there are some wording in the messages that have a different effect that others. We see an overall tendency of negative reactions even if Trump expresses promising words and positive future ambitions about companies. Since we cannot find results indicating that positive news provides positive returns, these results are not consistent with the theoretical models (Barber & Odean, 2008) or what Sprenger et al (2014b) found about positive reactions to positive sentiment in tweets. This also accounts for the change in CAR associated with *negative* public information, since the effect of removing outlier leads to a *positive* estimate.

In his private opinion the content do not seem to matter, as we observe a larger negative effect for positive private opinions than negative, which could set a question mark to whether traders listen to his opinions or the existing of noise traders reaction on attention (Barber & Odean, 2008). As mentioned, these results are not statistically significant but imply tendencies that could be further investigated in future studies when the available data is greater. The existing of noise trader is further questioned by the statistically significant weak reactions to negative private opinions when outlier is removed.

The categories threat and teaser can be used to draw parallels to the studies done by Bollen et al. (2010), Zhang et al. (2011) and Tetlock (2007). If we compare the significant results associated with threat to fear, we obtain consistent results with other studies which also support that investors are sensitive to negative news. However, according to literature hopeful messages, like teasers should influence a positive stock price reaction. With the information Trump as access to as president one would assume that investors would react to positive future ambitions. We question here whether Trumps intended tweet is not recognized by rational or irrational traders.

The findings from this analysis correspond to the discussion of the content analysis, and only supports what we already have seen. The point of this section could be an investigation of whether all negative tweets are associated with the *same* type of reaction in the financial markets where we discriminate based on sentiment. Overall, most of the estimates change in CAR is quite small. However, the estimates suggest that the economic consequence of tweets are greatest for the predictor Threats which has the largest decline in CAR and for Public negative information which has the highest positive effect when controlling for outliers, the opposite of what we expected. Based on these results we can highlight some new tendencies to the discussion of tweet impact.

Shareholders of companies that are being exposed to a *threat* seem to lose more value compared to other negative statements. When we observe a decline in abnormal return, we could argue that some traders create a downward pressure on the prices and want to sell their stocks. Based on our findings we cannot say certain that these reactions are caused by the tweet itself or other reasons that create downward pressure on prices. That said, this effect we see could be temporarily so we cannot assert that shareholders shouldn't sit tight and wait. Other than that, we have questioned the intended purpose of the tweets compared to observed tendencies in the abnormal return, and the effect of Trump opinions.

4.3 Market cap analysis

The fourth hypothesis is whether the abnormal stock return is related to company size and that there is a greater effect for smaller companies when being in the spotlight of the President's tweets, then for larger companies. We measure company size as market cap.

To test the fourth hypothesis, we perform two different regression analysis. The first regression model (Model 3) use market cap as a categorical variable and the second model (Model 4) use market cap as a continuous variable. We run these regressions on full sample and sample excluding outliers.

Table 4.7 display the result from the regression using categorical predictors for total sample.

Table 4.7: Regression results from model 3

	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.007	-0.005	-0.002
	(0.006)	(0.006)	(0.005)
Large Cap	0.027	0.025	0.016
	(0.017)	(0.017)	(0.016)
Mega Cap	0.020	0.021	0.015
	(0.017)	(0.017)	(0.016)
Constant	-0.025	-0.027	-0.019
	(0.018)	(0.017)	(0.016)
Observations	68	67	65
Adjusted R^2	0.068	0.071	0.002
F	1.636	1.295	0.490
p	0.190	0.284	0.691

*Note: Regression results from Model 3 size analysis with size as a categorical variable using FF3M for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. For all benchmark models see appendix 11.5. * p < 0.10, ** p < 0.05, *** p < 0.01*

Table 4.7 visualize the result from regression model 3 using FF3M. Using market model and CAPM we obtain similar results and none of the models reveal statistically significant results, as seen in appendix 11.5. Based on the robustness analysis included in appendix 11.5, we find results that the total sample is a solid sample for all tests, but when we remove outliers, we obtain heteroskedastic results and skews distributions making it difficult to obtain reliable results. There is also moderate correlation between the independent variables, but all values are below five.

From model 3 using the total sample, we can observe a larger effect associated with companies categorized as mid cap companies, compared to the two larger market cap groups which are associated with quite similar estimates. When controlling for outliers we see a small change in the predictors Large cap and Mega cap, however these predictors are insignificant compared to the reaction for Mid cap companies.

The results are supported by model 3a and b using subsamples in table 4.8, where we find statistically significant results associated with a decline in CAR for Mid cap companies for negative tweets. It should be mentioned that the intercept in the total regression model is regarding positive tweets for Mid Cap which is not included in the sample and makes this estimate not valid. This regression analysis also supports that the negative tweets are associated with larger decline in CAR compared to positive tweets which supports previous discussions.

Table 4.8: Regression results from Model 3a and Model 3b

3a: Positive subsample	Full	Excl. outliers	Excl. more outliers
Mega Cap	-0.006	-0.001	-0.001
	(0.009)	(0.007)	(0.007)
Constant	0.002	-0.003	-0.003
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.017	-0.027	-0.027
F	0.441	0.013	0.013
p	0.511	0.909	0.909

3b: Negative subsample	Full	Excl. outliers	Excl. more outliers
Large Cap	0.028	0.028	0.017
	(0.018)	(0.018)	(0.017)
Mega Cap	0.019	0.019	0.014
	(0.018)	(0.018)	(0.016)
Constant	-0.032*	-0.032*	-0.021
	(0.017)	(0.017)	(0.016)
Observations	28	28	26
Adjusted R^2	0.066	0.066	0.004
F	1.363	1.363	0.497
p	0.274	0.274	0.615

Note: Regression results from Model 3a and 3b size analysis of subsamples using FF3M. Model 3a include positive subsample n=40, positive subsample excluding severe outliers n=39 and positive subsample excluding mild and severe outliers n=39. Model 3b include negative subsample n=28, negative subsample excluding severe outliers n=28 and negative subsample excluding mild and severe outliers n=26 For all benchmark models see appendix 11.6 and 11.7.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table 4.8 display the regression results for the subsamples separately. When investigating only the negative subsample the intercept is significant in the full sample and sample excluding outliers, lending further support to the argument above that mid cap companies is greater affected then larger companies. The change in the intercept in model 3b can be explained by the removal of the outliers, where one of the negative outliers is categorized as Mid cap. Even if we do not obtain statistically significant results, we still obtain a greater effect on company categorized as mid cap companies.

Table 4.9: Regression results from Model 4

	Full	Excl. outliers	Excl. more outliers
Negative	-0.013*	-0.010	-0.005
	(0.007)	(0.006)	(0.006)
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.000	-0.005	-0.005
	(0.006)	(0.004)	(0.004)
Observations	68	67	65
Adjusted R^2	0.023	0.017	-0.011
F	1.806	1.310	0.466
p	0.172	0.277	0.629

*Note: Regression results from Model 4 size analysis with size as continuous variable using FF3M for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. For all benchmark models see appendix 11.8. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table 4.9 present the result from the regression using size as a continuous variable. In this regression model we cannot see any clear pattern for change in CAR related to size of the companies in the sample. The predictor Market cap shows an expected associated change in the CAR on average, if market cap increases by 1 billion dollars and is approximately zero for all sample sizes and for all benchmark models. Also, these results are insignificant. Regarding evidence of size effects, the goodness to fit results suggest this is an insufficient model. We did the same regression on the subsamples, also not resulting in any effect, see appendix 11.9 and and 11.10.

To summarize these results, when using categorical variables, the results indicated that Mid cap companies abnormal return is greater affected then for large and mega cap companies on negative tweets. These findings are consistent with Tetlock (2007) findings that suggests different effects of negative sentiment on company size. But since the results overall are not statistically significant, we cannot lend support to hypothesis 4 that the company's abnormal stock return is less affected as the company's market cap increases.

However, it should be noticed that we have no tweets containing small cap companies in our sample to support the findings of Tetlock (2007) further. However, other researchers can investigate this further when these companies are included in Trumps' tweets or similar studies.

4.4 Industry analysis

The fifth hypothesis is whether the effect from being in the spotlight of Trump's tweets on the companies' abnormal stock return are different according to industry. To test the fifth hypothesis, we perform a regression analysis using industries represented in the sample as categorical predictors. The categories are internet content & information-companies, industry manufacturer, consumer cyclical or drug manufacturers and the categories can be both positive and negative. We run the regressions on full sample and sample excluding outliers.

Model 5 in table 4.10 presents the results for the regression using total sample and model 5a and 5b in table 4.11 show the results from subsample regressions. The omitted variable is internet content & information-companies.

Table 4.10: Regression results from Model 5

	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.014*	-0.011	-0.006
	(0.007)	(0.007)	(0.006)
Consumer Cyclical	-0.002	-0.002	0.003
	(0.010)	(0.010)	(0.008)
Industrial manf.	-0.002	-0.005	-0.001
	(0.009)	(0.008)	(0.007)
Drug manuf.	-0.015*	-0.015*	-0.014**
	(0.009)	(0.008)	(0.007)
Constant	0.003	0.001	-0.002
	(0.009)	(0.008)	(0.007)
Observations	68	67	65
Adjusted R^2	0.008	0.002	-0.011
F	2.013	2.048	2.776
p	0.103	0.099	0.035

*Note: Regression results from Model 5 industry analysis with industry as categorical variable using FF3M for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. For all benchmark models see appendix 11.11. * p < 0.10, ** p < 0.05, *** p < 0.01*

The results of model 5 table 4.10 indicate the same results using all benchmark models, except the estimate for drug manufacturers where market model estimates a much smaller associated change on CAR, on average, compared to CAPM and FF3M, as seen appendix 11.11. The robust analysis for the regression is included in appendix 11.11 and indicates that all samples are solid and only moderate correlation.

Table 4.11: Regression results from Model 5a and Model 5b

	5a: Positive subsample			5b: Negative subsample		
	Full	**Excl. outliers**	**Excl. more outliers**	**Full**	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	0.018*	0.018*	0.018*	-0.015	-0.015	-0.007
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.008)
Industrial manf.	0.019***	0.014***	0.014***	-0.019**	-0.019**	-0.014*
	(0.007)	(0.005)	(0.005)	(0.009)	(0.009)	(0.007)
Drug manuf.	-0.005	-0.005	-0.005	-0.016***	-0.016***	-0.016***
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Constant	-0.016***	-0.016***	-0.016***	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Observations	40	39	39	28	28	26
Adjusted R^2	-0.014	0.017	0.017	-0.078	-0.078	-0.078
F	5.394	6.297	6.297	40.739	40.739	40.179
p	0.004	0.002	0.002	0.000	0.000	0.000

Note: Regression results from Model 5a and 5b industry analysis of subsamples using FF3M. Model 3a include positive subsample n=40, positive subsample excluding severe outliers n=39 and positive subsample excluding mild and severe outliers n=39. Model 2b include negative subsample n=28, negative subsample excluding severe outliers n=28 and negative subsample excluding mild and severe outliers n=26 For all benchmark models see appendix 11.12 and 11.13.
** p < 0.10, ** p < 0.05, *** p < 0.01*

Model 5a and b using subsamples are shown in Table 4.11. The models seem to better describe the relationship between industries and positive tweets and negative tweets, respectively. Nevertheless, the results vary in significance using different the benchmark models in appendix 11.12 and 11.13. Model 5a are joint significantly in all benchmark models, while 5b is only joint significantly in FF3M.

From this model we observe that the effect of industry on CAR differ substantially according to whether the tweet is positive and negative, and using only the total sample regression in model 5 we could argue that these effects are not clear. The results differ when analyzing the total sample versus dividing the regression model into subsample. It is reasonable to assume based on previous results that the effect of positive and negative events affects differently.

In model 5a, using the positive subsample, we find a tendency that internet content & information and drug manufacturers are associated with a larger *decline* in CAR on average compared to the other two categories using all benchmark models. The other industries have small or close to zero reactions. When using the market model all predictors are statistically significant, while in CAPM and FF3M all predictor except drug manufacturers are statistically significant. That said, especially internet and drug companies have relatively few observations in which we question the validly of these statistically significant results.

In line with his "America First" strategy, he often states negatively about industrial companies, which we see in the results is model 5b is associated with a negative effect on CAR. The predictor is statistically significant in CAPM and FF3M.

Based on these models and such striking results, we recognize that there are different affects to the industries in the sample, however we find it difficult to see specific trend on an overall basis and therefore difficult to lend support to hypothesis 5 that industries are affected differently. Also, due to the fact that the benchmark models reveal different results. The results from this analysis lends no implications for investors and company owners in a significant matter.

Based on our finding regarding company characteristics we argue that this could be interesting subject for future research.

4.5 Volatility

Several researchers have shown that publicity on internet message boards and Twitter can influence the volatility in the market index and single stocks (Antweiler & Frank, 2004; Sprenger et al., 2014b). To look at volatility, we calculated the standard deviation (SD) for each event in a window prior and past the event. The window prior is from t_1=-5 to t_2=-9. We chose this window to try to get the best estimates for what the “normal” SD is. The past window is from t_1=0 to t_2=4. We then calculated the increase or decrease in standard deviation by subtracting the prior window from the past window.

However, the following discussion is only supportive analysis to our main study, and we provide possible explanations to fluctuation based on previous research.

4.5.1 Positive events

Table 4.12 sums up the change in standard deviation in the positive subsample. As the results show, 26 of the totals of 40 events when not removing outliers har an increase in SD and 25 when removing the one extreme outlier. The increase for event 14 was 0.044 SD.

Table 4.12: Summarization of change in SD for positive events

	Decrease in SD	*Increase in SD*	*Min*	*Max*	*Mean*
Full	14 (35 %)	26 (65 %)	-0.023	0.044	0.003
Excl. outliers	14 (36 %)	25 (64 %)	-0.023	0.017	0.002
Excl. more outliers	14 (36 %)	25 (64 %)	-0.023	0.017	0.002

Note: A summarization of the change in standard deviation for the positive subsample when and when not excluding outliers, with the min, max and mean change in SD.

The results in table 4.12 also show that the mean of the change in SD is weak positive close to zero. Figure 4.1 is a visualization of distribution of the increase or decrease. The darker pole indicates the interval (-0.003, 0.002) which contain zero. As we see in both sample sizes, 11 of the positive events has a close to zero change in standard deviation. The distribution of the results is slightly shifted to the right, indicating that a majority of the events has an increase in standard deviation above zero between the two estimation windows.

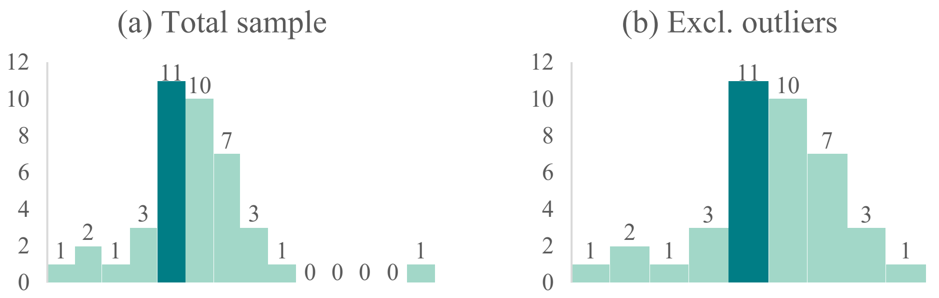

Figure 4.1: Difference/change in standard deviation from prior window (-9,-5) and past window (0,4). Figure (a) is for the positive subsample n=40 and figure (b) is the positive subsample when excluding the one severe outlier n=39. In both figures the darker pole visualize the interval that contain zero (-0.003, 0.002)

To test the results shown above we test for normality and significance. The results from the test are shown in table 4.13 below.

Table 4.13: Normality and significance test of SD

		Shapiro-Wilk W test		Wilcoxon Signed-rank test	
	n	z-value	p-value	z-value	p-value
Full	40	3.053	0.001***	2.083	0.037**
Excl. outliers	39	1.870	0.031**	1.884	0.060*
Excl. more outliers	39	1.870	0.031**	1.884	0.060*

*Note: * p < 0.10, ** p < 0.05, *** p < 0.01.*

When testing the change in SD for the positive subsample, the normality test indicate that the sample is not normally distributed. The full positive subsample is statistically significant and indicate that there is a significant change in standard deviation. When removing the one extreme outlier, the results are less but still significant indicating that we do find evidence for an increase in volatility for the positive subsample.

4.5.2 Negative events

Table 4.14 sums up the change in standard deviation in the negative subsample. As the results show, 19 of the totals of 28 (68 %) events when not removing outliers har an increase in SD and 17 (66 %) when removing the two mild outlier.

Table 4.14: Summarization of change in SD for negative events

	Decrease in SD	*Increase in SD*	*Min*	*Max*	*Mean*
Full	9 (32 %)	19 (68 %)	-0.051	1.843	0.237
Excl. outliers	9 (32 %)	19 (68 %)	-0.051	1.843	0.190
Excl. more outliers	9 (34 %)	17 (66 %)	-0.051	1.843	0.190

The results in table 4.14 also show that the mean of the change in SD is positive, indicating that there is a change in SD. Figure 4.2 is a visualization of distribution of the increase or decrease. The darker pole indicates the interval (-0.005, 0.001) which contain zero. As we see in both sample sizes, 4 of the negative events has a close to zero change in standard deviation. In comparison to the positive subsample whose majority of events was close to zero, the distribution of the results is shifted to the right, indicating that a majority of the events has an increase in standard deviation above zero between the two estimation windows.

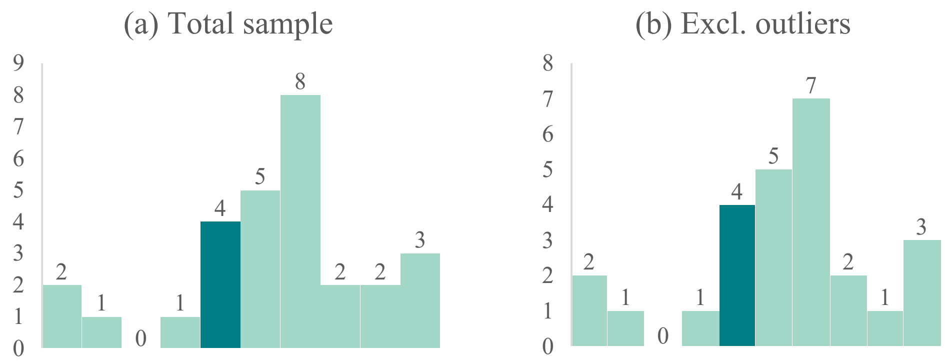

Figure 4.2: Difference/change in standard deviation from prior window (-9,-5) and past window (0,4). Figure (a) is for the full negative subsample N= 28 and figure (b) is the negative subsample when excluding outliers N=26. In both figures the darker pole visualize the interval that contain zero.

To test the results shown above we test for normality and significance. According to the normality the negative subsample is not normally distributed and because of that the signed-rank test is used to test for significance. The results are shown in table 4.15 below

Table 4.15: Normality and significance test for panels for negative events

	n	Shapiro-Wilk W test z-value	p-value	Wilcoxon Signed-rank test z-value	p-value
Full	28	2.863	0.001***	2.083	0.038**
Excl. outliers	28	2.863	0.001***	2.083	0.038**
Excl. more outliers	26	1.828	0.035**	1.931	0.057*

*Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

The results reveal that the sample with and without outliers are statistically significant using the rank-test which indicates that there is a significant change in standard deviation. When removing the outliers, the p-value increases but are still significant.

What we observe in this additive study is that we find changes in the stock volatility which is consistent with other researchers presented in this study. In our study we find a tendency that the both positive and negative publicity on Trump's twitter account regarding publicly traded companies, leads to an *increase* in stock volatility which is similar to what is expected for most types of announcements (Neuhierl et al., 2013).

4.6 Trading volume

Our procedure for this additive analysis is like the abnormal returns, however we cannot call it abnormal trading volume as we do not have a benchmark model to compare expected or normal trading volume. We calculate the change in trading volume for each day for each company and separated the sample based on positive and negative tweets as we have done otherwise in the analysis. We estimated the average cumulative change in trading volume (%) for the full sample and sample excluding outliers, for both positive and negative events.

The following graphs in figure 4.3 and 4.4 display the change in the daily trading volume. The information in this plot is the direction of the graphs. An upward (downward) slope in the graph refers to an increase (decrease) in trading volume.

However, the following discussion is only supportive analysis to our main study, and we provide possible explanations to fluctuation based on previous research.

4.6.1 Positive subsample

Figure 4.3 illustrate the percentage change in cumulative average change in trading volume for positive events.

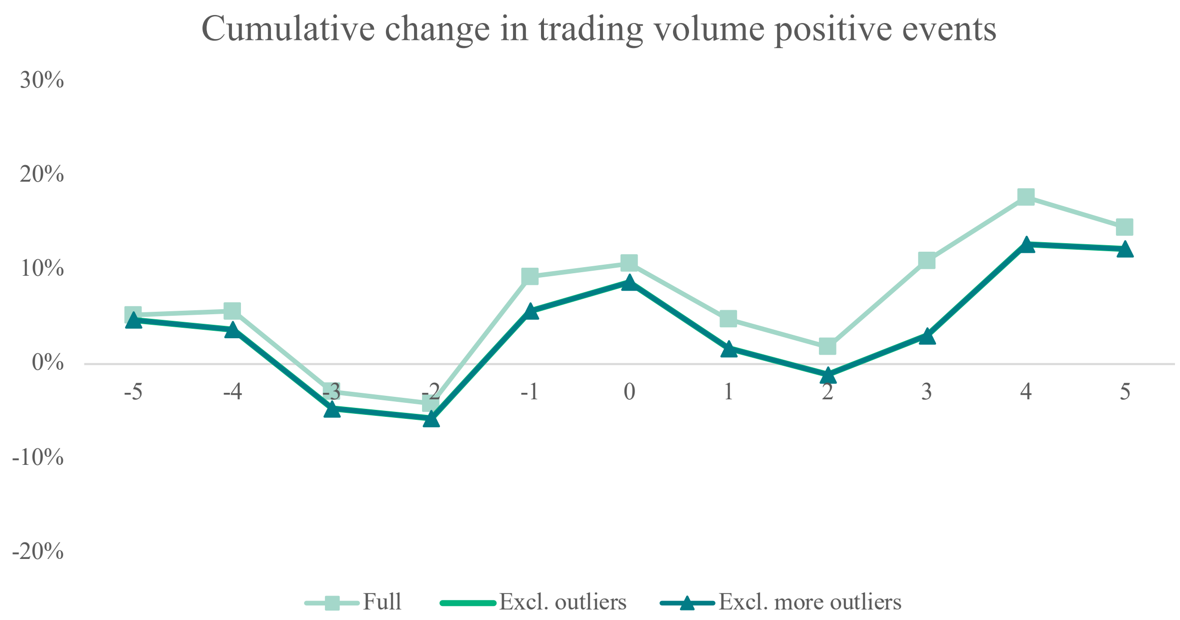

Figure 4.3: Cumulative change in trading volume for positive events for t_{-5} to t_5. Observations in the positive subsample n=40, positive subsample excluding severe outliers n=39 and positive subsample excluding mild and severe outliers n=39.

For the full sample and sample without outliers, the graphs reveal that the slope decreases after event time (t=0). There is not much difference between the figures when removing the one severe outlier and as before there are no mild outliers in the positive subsample.

Between t_{-2} and t_0 we observe an on average increase in trading volume for all sample sizes. From t_0 to t_2 the line in downward sloping, which indicates a decline in trading volume after the publication of a positive tweet. This can indicate results of semi-strong market efficiency that the market reacts after new information become publicly available (Malkiel & Fama, 1970), meaning we observe that something happens that is not like what happened the days prior the event. However, another issue is why we observe *a decline* after press releases or in our case tweets from Donald Trump which may or may not include valuable information. These graphs we observe here has nothing to do with returns, only that we see a tendency that traders linger. Investors might stop trading because they are not sure what these news means and, as Neuhierl et al. (2013) describes, news elements cause higher level of uncertainty because of the general news element. Also, these reasons are like Antweiler and Frank (2004) who found evidence that greater disagreements on one day predict that the number of trades on the following day will go down.

These results support our indicate findings in the regression in part 4.1 that tweets categorized as positive has a small negative close to zero insignificantly effect on CAR as a results of lower trading volume.

4.6.2 Negative subsample

Figure 4.4 illustrates the change in cumulative average change in trading volume for negative events for sample with and without outliers.

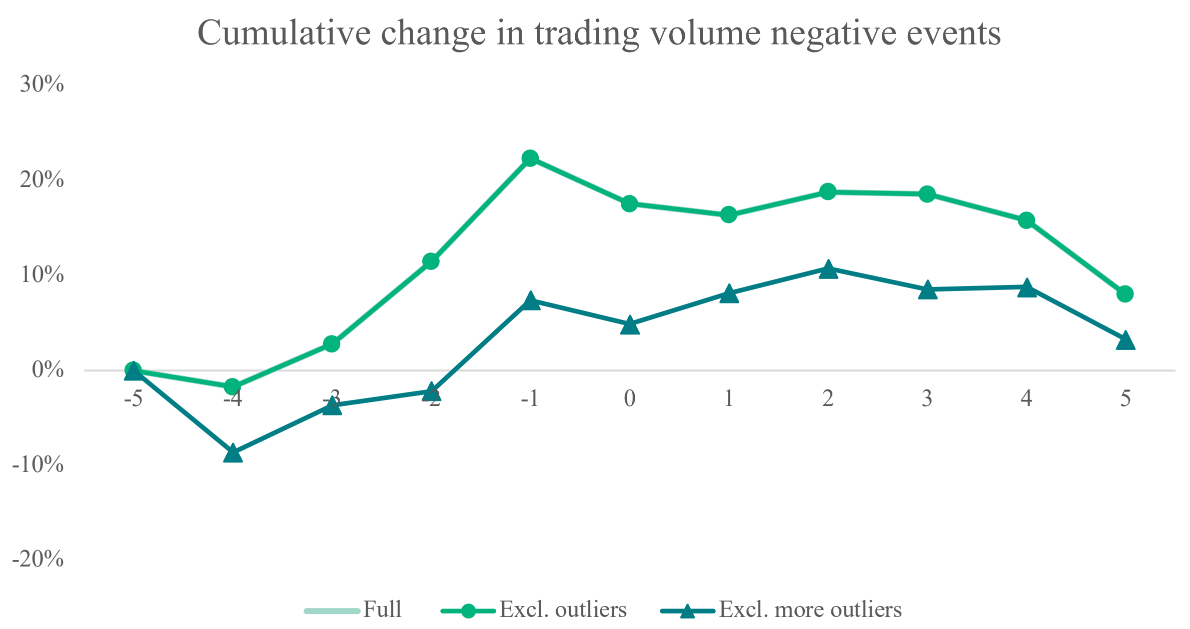

Figure 4.4: Cumulative change in trading volume for negative events for t_{-5} to t_5. Observations for the negative subsample n=28, negative subsample excluding severe outliers n=28 and negative subsample excluding mild and severe outliers n=26

When not removing outliers, we observe a small decline from t=0 to t=1. When removing the mild outliers from the negative subsample, there is an increase in average trading volume. As for the difference between full sample and removing outliers, we can observe same kind of tendencies as discussed before, referring to press releases and uncertainty about news element in the window t=-1,t=0 (Neuhierl et al., 2013). However, after t=0 we find some differences between the lines in figure 4.4.

The dark blue line, controlled for outliers, slightly increases while the green line shows a slacker decline. Based on our study, explaining the differences here is out of our control.

However, if we look at the dark blue line in which we believe is controlling for a market reaction to an unknown news element, we observe a slight increase in trading volume after Trump tweets. This *increase* in trading volume followed by negative publicity of Twitter is similar to result from Tetlock (2007) and De Long et al. (1990) which pessimistic cover in the media was followed by a downward pressure on prices and *higher* trading volume.

To our extent, if we could assume that the tweets do not that tweets do not contain any financial news (that rational or institutional traders will not react to), we could argue that we can indicate an effect of noise traders act noise as exclusive information (Hervé et al., 2019). If noise traders overreact to this information, as Tetlock (2007) describes we will observe an increase in trading volume because noise traders want to sell their stocks and they will do so to the rational traders that do not believe that negative tweets are something to worry about. Indeed, this could be supported by Barber and Odean (2008) evidence of individual investor's behavior be controlled to a larger scale by attention in the media and personal preferences which could for example be regarding Donald Trump as an influential role model.

Since these thoughts are only based on what we have seen from other researchers and theory, we cannot conclude based on this plot that we have evidence of that the change in trading volume is caused by the events itself, but we can observe some changes that could be corresponding to other researchers' findings. These findings also support the results of the regression in part 4.1 of content, where the insufficient results indicated that negative tweets were associated with a decrease in the abnormal return. However, more investigating is needed for this type of conclusion. Supported by Fama and French (2004), you can never completely isolate the effects of one single event because the market reacts to all kinds of factors simultaneously. This is also regarding the use of benchmark models that cannot perfectly capture the total variation of stock returns.

5 Conclusion

This study has explored how stocks prices are affected by being targeted in Donald Trump´s company-specific tweets during his time as President of the USA. Tweets mentioning publicly traded companies were collected and sorted into categories based on content and company characteristics. First, an event study was conducted to investigate whether there was presence of any abnormality in stock prices surrounding events and second we attempted to identify possible predictors for abnormal return using cross-sectional regression with explanatory variables. The positive and negative tweets were studies separately. The results were supported by an additive analysis on stock volatility and trading volume.

This study continues the research done by Bollen et al. (2010), Zhang et al. (2011) and Sprenger et al. (2014a; 2014b). Closest related to our study is Sprenger et al. (2014a; 2014b) as they study company-specific tweets from several Twitter user and the effect on the representative stocks. Our study builds on the same foundation, but we narrow the study by investigating one of the most powerful individuals in the Western world. The study contribute research by connecting Trump as a public and political figure and the market effects of his use of the unfiltered medium Twitter to spread both private and public information targeting companies. Our findings confirm and validate results from recent studies of the relationship between Trump and Twitter by including more events and multiple pricing models. Further, the study extends the existing research by investigating if abnormal return can affect differently based on company characteristics.

The results in this study should be considered as tendencies and not conclusion since we find it difficult secure the whether there is presence of other possible underlying company events that affect the abnormal return in the event window. Overall, the President's tweets did not yield a significant response to the stock market. The results indicate that most of the tweets are replicates of what the market already know, and that they did not contribute with new information.

That said, we can identify some differences in effect regarding positive and negative publicity in line with other studies. When we consider the sentiment of the tweet, the results indicate that tweets with a strong negative sentiment, like threatening messages leads to a negative response from the stock market in an economically meaningful way. This is supported literature (Bollen et al., 2010; Sprenger et al., 2014a, 2014b; Zhang et al., 2011) and confirms that investors are more sensitive to negative news.

The results find tendencies that when Trump shares his personal opinion on Twitter, the market react more negatively to positive tweets then negative. Further, we find evidence that positive teasers are associated with a decline in CAR, which is the opposite of what we expected based on literature. Most surprisingly, the results indicated after excluding outliers that negative tweets containing assumable already known information is associated with an increase in abnormal return. This we believe should be investigated further.

Based on the sample we discriminate by company size and industry, and the results found tendencies to a different effect according to smaller companies and certain industries when separating the sample based on positive and negative tweets. For the negative events we observe a greater effect on abnormal return for mid cap companies and industry manufacturers. Surrounding Trumps tweets the results indicate a tendency of increased stock volatility regardless of content, and an increase in trading volume for negative events.

It is reasonable to assume that Trump tweets with the intention of influence people or businesses. Based on the results from this study, the effect can be questionable. It can seem that being powerful and having a great number of followers is not necessarily the criterion for affecting stock price, which we can parallel findings from Sprenger et al. (2014b) suggesting content and quality is more crucial than number of tweets. However, we cannot claim that the use of Twitter is useless to affect investors and companies. The intention of the paper is not to consult other future presidents or politicians on the use of social media, but to contribute to an important discussion. Since Trump is famous for the use of Twitter, the purpose of the use could also be draw attention and maintain a popular public figure. Therefore, a suggestion for further research could be to follow the same study for other presidents and influencers.

Based on this study we find no significant implications for market participants. For traders we cannot claim that there is a large gain in following Trump on Twitter to decide good trades in the several days, followed up by markets efficiency where there are no opportunities for profit trading. However, we can observe tendencies of induced trading activity associated with negative tweets, but if this is solely because of the tweet it is difficult to say. Similar for the company owners and shareholders, achieving publicity in Trump's tweets seem to have little to marginal effect, and they should not fear negative publicity because it seems to have economically small effects.

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7 Appendix

Appendix 1: Company data

Company	Ticker	Market Cap	Market Cap category	Industry group
Amazon	AMZN	1 057 000 000 000.00	Mega Cap	Consumer Cyclical
Apple	AAPL	1 397 000 000 000.00	Mega Cap	Consumer Cyclical
Boeing	BA	193 454 000 000.00	Large Cap	Industrials
Catepillar	CAT	73 747 000 000.00	Large Cap	Industrials
Exxon Mobile	XOM	253 364 000 000.00	Mega Cap	Industrials
Facebook	FB	604 808 000 000.00	Mega Cap	Internet Content & Information
Fiat Chrysler Automobiles	FCAU	25 813 000 000.00	Large Cap	Industrials
Ford Motor Company	F	31 938 000 000.00	Large Cap	Industrials
General Motors	GM	48 515 000 000.00	Large Cap	Industrials
Google /Alphabet	GOOGL	1 030 000 000 000.00	Mega Cap	Internet Content & Information
Harley Davidson	HOG	5 178 000 000.00	Mid Cap	Industrials
Deree&Company	DE	52 907 000 000.00	Large Cap	Industrials
Lockheed Martin	LMT	124 010 000 000.00	Large Cap	Industrials
Merck	MRK	218 038 000 000.00	Mega Cap	Drug Manufactures
Nike	NKE	154 966 000 000.00	Large Cap	Consumer Cyclical
Nordstrom	JWN	5 869 000 000.00	Mid Cap	Consumer Cyclical
Novartis	NVS	220 314 000 000.00	Mega Cap	Drug Manufactures
Pfizer	PFE	209 190 000 000.00	Mega Cap	Drug Manufactures
Rexnord Corp.	RXN	4 109 000 000.00	Mid Cap	Industrials
Toyota Motor Corporation	TM	199 648 000 000.00	Large Cap	Industrials
Twitter	TWTR	27 792 000 000.00	Large Cap	Internet Content & Information
United Technologies Corp.	UTX	134 685 000 000.00	Large Cap	Industrials
Walmart	WMT	327 685 000 000.00	Mega Cap	Consumer Cyclical

Note: List with company with ticker, market capitalization with associated market cap group and industry group.

Appendix 2: Event data[1]

#	Name	Ticker	Date[2]	Business Day	Trading day	Content	Sentiment
1	Ford Motor Company	F	11/18/16	Business Day	11/18/16	Positive	Public
2	United Technologies Corp.	UTX	11/24/16	Non-Business-Day (Holiday)	11/25/16	Positive	Teaser
3	United Technologies Corp.	UTX	11/30/16	Business Day	11/30/16	Positive	Teaser
4	United Technologies Corp.	UTX	12/01/16	Business Day	12/01/16	Positive	Teaser
5	Rexnord Corp.	RXN	12/03/16	Non-Business-Day (Saturday)	12/05/16	Negative	Public
6	Boeing	BA	12/06/16	Business Day	12/06/16	Negative	Private
7	Exxon Mobile	XOM	12/11/16	Non-Business-Day (Sunday)	12/12/16	Positive	Teaser
8	Exxon Mobile	XOM	12/13/16	Business Day	12/13/16	Positive	Public
9	Boeing	BA	12/23/16	Business Day	12/23/16	Positive	Private
10	Lockheed Martin	LMT	12/23/16	Business Day	12/23/16	Negative	Private
11	General Motors	GM	01/03/17	Business Day	01/03/17	Negative	Public
12	Ford Motor Company	F	01/04/17	Business Day	01/04/17	Positive	Public
13	Toyota Motor Corporation	TM	01/06/17	Business Day	01/06/17	Negative	Threat
14	Fiat Chrysler Automobiles	FCAU	01/09/17	Business Day	01/09/17	Positive	Public
15	Ford Motor Company	F	01/09/17	Business Day	01/09/17	Positive	Public
16	Walmart	WMT	01/18/17	Business Day	01/18/17	Positive	Private
17	General Motors	GM	01/18/17	Business Day	01/18/17	Positive	Private
18	Ford Motor Company	F	01/25/17	Business Day	01/25/17	Positive	Teaser
19	General Motors	GM	01/25/17	Business Day	01/25/17	Positive	Teaser
20	Nordstrom	JWN	02/08/17	Business Day	02/08/17	Negative	Private
21	Boeing	BA	02/17/17	Business Day	02/17/17	Positive	Teaser
22	Exxon Mobile	XOM	03/07/17	Business Day	03/07/17	Positive	Public
23	Ford Motor Company	F	03/28/17	Business Day	03/28/17	Positive	Public
24	Rexnord Corp.	RXN	05/08/17	Business Day	05/08/17	Negative	Threat
25	Merck	MRK	07/21/17	Business Day	07/21/17	Positive	Public
26	Pfizer	PFE	07/21/17	Business Day	07/21/17	Positive	Public
27	Amazon.com	AMZN	07/25/17	Business Day	07/25/17	Negative	Private
28	Toyota Motor Corporation	TM	08/04/17	Business Day	08/04/17	Positive	Public
29	Merck	MRK	08/14/17	Business Day	08/14/17	Negative	Private

[1] Events colored in light grey are events removed from the sample due to either confounding effects from earnings announcements or cluster effects.
[2] Published day adjusted for time. Se appendix called "Tweets" for time stamp in ETC.

30	Merck	MRK	08/15/17	Business Day	08/15/17	Negative	Private
31	Amazon.com	AMZN	08/16/17	Business Day	08/16/17	Negative	Private
32	Amazon.com	AMZN	12/29/17	Business Day	12/29/17	Negative	Private
33	Toyota Motor Corporation	TM	01/11/18	Business Day	01/11/18	Positive	Public
34	Fiat Chrysler Automobiles	FCAU	01/12/18	Business Day	01/12/18	Positive	Public
35	Apple	AAPL	01/18/18	Business Day	01/18/18	Positive	Private
36	Amazon.com	AMZN	03/29/18	Business Day	03/29/18	Negative	Private
37	Amazon.com	AMZN	03/31/18	Non-Business-Day (Saturday)	04/02/18	Negative	Private
38	Amazon.com	AMZN	04/03/18	Business Day	04/03/18	Negative	Private
39	Apple	AAPL	04/25/18	Business Day	04/25/18	Positive	Teaser
40	Harley Davidson	HOG	06/26/18	Business Day	06/26/18	Negative	Private
41	Harley Davidson	HOG	06/27/18	Business Day	06/27/18	Negative	Private
42	Harley Davidson	HOG	07/03/18	Business Day	07/03/18	Negative	Private
43	Pfizer	PFE	07/10/18	Business Day	07/10/18	Negative	Private
44	Pfizer	PFE	07/11/18	Business Day	07/11/18	Positive	Teaser
45	Novartis	NVS	07/19/18	Business Day	07/19/18	Positive	Private
46	Pfizer	PFE	07/19/18	Business Day	07/19/18	Positive	Private
47	Ford Motor Company	F	07/26/18	Business Day	07/26/18	Positive	Private
48	Boeing	BA	08/04/18	Non-Business-Day (Saturday)	08/06/18	Positive	Teaser
49	Apple	AAPL	08/11/18	Non-Business-Day (Saturday)	08/13/18	Positive	Teaser
50	Harley Davidson	HOG	08/12/18	Non-Business-Day (Sunday)	08/13/18	Negative	Threat
51	Nike	NKE	09/05/18	Business Day	09/05/18	Negative	Private
52	Nike	NKE	09/07/18	Business Day	09/07/18	Negative	Private
53	Apple	AAPL	09/08/18	Non-Business-Day (Saturday)	09/10/18	Negative	Threat
54	General Motors	GM	11/28/18	Business Day	11/28/18	Negative	Threat
55	General Motors	GM	11/29/18	Business Day	11/29/18	Negative	Private
56	Fiat Chrysler Automobiles	FCAU	02/27/19	Business Day	02/27/19	Positive	Public
57	Toyota Motor Corporation	TM	03/15/19	Business Day	03/15/19	Positive	Public
58	General Motors	GM	03/17/19	Non-Business-Day (Sunday)	03/18/19	Negative	Private
59	Toyota Motor Corporation	TM	03/17/19	Non-Business-Day (Sunday)	03/18/19	Positive	Public
60	Google	GOOGL	03/17/19	Non-Business-Day (Sunday)	03/18/19	Negative	Private
61	Ford Motor Company	F	03/21/19	Business Day	03/21/19	Positive	Public
62	Google	GOOGL	03/28/19	Business Day	03/28/19	Positive	Teaser
63	Boeing	BA	04/15/19	Business Day	04/15/19	Negative	Private
64	Harley Davidson	HOG	04/23/19	Business Day	04/23/19	Negative	Public
65	Twitter	TWTR	04/24/19	Business Day	04/24/19	Positive	Teaser

66	General Motors	GM	05/08/19	Business Day	05/08/19	Positive	Public
67	Lockheed Martin	LMT	07/11/19	Business Day	07/11/19	Positive	Public
68	Facebook	FB	07/12/19	Business Day	07/12/19	Negative	Private
69	Google	GOOGL	07/26/19	Business Day	07/26/19	Negative	Threat
70	Apple	AAPL	07/26/19	Business Day	07/26/19	Negative	Threat
71	Boeing	BA	08/08/19	Business Day	08/08/19	Positive	Private
72	John Deere	DE	08/08/19	Business Day	08/08/19	Positive	Private
73	Caterpillar	CAT	08/08/19	Business Day	08/08/19	Positive	Private
74	Walmart	WMT	08/16/19	Business Day	08/16/19	Positive	Public
75	Apple	AAPL	08/17/19	Non-Business-Day (Saturday)	08/19/19	Positive	Teaser
76	Google	GOOGL	08/19/19	Business Day	08/19/19	Negative	Threat
77	Ford Motor Company	F	08/22/19	Business Day	08/22/19	Negative	Private
78	General Motors	GM	08/22/19	Business Day	08/22/19	Positive	Private
79	General Motors	GM	08/30/19	Business Day	08/30/19	Negative	Private
80	General Motors	GM	09/16/19	Business Day	09/16/19	Positive	Teaser
81	Facebook	FB	09/20/19	Business Day	09/20/19	Positive	Teaser
82	Apple	AAPL	10/01/19	Business Day	10/01/19	Positive	Public
83	Fiat Chrysler Automobiles	FCAU	10/31/19	Business Day	10/31/19	Positive	Private
84	General Motors	GM	10/31/19	Business Day	10/31/19	Positive	Private
85	Toyota Motor Corporation	TM	10/31/19	Business Day	10/31/19	Positive	Private
86	General Motors	GM	11/01/19	Business Day	11/01/19	Positive	Public
87	Walmart	WMT	11/14/19	Business Day	11/14/19	Positive	Public
88	Apple	AAPL	11/21/19	Business Day	11/21/19	Positive	Private
89	Apple	AAPL	11/24/19	Non-Business-Day (Sunday)	11/25/19	Positive	Private

Note: Events listed with ticker, day of posting, whether the day of posting was a business day and trading day. The events are listed with content and sentiment categorization information. The events in dark grey are excluded from the sample because of confounding effects.

Appendix 3: Earning announcements

Ticker	2016 Q4	2017 Q1	2017 Q2	2017 Q3	2017 Q4	2018 Q1	2018 Q2	2018 Q3
AMZN	02.02.17	04.27.17	07.27.17	10.26.17	02.01.18	04.26.18	07.26.18	10.25.18
AAPL	01.31.17	05.02.17	08.01.17	11.02.17	02.01.18	05.01.18	07.31.18	11.01.18
BA	01.25.17	04.26.17	07.26.17	10.25.17	01.31.18	04.25.18	07.25.18	10.24.18
CAT	01.26.17	04.25.17	07.25.17	10.24.17	01.25.18	04.24.18	07.30.18	10.23.18
XOM	01.31.17	04.28.17	07.28.17	10.27.17	02.02.18	04.27.18	07.27.18	11.02.18
FB	02.01.17	05.03.17	07.26.17	11.01.17	01.31.18	04.25.18	07.25.18	10.30.18
FCAU	01.26.17	04.26.17	07.27.17	10.24.17	01.25.18	04.26.18	07.25.18	10.30.18
F	01.26.17	04.27.17	07.26.17	10.26.17	01.24.18	04.25.18	**07.25.18**	10.24.18
GM	02.07.17	04.28.17	07.25.17	10.24.17	02.06.18	04.26.18	07.25.18	10.31.18
GOOGL	01.26.17	04.27.17	07.24.17	10.26.17	02.01.18	04.23.18	07.23.18	10.25.18
HOG	01.31.17	04.18.17	07.18.17	10.17.17	01.30.18	04.24.18	07.24.18	10.23.18
DE	02.17.17	05.19.17	08.18.17	11.22.17	02.16.18	05.18.18	08.17.18	11.21.18
LMT	01.24.17	04.25.17	07.18.17	10.24.17	01.29.18	04.24.18	07.24.18	10.23.18
MRK	02.02.17	05.02.17	07.28.17	10.27.17	02.02.18	05.01.18	07.27.18	10.25.18
NKE	12.20.16	03.21.17	06.29.17	09.26.17	12.21.17	03.22.18	06.28.18	09.25.18
JWN	02.23.17	05.11.17	08.10.17	11.09.17	03.01.18	05.17.18	08.16.18	11.15.18
NVS	01.25.17	04.25.17	07.18.17	10.24.17	01.24.18	04.19.18	**07.18.18**	11.18.18
PFE	01.31.17	05.02.17	08.01.17	10.31.17	01.30.18	05.01.18	07.31.18	10.30.18
RXN	02.01.17	05.17.17	05.02.17	11.01.17	01.31.18	05.14.18	07.30.18	10.30.18
TM	02.06.17	05.10.17	**08.04.17**	11.07.17	02.06.18	05.09.18	08.03.18	11.06.18
TWTR	02.09.17	04.26.17	07.27.17	10.26.17	02.08.18	04.25.18	07.27.18	10.25.18
UTX	01.25.17	04.26.17	07.25.17	10.24.17	01.24.18	04.24.18	07.24.18	10.23.18
WMT	02.21.17	05.17.17	08.17.17	11.16.17	02.20.18	05.17.18	08.16.18	11.15.18

Ticker	2018 Q4	2019 Q1	2019 Q2	2019 Q3	2019 Q4	Source
AMZN	01.31.19	04.25.19	07.25.19	10.24.19	01.30.20	(Amazon.com, 2020)
AAPL	01.29.19	04.30.19	07.30.19	10.30.19	01.28.20	(Apple, 2020)
BA	01.30.19	04.24.19	07.24.19	10.23.19	01.29.20	(Boeing, 2020)
CAT	01.28.19	04.24.19	07.24.19	10.23.19	01.31.20	(Caterpillar, 2020)
XOM	02.01.19	04.26.19	08.02.19	11.01.19	01.31.20	(Exxon Mobil Corporation, 2020)
FB	01.30.19	04.24.19	07.24.19	10.30.19	01.29.20	(Facebook, 2020)
FCAU	02.07.19	05.03.19	07.31.19	**10.31.19**	02.06.20	(Fiat Chrysler Automobiles, 2020)
F	01.23.19	04.25.19	07.24.19	10.23.19	02.04.20	(Ford Motor Company, 2020)
GM	02.06.19	04.30.19	08.01.19	**10.29.19**	02.05.20	(General Motors, 2020)
GOOGL	02.04.19	04.29.19	**07.25.19**	10.28.19	02.03.20	(Alphabet, 2020)
HOG	01.29.19	**04.23.19**	07.23.19	10.22.19	01.28.20	(Harley-Davidson, 2020)
DE	02.15.19	05.17.19	08.16.19	11.27.19	02.21.20	(Deere & Company, 2020)
LMT	01.29.19	04.23.19	07.23.19	10.22.19	01.28.20	(Lockheed Martin Corporation, 2020)
MRK	02.01.19	04.30.19	07.30.19	10.29.19	02.05.20	(Merck Sharp & Dohme Corp., 2020)
NKE	12.20.18	03.21.19	06.27.19	09.24.19	12.19.19	(Nike, 2020)
JWN	02.28.19	05.21.19	08.21.19	11.21.19	N/A	(Nordstrom, 2020)
NVS	01.30.19	04.24.19	07.18.19	10.22.19	01.29.20	(Novartis, 2020)
PFE	01.29.19	04.30.19	07.29.19	10.29.19	01.28.20	(Pfizer, 2020)
RXN	01.30.19	05.08.19	07.30.19	10.29.19	01.29.20	(Rexnord Corporation, 2020)
TM	02.06.19	05.08.19	08.02.19	11.07.19	02.06.20	(Toyota Motor Corporation, 2020)
TWTR	02.07.19	**04.23.19**	07.26.19	10.24.19	02.06.20	(Twitter, 2020b)
UTX	01.23.19	04.23.19	07.23.19	10.22.19	01.28.20	(Raytheon Technologies Corporation, 2020)
WMT	02.19.19	05.16.19	**08.15.19**	**11.14.19**	N/A	(Walmart, 2020)

Appendix 4: Normality and significance results for different event windows

		Market Model					
		Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
		z-value	p-value	z-value	p-value	t-value	p-value
Total	(-1,1)	3.572	0.000***	-1.466	0.143	-0.781	0.438
	(-1,2)	3.824	0.000***	-1.900	0.057*	-1.306	0.196
	(0)	3.177	0.000***	-0.941	0.347	-0.385	0.701
	(0,1)	2.947	0.002***	-0.257	0.798	-0.225	0.823
	(0,2)	1.045	0.148	-1.075	0.282	-0.994	0.324
Positive	(-1,1)	3.889	0.000***	0.040	0.968	0.814	0.421
	(-1,2)	4.141	0.000***	-0.927	0.354	-0.036	0.971
	(0)	2.207	0.014**	0.699	0.485	0.830	0.412
	(0,1)	0.233	0.408	-0.121	0.904	-0.136	0.893
	(0,2)	2.213	0.013**	-1.425	0.154	-1.148	0.258
Negativ	(-1,1)	1.007	0.157	-2.186	0.029**	-1.863	0.073*
	(-1,2)	0.961	0.168	-1.799	0.072*	-1.965	0.060*
	(0)	2.385	0.009***	-2.300	0.022**	-1.556	0.131
	(0,1)	2.567	0.005***	-0.228	0.820	-0.179	0.860
	(0,2)	-0.322	0.626	-0.023	0.981	-0.225	0.824

		Capital Asset Pricing Model					
		Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
		z-value	p-value	z-value	p-value	t-value	p-value
Total	(-1,1)	3.187	0.001***	-1.998	0.046**	-1.392	0.168
	(-1,2)	3.385	0.000***	-2.524	0.012**	-2.020	0.047**
	(0)	2.700	0.003***	-1.314	0.189	-0.834	0.407
	(0,1)	2.138	0.016**	-1.204	0.228	-0.882	0.381
	(0,2)	-0.162	0.564	-1.968	0.049**	-1.788	0.078
Positive	(-1,1)	3.778	0.000***	-0.403	0.687	0.473	0.639
	(-1,2)	4.080	0.000***	-1.237	0.216	-0.359	0.721
	(0)	2.096	0.018**	0.605	0.545	0.579	0.566
	(0,1)	-0.628	0.752	-0.712	0.476	-0.470	0.641
	(0,2)	1.283	0.100	-1.828	0.068	-1.465	0.151
Negativ	(-1,1)	0.805	0.210	-2.368	0.018**	-2.390	0.024**
	(-1,2)	0.578	0.282	-2.573	0.010**	-2.668	0.013**
	(0)	1.998	0.023**	-2.482	0.013**	-1.938	0.063*
	(0,1)	2.273	0.012**	-0.979	0.328	-0.762	0.453
	(0,2)	0.240	0.405	-1.070	0.285	-1.035	0.310

		Fama French Three Factor Model					
		Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
		z-value	p-value	z-value	p-value	t-value	p-value
Total	(-1,1)	2.973	0.001***	-1.790	0.073**	-1.191	0.238
	(-1,2)	3.567	0.000***	-2.102	0.036**	-1.676	0.098*
	(0)	3.022	0.001***	-1.082	0.279	-0.594	0.554
	(0,1)	1.534	0.063**	-1.082	0.278	-0.767	0.446
	(0,2)	-0.108	0.543	-1.546	0.122	-1.450	0.152
Positive	(-1,1)	3.722	0.000***	0.027	0.979	0.689	0.495
	(-1,2)	3.963	0.000***	-0.699	0.485	-0.084	0.934
	(0)	2.787	0.003***	0.605	0.545	0.652	0.519
	(0,1)	-0.362	0.641	-0.470	0.638	-0.180	0.858
	(0,2)	1.756	0.040**	-1.505	0.132	-1.189	0.242
Negativ	(-1,1)	0.397	0.346	-2.550	0.011**	-2.413	0.023**
	(-1,2)	0.835	0.202	-2.505	0.012**	-2.566	0.016**
	(0)	2.018	0.022**	-2.186	0.029**	-1.609	0.119
	(0,1)	2.259	0.012**	-1.116	0.265	-0.873	0.390
	(0,2)	-0.017	0.507	-0.592	0.554	-0.845	0.406

*Note: Note: Test results from Shapiro-Wilk W test for normality and rank test and t-test for significance on CAR for different event window for the total sample and the two subsamples. * p < 0.10, ** p < 0.05, *** p < 0.01*

Appendix 5: Outliers – calculation

	Market Model	CAPM	FF3M
Median	-0.007	-0.009	-0.010
(Q1) Lower quartil 25%	-0.017	-0.024	-0.022
(Q3) Upper quartil 75%	0.008	0.007	0.008
IQ: Interquartil range (Q3-Q1)	0.025	0.030	0.029
Lower inner fence Q1-1.5*IQ	-0.055	-0.069	-0.066
Upper inner fence Q3 +1.5*IQ	0.046	0.052	0.052
Lower outer fence Q1-3*IQ	-0.092	-0.114	-0.110
Upper outer fence Q3+3*IQ	0.083	0.097	0.096

Appendix 6: Outliers

Mild outliers	Ticker	Event	Content	Market Model	CAPM	FF3M
	RXN	5	Negative	-0.074	-0.077	-0.087
	AMZN	36	Negative	-0.081	-0.089	-0.076

Severe outliers	Ticker	Event	Content	Market Model	CAPM	FF3M
	FCAU	14	Positive	0.121	0.115	0.124

Appendix 7: Cumulative abnormal return for positive events

Event	Ticker	Date	MM	CAPM	FF3M	
1	F	11.18.2016	-2.087 %	-2.473 %	-3.035 %	
2	UTX	11.25.2016	1.577 %	1.554 %	1.572 %	
3	UTX	11.30.2016	-0.005 %	-0.024 %	-1.153 %	
7	XOM	12.12.2016	2.100 %	2.389 %	2.314 %	
9	BA	12.23.2016	-0.049 %	-0.034 %	0.055 %	
12	F	01.04.2017	3.187 %	2.848 %	4.134 %	
14	FCAU	01.09.2017	12.069 %	11.543 %	12.374 %	Severe outlier
15	F	01.09.2017	-0.854 %	-1.352 %	-0.874 %	
16	WMT	01.18.2017	0.450 %	0.183 %	0.230 %	
17	GM	01.18.2017	-0.730 %	-0.934 %	-0.330 %	
18	F	01.25.2017	-0.018 %	-0.519 %	-0.806 %	
19	GM	01.25.2017	-0.648 %	-1.141 %	-1.400 %	
21	BA	02.17.2017	2.587 %	2.375 %	2.763 %	
22	XOM	03.07.2017	-0.146 %	-0.059 %	0.193 %	
23	F	03.28.2017	-0.497 %	-0.604 %	-1.518 %	
25	MRK	07.21.2017	-0.546 %	-1.520 %	-1.472 %	
26	PFE	07.21.2017	-1.422 %	-2.390 %	-2.380 %	
33	TM	01.11.2018	2.419 %	1.761 %	1.609 %	
34	FCAU	01.12.2018	1.377 %	0.682 %	1.423 %	
35	AAPL	01.18.2018	-2.637 %	-3.090 %	-3.892 %	
39	AAPL	04.25.2018	-1.897 %	-2.640 %	-2.551 %	
46	PFE	07.19.2018	-1.170 %	-2.326 %	-2.448 %	
48	BA	08.06.2018	-2.368 %	-2.883 %	-3.731 %	
49	AAPL	08.13.2018	2.286 %	1.758 %	1.468 %	
56	FCAU	02.27.2019	-1.058 %	-1.948 %	-1.379 %	
57	TM	03.15.2019	-0.101 %	-0.514 %	-0.609 %	
61	F	03.21.2019	-0.837 %	-1.062 %	1.494 %	
62	GOOGL	03.28.2019	-1.690 %	-2.191 %	-1.274 %	
66	GM	05.08.2019	0.965 %	0.722 %	0.742 %	
67	LMT	07.11.2019	-1.753 %	-1.733 %	-1.875 %	
71	BA	08.08.2019	0.746 %	1.621 %	1.586 %	
72	DE	08.08.2019	-4.020 %	-3.143 %	-2.817 %	
73	CAT	08.08.2019	-4.349 %	-3.450 %	-2.744 %	
75	AAPL	08.19.2019	1.341 %	2.120 %	3.073 %	
78	GM	08.22.2019	-1.411 %	-0.589 %	-0.213 %	
80	GM	09.16.2019	-2.360 %	-2.381 %	-2.470 %	
81	FB	09.20.2019	-2.226 %	-2.058 %	-1.975 %	
82	AAPL	10.01.2019	3.664 %	4.121 %	3.029 %	
85	TM	10.31.2019	0.379 %	1.384 %	1.406 %	
88	AAPL	11.21.2019	-0.889 %	-0.105 %	-0.030 %	

Appendix 8: Cumulative abnormal return for negative events

Event	Ticker	Date	MM	CAPM	FF3M	
5	RXN	12.05.2016	-7.390 %	-7.708 %	-8.684 %	Mild outlier
6	BA	12.06.2016	-0.974 %	-1.354 %	-1.715 %	
10	LMT	12.23.2016	-1.106 %	-1.156 %	-1.162 %	
11	GM	01.03.2017	2.491 %	2.210 %	2.955 %	
13	TM	01.06.2017	-0.987 %	-1.330 %	-1.093 %	
20	JWN	02.08.2017	4.003 %	3.539 %	3.968 %	
24	RXN	05.08.2017	-3.412 %	-4.230 %	-4.345 %	
27	AMZN	07.25.2017	1.539 %	0.651 %	0.709 %	
29	MRK	08.14.2017	-0.076 %	-0.826 %	-1.305 %	
31	AMZN	08.16.2017	-0.820 %	-1.800 %	-2.078 %	
32	AMZN	12.29.2017	0.000 %	-0.293 %	-0.838 %	
36	AMZN	03.29.2018	-8.079 %	-8.919 %	-7.559 %	Mild outlier
38	AMZN	04.03.2018	-1.241 %	-2.357 %	-1.305 %	
40	HOG	06.26.2018	-3.744 %	-3.860 %	-3.615 %	
42	HOG	07.03.2018	-0.022 %	-1.320 %	-1.131 %	
43	PFE	07.10.2018	-0.103 %	-1.161 %	-1.462 %	
50	HOG	08.13.2018	-5.181 %	-5.704 %	-5.384 %	
51	NKE	09.05.2018	-1.914 %	-2.703 %	-2.642 %	
53	AAPL	09.10.2018	-1.577 %	-2.539 %	-3.109 %	
54	GM	11.28.2018	-1.877 %	-2.361 %	-1.654 %	
58	GM	03.18.2019	-3.352 %	-3.686 %	-2.480 %	
60	GOOGL	03.18.2019	2.056 %	1.779 %	0.434 %	
63	BA	04.15.2019	1.282 %	0.594 %	0.347 %	
68	FB	07.12.2019	0.326 %	0.260 %	-0.067 %	
70	AAPL	07.26.2019	0.432 %	0.473 %	0.930 %	
76	GOOGL	08.19.2019	-1.507 %	-0.781 %	0.152 %	
77	F	08.22.2019	-0.967 %	-0.155 %	0.414 %	
79	GM	08.30.2019	3.075 %	3.581 %	3.700 %	

Appendix 9: Descriptive statistics of CAR

9.1 Total sample

Market Model					
	Mean	Median	Min	Max	Number if events
Full	-0.44 %	-0.69 %	-8.08 %	12.07 %	68
Excl. outliers	-0.62 %	-0.73 %	-8.08 %	4.00 %	67
Excl. more outliers	-0.41 %	-0.65 %	-5.18 %	4.00 %	65

Capital Asset Pricing Model					
	Mean	Median	Min	Max	Number if events
Full	-0.69 %	-0.88 %	-8.92 %	11.54 %	68
Excl. outliers	-0.88 %	-0.93 %	-8.92 %	4.12 %	67
Excl. more outliers	-0.65 %	-0.83 %	-5.70 %	4.12 %	65

Fama-French Three Factor Model					
	Mean	Median	Min	Max	Number if events
Full	-0.59 %	-0.98 %	-8.68 %	12.37 %	68
Excl. outliers	-0.78 %	-1.09 %	-8.68 %	4.13 %	67
Excl. more outliers	-0.56 %	-0.87 %	-5.38 %	4.13 %	65

Note: Summarization of total sample with the mean, median, min and max values and the number of observations of CAR.

9.2 Positive subsample

Market Model	Mean	Median	Min	Max	Number of events
Full	-0.02 %	-0.52 %	-4.35 %	12.07 %	40
Excl. outliers	-0.33 %	-0.55 %	-4.35 %	3.66 %	39
Excl. more outliers	-0.33 %	-0.55 %	-4.35 %	3.66 %	39

Capital Asset Pricing Model	Mean	Median	Min	Max	Number of events
Full	-0.15 %	-0.55 %	-3.45 %	11.54 %	40
Excl. outliers	-0.45 %	-0.59 %	-3.45 %	4.12 %	39
Excl. more outliers	-0.45 %	-0.59 %	-3.45 %	4.12 %	39

Fama French Three Factor Model	Mean	Median	Min	Max	Number of events
Full	-0.04 %	-0.47 %	-3.89 %	12.37 %	40
Excl. outliers	-0.36 %	-0.61 %	-3.89 %	4.13 %	39
Excl. more outliers	-0.36 %	-0.61 %	-3.89 %	4.13 %	39

Note: Summarization of positive sample with the mean, median, min and max values and the number of observations of CAR.

9.3 Negative subsample

Market Model					
	Mean	Median	Min	Max	Number of events
Full	-1.04 %	-0.97 %	-8.08 %	4.00 %	28
Excl. outliers	-1.04 %	-0.97 %	-8.08 %	4.00 %	28
Excl. more outliers	-0.53 %	-0.89 %	-5.18 %	4.00 %	26

Capital Asset Pricing Model					
	Mean	Median	Min	Max	Number of events
Full	-1.47 %	-1.24 %	-8.92 %	3.58 %	28
Excl. outliers	-1.47 %	-1.24 %	-8.92 %	3.58 %	28
Excl. more outliers	-0.94 %	-1.16 %	-5.70 %	3.58 %	26

Fama French Three Factor Model					
	Mean	Median	Min	Max	Number of events
Full	-1.38 %	-1.23 %	-8.68 %	3.97 %	28
Excl. outliers	-1.38 %	-1.23 %	-8.68 %	3.97 %	28
Excl. more outliers	-0.86 %	-1.15 %	-5.38 %	3.97 %	26

Note: Summarization of negative subsample with the mean, median, min and max values and the number of observations of CAR.

Appendix 10: Statistical inference of the event window

10.1 Total sample

Market Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	3.824	0.000***	-1.900	0.057*	-1.306	0.196
Excl. outliers	1.891	0.029**	-2.155	0.031**	-2.212	0.031**
Excl. more outliers	-0.556	0.711	-1.820	0.068	-1.661	0.102

Capital Asset Pricing Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	3.385	0.000***	-2.524	0.012**	-2.020	0.047**
Excl. outliers	1.598	0.055*	-2.792	0.005***	-2.965	0.004***
Excl. more outliers	-0.568	0.715	-2.487	0.013	-2.534	0.014

Fama-French Three Factor Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	3.567	0.000***	-2.102	0.036**	-1.676	0.098*
Excl. outliers	1.363	0.087*	-2.361	0.018**	-2.624	0.011**
Excl. more outliers	-0.148	0.559	-2.036	0.042	-2.140	0.036

*Note: Normality test and significance test for event window (-1,2) using for the total sample n=68, total sample excluding severe outliers n=67 and total sample excluding both mild and severe outliers n=65. * p < 0.10, ** p < 0.05, *** p < 0.01*

10.2 Positive subsample

Market Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	4.141	0.000***	-0.927	0.354	-0.036	0.971
Excl. outliers	-0.959	0.831	-1.242	0.214	-1.090	0.285
Excl. more outliers	-0.959	0.831	-1.242	0.214	-1.090	0.285

Capital Asset Pricing Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	4.080	0.000***	-1.237	0.216	-0.359	0.721
Excl. outliers	0.908	0.182	-1.563	0.118	-1.466	0.151
Excl. more outliers	0.908	0.182	-1.563	0.118	-1.466	0.151

Fama-French Three Factor Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	3.963	0.000***	-0.699	0.485	-0.084	0.934
Excl. outliers	0.316	0.376	-1.005	0.315	-1.087	0.284
Excl. more outliers	0.316	0.376	-1.005	0.315	-1.087	0.284

Note: Normality test and significance test for event window (-1,2) using for the positive subsample n=40, positive subsample excluding severe outliers n=39 and positive subsample excluding both mild and severe outliers n=39.

** p < 0.10, ** p < 0.05, *** p < 0.01*

10.3 Negative subsample

Market Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	0.961	0.168	-1.799	0.072*	-1.965	0.060*
Excl. outliers	0.961	0.168	-1.799	0.072*	-1.965	0.060*
Excl. more outliers	-1.307	0.904	-1.308	0.191	-1.249	0.223

Capital Asset Pricing Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	0.578	0.282	-2.573	0.010**	-2.668	0.013**
Excl. outliers	0.578	0.282	-2.573	0.010**	-2.668	0.013**
Excl. more outliers	-1.221	0.889	-2.172	0.029**	-2.127	0.043**

Fama-French Three Factor Model						
	Shapiro-Wilk W test		Wilcoxon Signed-rank test		T-test	
	z-value	p-value	z-value	p-value	t-value	p-value
Full	0.835	0.202	-2.505	0.012**	-2.566	0.016**
Excl. outliers	0.835	0.202	-2.505	0.012**	-2.566	0.016**
Excl. more outliers	-0.546	0.707	-2.095	0.036**	-2.003	0.056*

Note: Normality test and significance test for event window (-1,2) using for the negative subsample n=28, negative subsample excluding severe outliers n=28 and negative subsample excluding both mild and severe outliers n=26.
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Appendix 11: Regression results

11.1 Model 1: Content analysis

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.010	-0.007	-0.002
	(0.007)	(0.006)	(0.005)
Constant	-0.000	-0.003	-0.003
	(0.004)	(0.003)	(0.003)
Observations	68	67	65
Adjusted R^2	0.019	0.009	-0.013
F	2.284	1.389	0.151
p	0.135	0.243	0.699

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.013*	-0.010	-0.005
	(0.007)	(0.006)	(0.005)
Constant	-0.002	-0.005	-0.005
	(0.004)	(0.003)	(0.003)
Observations	68	67	65
Adjusted R^2	0.039	0.029	-0.002
F	3.594	2.605	0.828
p	0.062	0.111	0.366

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.010	-0.007	-0.002
	(0.007)	(0.006)	(0.005)
Constant	-0.000	-0.003	-0.003
	(0.004)	(0.003)	(0.003)
Observations	68	67	65
Adjusted R^2	0.019	0.009	-0.013
F	2.284	1.389	0.151
p	0.135	0.243	0.699

*Note: Regression results from Model 1 content analysis using for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Breuch-Pegan	0.837	0.020**	0.444
White-test	0.912	0.055*	0.425
Heteroskedasticity	0.912	0.055*	0.425
Skewness	0.137	0.043**	0.638
Kurtosis	0.247	0.193	0.678

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Breuch-Pegan	0.659	0.018**	0.382
White-test	0.797	0.047**	0.333
Heteroskedasticity	0.797	0.047**	0.333
Skewness	0.119	0.072*	0.214
Kurtosis	0.242	0.270	0.303

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Breuch-Pegan	0.968	0.059*	0.721
White-test	0.982	0.099*	0.689
Heteroskedasticity	0.982	0.099*	0.689
Skewness	0.135	0.086*	0.210
Kurtosis	0.260	0.325	0.259

*Note: Robust analysis of regression Model 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.2 Model 2: Sentiment analysis

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Teaser	0.019**	0.019**	0.019**
	(0.008)	(0.008)	(0.008)
Private Neg	0.015	0.019**	0.019**
	(0.009)	(0.008)	(0.008)
Private Pos	0.008	0.008	0.008
	(0.008)	(0.008)	(0.008)
Public Neg	-0.004	-0.004	0.045***
	(0.037)	(0.037)	(0.007)
Public Pos	0.029***	0.022***	0.022***
	(0.011)	(0.008)	(0.008)
Constant	-0.020***	-0.020***	-0.020***
	(0.007)	(0.007)	(0.007)
Observations	68	66	65
Adjusted R^2	0.052	0.067	0.098
F	1.990	2.140	3.170
p	0.093	0.073	0.061

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Teaser	0.021**	0.021**	0.021**
	(0.010)	(0.010)	(0.010)
Private Neg	0.013	0.013	0.018*
	(0.010)	(0.010)	(0.009)
Private Pos	0.014	0.014	0.014
	(0.009)	(0.009)	(0.009)
Public Neg	-0.004	-0.004	0.046***
	(0.038)	(0.038)	(0.008)
Public Pos	0.029**	0.021**	0.021**
	(0.012)	(0.009)	(0.009)
Constant	-0.024***	-0.024***	-0.024***
	(0.008)	(0.008)	(0.008)
Observations	68	67	65
Adjusted R^2	0.030	0.012	0.050
F	1.499	1.319	.
p	0.203	0.268	.

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Teaser	0.018	0.018	0.018
	(0.011)	(0.011)	(0.011)
Private Neg	0.011	0.011	0.015
	(0.010)	(0.010)	(0.010)
Private Pos	0.012	0.012	0.012
	(0.010)	(0.010)	(0.010)
Public Neg	-0.008	-0.008	0.050***
	(0.044)	(0.044)	(0.009)
Public Pos	0.028**	0.020**	0.020**
	(0.013)	(0.010)	(0.010)
Constant	-0.021**	-0.021**	-0.021**
	(0.009)	(0.009)	(0.009)
Observations	68	67	65
Adjusted R^2	0.031	0.006	0.046
F	1.166	1.003	.
p	0.336	0.424	.

*Note: Regression results from Model 2 sentiment analysis for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. * p < 0.10, ** p < 0.05, *** p < 0.01*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Private Neg	2.68	2.66	2.58
Public Pos	2.51	2.43	2.42
Teaser	2.31	2.29	2.29
Private Pos	2.16	2.14	2.14
Public Neg	1.25	1.25	1.13
Breuch-Pegan	0.244	0.039**	0.976
White-test	0.424	0.000***	0.922
Heteroskedasticity	0.424	0.000***	0.922
Skewness	0.368	0.866	0.329
Kurtosis	0.238	0.631	0.138

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Private Neg	2.68	2.66	2.58
Public Pos	2.51	2.44	2.42
Teaser	2.31	2.30	2.29
Private Pos	2.16	2.15	2.14
Public Neg	1.25	1.25	1.13
Breuch-Pegan	0.567	0.044**	0.797
White-test	0.448	0.037**	0.924
Heteroskedasticity	0.448	0.037**	0.924
Skewness	0.355	0.779	0.268
Kurtosis	0.235	0.397	0.924

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Private Neg	2.68	2.66	2.58
Public Pos	2.51	2.44	2.42
Teaser	2.31	2.30	2.29
Private Pos	2.16	2.15	2.14
Public Neg	1.25	1.25	1.13
Breuch-Pegan	0.644	0.003***	0.633
White-test	0.200	0.000***	0.843
Heteroskedasticity	0.200	0.000***	0.843
Skewness	0.390	0.967	0.298
Kurtosis	0.276	0.419	0.069

*Note: Robust analysis of regression Model 2. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.3 Model 2a – positive subsample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	0.021^{**}	0.014^{*}	0.014^{*}
	(0.010)	(0.007)	(0.007)
Teaser	0.011	0.011	0.011
	(0.007)	(0.007)	(0.007)
Constant	-0.012^{**}	-0.012^{**}	-0.012^{**}
	(0.005)	(0.005)	(0.005)
Observations	40	39	39
Adjusted R^2	0.058	0.051	0.051
F	2.582	2.161	2.161
p	0.089	0.130	0.130

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	0.015	0.007	0.007
	(0.010)	(0.007)	(0.007)
Teaser	0.007	0.007	0.007
	(0.008)	(0.008)	(0.008)
Constant	-0.010^{*}	-0.010^{*}	-0.010^{*}
	(0.005)	(0.005)	(0.005)
Observations	40	39	39
Adjusted R^2	-0.001	-0.027	-0.027
F	1.064	0.562	0.562
p	0.355	0.575	0.575

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	0.016	0.008	0.008
	(0.011)	(0.008)	(0.008)
Teaser	0.005	0.005	0.005
	(0.008)	(0.008)	(0.008)
Constant	-0.008	-0.008	-0.008
	(0.005)	(0.005)	(0.005)
Observations	40	39	39
Adjusted R^2	0.005	-0.028	-0.028
F	1.080	0.556	0.556
p	0.350	0.578	0.578

Note: Regression results from Model 2 sentiment analysis for the positive subsample n=40, the positive subsample excluding severe outliers n=39 and the positive subsample excluding mild and severe outliers n=39.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	1.47	1.45	1.45
Teaser	1.47	1.45	1.45
Breuch-Pegan	0.013	0.851	0.851
White-test	0.431	0.894	0.894
Heteroskedasticity	0.431	0.894	0.894
Skewness	0.203	0.060	0.060
Kurtosis	0.295	0.048	0.048

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	1.47	1.45	1.45
Teaser	1.47	1.45	1.45
Breuch-Pegan	0.014	0.670	0.670
White-test	0.419	0.779	0.779
Heteroskedasticity	0.419	0.779	0.779
Skewness	0.190	0.140	0.140
Kurtosis	0.304	0.043	0.043

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	1.47	1.45	1.45
Teaser	1.47	1.45	1.45
Breuch-Pegan	0.010	0.648	0.648
White-test	0.418	0.574	0.574
Heteroskedasticity	0.418	0.574	0.574
Skewness	0.209	0.348	0.348
Kurtosis	0.301	0.034	0.034

*Note: Robust analysis of regression Model 2a. * p < 0.10, ** p < 0.05, *** p < 0.01*

11.4 Model 2b – negative subsample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	-0.019	-0.023	0.026^{***}
	(0.038)	(0.037)	(0.005)
Threat	-0.015	-0.019^{**}	-0.019^{**}
	(0.009)	(0.008)	(0.008)
Constant	-0.005	-0.001	-0.001
	(0.006)	(0.005)	(0.005)
Observations	28	27	26
Adjusted R^2	-0.001	0.081	0.175
F	1.359	2.751	.
p	0.275	0.084	.

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	-0.017	-0.017	0.028^{***}
	(0.038)	(0.038)	(0.005)
Threat	-0.013	-0.013	-0.018^{*}
	(0.010)	(0.010)	(0.009)
Constant	-0.010	-0.010	-0.006
	(0.007)	(0.007)	(0.005)
Observations	28	28	26
Adjusted R^2	-0.020	-0.020	0.137
F	0.918	0.918	.
p	0.413	0.413	.

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	-0.019	-0.019	0.036^{***}
	(0.044)	(0.044)	(0.005)
Threat	-0.011	-0.011	-0.015
	(0.010)	(0.010)	(0.010)
Constant	-0.010	-0.010	-0.006
	(0.006)	(0.006)	(0.005)
Observations	28	28	26
Adjusted R^2	-0.026	-0.026	0.148
F	0.629	0.629	3.170
p	0.541	0.541	0.061

Note: Regression results from Model 2b sentiment analysis for the negative subsample n=40, the negative subsample excluding severe outliers n=39 and the positive negative excluding mild and severe outliers n=39.

** p < 0.10, ** p < 0.05, *** p < 0.01*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	1.03	1.03	1.01
Teaser	1.03	1.03	1.01
Breuch-Pegan	0.559	0.559	0.965
White-test	0.079	0.079	0.684
Heteroskedasticity	0.079	0.079	0.684
Skewness	0.427	0.427	0.584
Kurtosis	0.315	0.315	0.928

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	1.03	1.03	1.01
Teaser	1.03	1.03	1.01
Breuch-Pegan	0.588	0.588	0.750
White-test	0.134	0.134	0.725
Heteroskedasticity	0.134	0.134	0.725
Skewness	0.516	0.516	0.251
Kurtosis	0.369	0.369	0.644

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Public	1.03	1.03	1.01
Teaser	1.03	1.03	1.01
Breuch-Pegan	0.024	0.024	0.378
White-test	0.004	0.004	0.666
Heteroskedasticity	0.004	0.004	0.666
Skewness	0.799	0.799	0.160
Kurtosis	0.352	0.352	0.898

*Note: Robust analysis of regression Model 2b. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.5 Model 3: Size analysis

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.005	0.000	0.000
	(0.006)	(0.005)	(0.005)
Large Cap	0.022	0.022	0.013
	(0.017)	(0.016)	(0.016)
Mega Cap	0.019	0.025	0.015
	(0.017)	(0.016)	(0.016)
Constant	-0.021	-0.027	-0.017
	(0.017)	(0.016)	(0.016)
Observations	68	66	65
Adjusted R^2	0.030	0.060	-0.008
F	1.011	0.864	0.392
p	0.394	0.464	0.759

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.007	-0.005	-0.002
	(0.007)	(0.006)	(0.005)
Large Cap	0.025	0.023	0.017
	(0.016)	(0.016)	(0.016)
Mega Cap	0.020	0.021	0.017
	(0.016)	(0.016)	(0.016)
Constant	-0.025	-0.027	-0.021
	(0.016)	(0.016)	(0.016)
Observations	68	67	65
Adjusted R^2	0.061	0.063	0.010
F	1.621	1.285	0.502
p	0.193	0.287	0.682

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.007	-0.005	-0.002
	(0.006)	(0.006)	(0.005)
Large Cap	0.027	0.025	0.016
	(0.017)	(0.017)	(0.016)
Mega Cap	0.020	0.021	0.015
	(0.017)	(0.017)	(0.016)
Constant	-0.025	-0.027	-0.019
	(0.018)	(0.017)	(0.016)
Observations	68	67	65
Adjusted R^2	0.068	0.071	0.002
F	1.636	1.295	0.490
p	0.190	0.284	0.691

*Note: Regression results from Model 3 size analysis for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. * p < 0.10, ** p < 0.05, *** p < 0.01*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large	3.94	3.84	4.31
Mega	3.63	3.58	4.05
Negative	1.20	1.20	1.17
Breuch-Pegan	0.263	0.000***	0.001***
White-test	0.764	0.006***	0.021**
Heteroskedasticity	0.764	0.006***	0.021**
Skewness	0.349	0.079*	0.012**
Kurtosis	0.227	0.400	0.004

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large	3.94	3.89	4.31
Mega	3.63	3.60	4.05
Negative	1.20	1.20	1.17
Breuch-Pegan	0.346	0.003***	0.008
White-test	0.888	0.251	0.037
Heteroskedasticity	0.888	0.251	0.037
Skewness	0.28	0.141	0.007
Kurtosis	0.213	0.195	0.958

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large	3.94	3.89	4.31
Mega	3.63	3.60	4.05
Negative	1.20	1.20	1.17
Breuch-Pegan	0.411	0.000***	0.014**
White-test	0.704	0.075*	0.043**
Heteroskedasticity	0.704	0.075*	0.043**
Skewness	0.349	0.152	0.004***
Kurtosis	0.251	0.198	0.959

*Note: Robust analysis of regression Model 3. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.6 Model 3a – positive sub sample

Regression results

Market Model			
	Full	Excl. outliers	Excl. more outliers
Mega Cap	-0.003	0.002	0.002
	(0.008)	(0.006)	(0.006)
Constant	0.001	-0.004	-0.004
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.024	-0.024	-0.024
F	0.128	0.099	0.099
p	0.722	0.755	0.755

Capital Asset Pricing Model			
	Full	Excl. outliers	Excl. more outliers
Mega Cap	-0.004	0.001	0.001
	(0.008)	(0.007)	(0.007)
Constant	-0.000	-0.005	-0.005
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.021	-0.027	-0.027
F	0.236	0.007	0.007
p	0.630	0.934	0.934

Fama-French Three Factor Model			
	Full	Excl. outliers	Excl. more outliers
Mega Cap	-0.006	-0.001	-0.001
	(0.009)	(0.007)	(0.007)
Constant	0.002	-0.003	-0.003
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.017	-0.027	-0.027
F	0.441	0.013	0.013
p	0.511	0.909	0.909

Note: Regression results from Model 3a size analysis for the positive subsample n=40, the positive subsample excluding severe outliers n=39 and the positive subsample excluding mild and severe outliers n=39.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Breuch-Pegan	0.089*	0.992	0.992
White-test	0.450	0.991	0.991
Heteroskedasticity	0.450	0.991	0.991
Skewness	0.185	0.116	0.116
Kurtosis	0.277	0.420	0.420

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Breuch-Pegan	0.298	0.290	0.290
White-test	0.618	0.176	0.176
Heteroskedasticity	0.618	0.176	0.176
Skewness	0.167	0.056	0.056
Kurtosis	0.289	0.122	0.122

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Breuch-Pegan	0.179	0.650	0.650
White-test	0.517	0.555	0.555
Heteroskedasticity	0.517	0.555	0.555
Skewness	0.165	0.286	0.286
Kurtosis	0.291	0.096	0.096

*Note: Robust analysis of regression Model 3a. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.7 Model 3b – negative sub sample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large Cap	0.022	0.022	0.012
	(0.017)	(0.017)	(0.017)
Mega Cap	0.019	0.019	0.016
	(0.018)	(0.018)	(0.016)
Constant	-0.026	-0.026	-0.017
	(0.016)	(0.016)	(0.016)
Observations	28	28	26
Adjusted R^2	0.021	0.021	-0.004
F	0.809	0.809	0.547
p	0.457	0.457	0.586

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large Cap	0.026	0.026	0.017
	(0.017)	(0.017)	(0.017)
Mega Cap	0.019	0.019	0.017
	(0.017)	(0.017)	(0.016)
Constant	-0.032**	-0.032**	-0.023
	(0.015)	(0.015)	(0.015)
Observations	28	28	26
Adjusted R^2	0.040	0.040	0.012
F	1.164	1.164	0.580
p	0.329	0.329	0.568

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large Cap	0.028	0.028	0.017
	(0.018)	(0.018)	(0.017)
Mega Cap	0.019	0.019	0.014
	(0.018)	(0.018)	(0.016)
Constant	-0.032*	-0.032*	-0.021
	(0.017)	(0.017)	(0.016)
Observations	28	28	26
Adjusted R^2	0.066	0.066	0.004
F	1.363	1.363	0.497
p	0.274	0.274	0.615

Note: Regression results from Model 3b size analysis for the negative subsample n=40, the negative subsample excluding severe outliers n=39 and the positive negative excluding mild and severe outliers n=39.

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large	1.71	1.71	1.85
Mega	1.71	1.71	1.85
Breuch-Pegan	0.000***	0.000***	0.002***
White-test	0.024**	0.024**	0.026**
Heteroskedasticity	0.024**	0.024**	0.026**
Skewness	0.174	0.174	0.056*
Kurtosis	0.242	0.242	0.474

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large	1.71	1.71	1.85
Mega	1.71	1.71	1.85
Breuch-Pegan	0.115	0.115	0.015**
White-test	0.483	0.483	0.074*
Heteroskedasticity	0.483	0.483	0.074*
Skewness	0.087	0.087	0.037
Kurtosis	0.063	0.063	0.432

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Large	1.71	1.71	1.85
Mega	1.71	1.71	1.85
Breuch-Pegan	0.017**	0.017**	0.010**
White-test	0.153	0.153	0.049**
Heteroskedasticity	0.153	0.153	0.049**
Skewness	0.147	0.147	0.036**
Kurtosis	0.057	0.057	0.376

*Note: Robust analysis of regression Model 3b. * p < 0.10, ** p < 0.05, *** p < 0.01*

11.8 Model 4: Size analysis – continuous

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.010	-0.007	-0.002
	(0.007)	(0.006)	(0.005)
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.001	-0.005	-0.005
	(0.005)	(0.004)	(0.003)
Observations	68	67	65
Adjusted R^2	0.005	0.000	-0.013
F	1.165	0.794	0.454
p	0.318	0.456	0.637

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.013*	-0.011	-0.005
	(0.007)	(0.006)	(0.006)
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.002	-0.006*	-0.007*
	(0.005)	(0.003)	(0.003)
Observations	68	67	65
Adjusted R^2	0.025	0.021	-0.000
F	1.803	1.352	0.613
p	0.173	0.266	0.545

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.013*	-0.010	-0.005
	(0.007)	(0.006)	(0.006)
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.000	-0.005	-0.005
	(0.006)	(0.004)	(0.004)
Observations	68	67	65
Adjusted R^2	0.023	0.017	-0.011
F	1.806	1.310	0.466
p	0.172	0.277	0.629

*Note: Regression results from Model 4 size analysis for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. * p < 0.10, ** p < 0.05, *** p < 0.01*

11.9 Model 4a – positive sub sample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Market Cap (B$)	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.000	-0.005	-0.005
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.026	-0.013	-0.013
F	0.000	0.358	0.358
p	0.998	0.554	0.554

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.002	-0.007^{*}	-0.007^{*}
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.026	-0.006	-0.006
F	0.021	0.478	0.478
p	0.884	0.494	0.494

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Market Cap (B$)	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.000	-0.005	-0.005
	(0.006)	(0.004)	(0.004)
Observations	40	39	39
Adjusted R^2	-0.026	-0.019	-0.019
F	0.010	0.184	0.184
p	0.921	0.670	0.670

Note: Regression results from Model 4a size analysis for the positive subsample n=40, the positive subsample excluding severe outliers n=39 and the positive subsample excluding mild and severe outliers n=39.

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.10 Model 4b – negative subsample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.012	-0.012	-0.008
	(0.008)	(0.008)	(0.006)
Observations	28	28	24
Adjusted R^2	-0.035	-0.035	-0.010
F	0.085	0.085	0.823
p	0.773	0.773	0.374

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.016^{*}	-0.016^{*}	-0.012
	(0.008)	(0.008)	(0.007)
Observations	28	28	26
Adjusted R^2	-0.037	-0.037	-0.027
F	0.033	0.033	0.400
p	0.858	0.858	0.533

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Market Cap (B$)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.015^{*}	-0.015^{*}	-0.010
	(0.008)	(0.008)	(0.007)
Observations	28	28	26
Adjusted R^2	-0.037	-0.037	-0.037
F	0.024	0.024	0.123
p	0.878	0.878	0.729

Note: Regression results from Model 4b size analysis for the negative subsample n=40, the negative subsample excluding severe outliers n=39 and the positive negative excluding mild and severe outliers n=39.

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.11 Model 5: Industry analysis

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.011	-0.008	-0.003
	(0.007)	(0.006)	(0.005)
Consumer Cyclical	0.002	0.002	0.008
	(0.012)	(0.011)	(0.009)
Industry manf.	-0.001	-0.003	-0.000
	(0.010)	(0.010)	(0.009)
Drug manuf.	-0.003	-0.002	-0.001
	(0.011)	(0.010)	(0.009)
Constant	0.000	-0.001	-0.004
	(0.010)	(0.010)	(0.008)
Observations	68	67	65
Adjusted R^2	-0.024	-0.028	-0.031
F	0.708	0.510	0.543
p	0.590	0.728	0.705

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.014*	-0.011	-0.006
	(0.007)	(0.007)	(0.006)
Consumer Cyclical	-0.002	-0.002	0.004
	(0.012)	(0.012)	(0.010)
Industry manf.	-0.003	-0.006	-0.003
	(0.011)	(0.010)	(0.009)
Drug manuf.	-0.013	-0.013	-0.012
	(0.011)	(0.011)	(0.009)
Constant	0.002	0.001	-0.002
	(0.011)	(0.010)	(0.009)
Observations	68	67	65
Adjusted R^2	0.004	-0.002	-0.013
F	1.490	1.351	1.569
p	0.216	0.261	0.194

Fama French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Negative	-0.014*	-0.011	-0.006
	(0.007)	(0.007)	(0.006)
Consumer Cyclical	-0.002	-0.002	0.003
	(0.010)	(0.010)	(0.008)
Industry manf.	-0.002	-0.005	-0.001
	(0.009)	(0.008)	(0.007)
Drug manuf.	-0.015*	-0.015*	-0.014**
	(0.009)	(0.008)	(0.007)
Constant	0.003	0.001	-0.002
	(0.009)	(0.008)	(0.007)
Observations	68	67	65
Adjusted R^2	0.008	0.002	-0.011
F	2.013	2.048	2.776
p	0.103	0.099	0.350

*Note: Regression results from Model 5 industry analysis for total sample n=68, total sample excluding severe outliers n=67 and total sample excluding mild and severe outliers n=65. * p < 0.10, ** p < 0.05, *** p < 0.01*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	3.67	3.64	3.54
Consumer Cyclical	3.21	3.20	3.08
Drug manuf.	1.86	1.86	1.86
Negative	1.05	1.05	1.05
Breuch-Pegan	0.896	0.127	0.927
White-test	0.993	0.548	0.646
Heteroskedasticity	0.993	0.548	0.646
Skewness	0.609	0.303	0.626
Kurtosis	0.244	0.239	0.372

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	3.67	3.64	3.54
Consumer Cyclical	3.21	3.20	3.08
Drug manuf.	1.86	1.86	1.86
Negative	1.05	1.05	1.05
Breuch-Pegan	0.946	0.144	0.689
White-test	0.994	0.423	0.395
Heteroskedasticity	0.994	0.423	0.395
Skewness	0.545	0.365	0.853
Kurtosis	0.234	0.277	0.244

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	3.67	3.64	3.54
Consumer Cyclical	3.21	3.20	3.08
Drug manuf.	1.86	1.86	1.86
Negative	1.05	1.05	1.05
Breuch-Pegan	0.633	0.275	0.328
White-test	0.991	0.466	0.501
Heteroskedasticity	0.991	0.466	0.501
Skewness	0.631	0.459	0.954
Kurtosis	0.252	0.248	0.334

*Note: Robust analysis of regression Model 5. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.12 Model 5a – positive sub sample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	0.023**	0.023**	0.023**
	(0.009)	(0.009)	(0.009)
Industry manf.	0.021***	0.017***	0.017***
	(0.006)	(0.004)	(0.004)
Drug manuf.	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
Constant	-0.020***	-0.020***	-0.020***
	(0.002)	(0.002)	(0.002)
Observations	40	39	39
Adjusted R^2	-0.036	-0.004	-0.004
F	7.220	7.714	7.714
p	0.001	0.000	0.000

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	0.025**	0.025**	0.025**
	(0.010)	(0.010)	(0.010)
Industry manf.	0.022***	0.018***	0.018***
	(0.006)	(0.004)	(0.004)
Drug manuf.	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)
Constant	-0.021***	-0.021***	-0.021***
	(0.000)	(0.000)	(0.000)
Observations	40	39	39
Adjusted R^2	0.001	0.054	0.054
F	7.324	10.308	10.308
p	0.001	0.000	0.000

Fama French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	0.018*	0.018*	0.018*
	(0.010)	(0.010)	(0.010)
Industry manf.	0.019***	0.014***	0.014***
	(0.007)	(0.005)	(0.005)
Drug manuf.	-0.005	-0.005	-0.005
	(0.004)	(0.004)	(0.004)
Constant	-0.016***	-0.016***	-0.016***
	(0.003)	(0.003)	(0.003)
Observations	40	39	39
Adjusted R^2	-0.014	0.017	0.017
F	5.394	6.297	6.297
p	0.004	0.002	0.002

Note: Regression results from Model 5a industry analysis for the positive subsample n=40, the positive subsample excluding severe outliers n=39 and the positive subsample excluding mild and severe outliers n=39.

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	4.50	4.46	4.46
Consumer Cyclical	3.71	3.69	3.69
Drug manuf.	2.31	2.31	2.31
Breuch-Pegan	0.145	0.103	0.103
White-test	0.874	0.351	0.351
Heteroskedasticity	0.874	0.351	0.351
Skewness	0.662	0.894	0.894
Kurtosis	0.273	0.765	0.765

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	4.50	4.46	4.46
Consumer Cyclical	3.71	3.69	3.69
Drug manuf.	2.31	2.31	2.31
Breuch-Pegan	0.114	0.039**	0.039**
White-test	0.893	0.089*	0.089*
Heteroskedasticity	0.893	0.089*	0.089*
Skewness	0.636	0.990	0.990
Kurtosis	0.281	0.327	0.327

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	4.50	4.46	4.46
Consumer Cyclical	3.71	3.69	3.69
Drug manuf.	2.31	2.31	2.31
Breuch-Pegan	0.098*	0.072*	0.072*
White-test	0.789	0.186	0.186
Heteroskedasticity	0.879	0.186	0.186
Skewness	0.629	0.557	0.557
Kurtosis	0.282	0.356	0.356

*Note: Robust analysis of regression Model 5a. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

11.13 Model 5b – negative sub sample

Regression results

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	-0.011	-0.011	-0.002
	(0.014)	(0.014)	(0.012)
Industry manf.	-0.019	-0.019	-0.014
	(0.012)	(0.012)	(0.012)
Drug manuf.	-0.004	-0.004	-0.004
	(0.009)	(0.009)	(0.009)
Constant	0.003	0.003	0.003
	(0.009)	(0.009)	(0.009)
Observations	28	28	26
Adjusted R^2	-0.063	-0.063	-0.038
F	1.370	1.370	0.799
p	0.276	0.276	0.508

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	-0.020	-0.020	-0.010
	(0.013)	(0.013)	(0.010)
Industry manf.	-0.023^{**}	-0.023^{**}	-0.019^{*}
	(0.011)	(0.011)	(0.010)
Drug manuf.	-0.014^{**}	-0.014^{**}	-0.014^{**}
	(0.007)	(0.007)	(0.007)
Constant	0.004	0.004	0.004
	(0.007)	(0.007)	(0.007)
Observations	28	28	26
Adjusted R^2	-0.058	-0.058	-0.051
F	1.993	1.993	1.673
p	0.142	0.142	0.202

Fama French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Consumer Cyclical	-0.015	-0.015	-0.007
	(0.011)	(0.011)	(0.008)
Industry manf.	-0.019**	-0.019**	-0.014*
	(0.009)	(0.009)	(0.007)
Drug manuf.	-0.016***	-0.016***	-0.016***
	(0.001)	(0.001)	(0.001)
Constant	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)
Observations	28	28	26
Adjusted R^2	-0.078	-0.078	-0.078
F	40.739	40.739	40.179
p	0.000	0.000	0.000

Note: Regression results from Model 5b industry analysis for the negative subsample n=40, the negative subsample excluding severe outliers n=39 and the positive negative excluding mild and severe outliers n=39.

** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Robust analysis

Market Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	2.83	2.83	2.67
Consumer Cyclical	2.71	2.71	2.54
Drug manuf.	1.55	1.55	1.54
Breuch-Pegan	0.323	0.323	0.198
White-test	0.659	0.659	0.455
Heteroskedasticity	0.659	0.659	0.455
Skewness	0.396	0.396	0.440
Kurtosis	0.236	0.236	0.718

Capital Asset Pricing Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	2.83	2.83	2.67
Consumer Cyclical	2.71	2.71	2.54
Drug manuf.	1.55	1.55	1.54
Breuch-Pegan	0.204	0.204	0.187
White-test	0.584	0.584	0.423
Heteroskedasticity	0.584	0.584	0.423
Skewness	0.455	0.455	0.555
Kurtosis	0.225	0.225	0.925

Fama-French Three Factor Model			
	Full	**Excl. outliers**	**Excl. more outliers**
Industry manf.	2.83	2.83	2.67
Consumer Cyclical	2.71	2.71	2.54
Drug manuf.	1.55	1.55	1.54
Breuch-Pegan	0.187	0.187	0.345
White-test	0.541	0.541	0.395
Heteroskedasticity	0.541	0.541	0.395
Skewness	0.703	0.703	0.310
Kurtosis	0.176	0.176	0.802

*Note: Robust analysis of regression Model 5b. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Appendix 12: Tweets

#	Company	Ticker	Date	Time (EST)	Tweet	Trading day[3]
1	Ford Motor Company	F	11/18/16	02:01	Just got a call from my friend Bill Ford Chairman of **Ford** who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico	11/18/16
	Ford Motor Company	F	11/18/16	02:15	I worked hard with Bill **Ford** to keep the Lincoln plant in Kentucky. I owed it to the great State of Kentucky for their confidence in me!	11/18/16
2	United Technologies Corp.	UTX	11/24/16	15:11	I am working hard even on Thanksgiving trying to get **Carrier A.C.** Company to stay in the U.S. (Indiana). MAKING PROGRESS - Will know soon!	11/25/16
3	United Technologies Corp.	UTX	11/30/16	03:40	I will be going to Indiana on Thursday to make a major announcement concerning **Carrier A.C**. staying in Indianapolis. Great deal for workers!	11/30/16
	United Technologies Corp.	UTX	11/30/16	03:50	Big day on Thursday for Indiana and the great workers of that wonderful state.We will keep our companies and jobs in the U.S. Thanks **Carrier**	11/30/16
4	United Technologies Corp.	UTX	12/01/16	03:48	Look forward to going to Indiana tomorrow in order to be with the great workers of **Carrier**. They will sell many air conditioners!	12/01/16
	United Technologies Corp.	UTX	12/01/16	14:38	Getting ready to leave for the Great State of Indiana and meet the hard working and wonderful people of **Carrier A.C.**	12/01/16
5	Rexnord Corp.	RXN	12/03/16	03:06	**Rexnord** of Indiana is moving to Mexico and rather viciously firing all of its 300 workers. This is happening all over our country. No more!	12/05/16
6	Boeing	BA	12/06/16	13:52	**Boeing** is building a brand new 747 Air Force One for future presidents but costs are out of control more than $4 billion. Cancel order!	12/06/16
7	Exxon Mobile	XOM	12/11/16	15:29	Whether I choose him or not for "State"- Rex Tillerson the Chairman & CEO of ExxonMobil is a world class player and dealmaker. Stay tuned!	12/12/16
8	Exxon Mobile	XOM	12/13/16	11:43	I have chosen one of the truly great business leaders of the world Rex Tillerson Chairman and CEO of **ExxonMobil** to be Secretary of State.	12/13/16

[3] Effective trading day on NYSE or NASDAQ. Tweets on non-business days or outside trading hours is moved to next trading day.

	Exxon Mobile	XOM	12/13/16	12:44	The thing I like best about Rex Tillerson is that he has vast experience at dealing successfully with all types of foreign governments.	12/13/16
9	Boeing	BA	12/22/16	22:26	Based on the tremendous cost and cost overruns of the Lockheed Martin F-35 I have asked **Boeing** to price-out a comparable F-18 Super Hornet!	12/23/16
10	Lockheed Martin	LMT	12/22/16	22:26	Based on the tremendous cost and cost overruns of the **Lockheed Martin** F-35 I have asked Boeing to price-out a comparable F-18 Super Hornet!	12/23/16
11	General Motors	GM	01/03/17	12:30	**General Motors** is sending Mexican made model of Chevy Cruze to U.S. car dealers-tax free across border. Make in U.S.A.or pay big border tax!	01/03/17
12	Ford Motor Company	F	01/04/17	13:19	Thank you to **Ford** for scrapping a new plant in Mexico and creating 700 new jobs in the U.S. This is just the beginning - much more to follow	01/04/17
13	Toyota Motor Corporation	TM	01/05/17	18:14	**Toyota Motor** said will build a new plant in Baja Mexico to build Corolla cars for U.S. NO WAY! Build plant in U.S. or pay big border tax.	01/06/17
14	Fiat Chrysler Automobiles	FCA	01/09/17	14:14	It's finally happening - **Fiat Chrysler** just announced plans to invest $1BILLION in Michigan and Ohio plants adding 2000 jobs. This after...	01/09/17
	Fiat Chrysler Automobiles	FCA	01/09/17	14:16	Ford said last week that it will expand in Michigan and U.S. instead of building a BILLION dollar plant in Mexico. Thank you Ford & Fiat C!	01/09/17
15	Ford Motor Company	F	01/09/17	14:14	It's finally happening - Fiat Chrysler just announced plans to invest $1BILLION in Michigan and Ohio plants adding 2000 jobs. This after...	01/09/17
	Ford Motor Company	F	01/09/17	14:16	**Ford** said last week that it will expand in Michigan and U.S. instead of building a BILLION dollar plant in Mexico. Thank you Ford & Fiat C!	01/09/17
16	Walmart	WMT	01/17/17	17:55	Thank you to General Motors and **Walmart** for starting the big jobs push back into the U.S.!	01/18/17
17	General Motors	GM	01/17/17	17:55	Thank you to **General Motors** and Walmart for starting the big jobs push back into the U.S.!	01/18/17
18	Ford Motor Company	F	01/25/17	00:46	Great meeting with **Ford** CEO Mark Fields and General Motors CEO Mary Barra at the @WhiteHouse today. https://t.co/T0eIgO6LP8	01/25/17

19	General Motors	GM	01/25/17	00:46	Great meeting with Ford CEO Mark Fields and **General Motors** CEO Mary Barra at the @WhiteHouse today. https://t.co/T0eIgO6LP8	01/25/17
20	Nordstrom	JWN	02/08/17	15:51	My daughter Ivanka has been treated so unfairly by **@Nordstrom**. She is a great person -- always pushing me to do the right thing! Terrible!	02/08/17
21	Boeing	BA	02/17/17	11:38	Going to Charleston South Carolina in order to spend time with **Boeing** and talk jobs! Look forward to it.	02/17/17
22	Exxon Mobile	XOM	03/06/17	21:19	President Trump Congratulates **Exxon Mobil** for Job-Creating Investment Program'https://t.co/adBzWhtq8S	03/07/17
	Exxon Mobile	XOM	03/07/17	03:49	Buy American & hire American are the principles at the core of my agenda which is: JOBS JOBS JOBS! Thank you @exxonmobil.	03/07/17
	Exxon Mobile	XOM	03/07/17	03:50	Thank you to @exxonmobil for your $20 billion investment that is creating more than 45000 manufacturing & construction jobs in the USA!	03/07/17
23	Ford Motor Company	F	03/28/17	10:36	Big announcement by **Ford** today. Major investment to be made in three Michigan plants. Car companies coming back to U.S. JOBS! JOBS! JOBS!	03/28/17
24	Rexnord Corp.	RXN	05/07/17	22:58	**Rexnord** of Indiana made a deal during the Obama Administration to move to Mexico. Fired their employees. Tax product big that's sold in U.S.	05/08/17
25	Merck	MRK	07/21/17	03:31	Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning **Merck** & Pfizer: https://t.co/QneN48bSiq https://t.co/5VtMfuY3PM	07/21/17
26	Pfizer	PFE	07/21/17	03:31	Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning Merck & **Pfize**r: https://t.co/QneN48bSiq https://t.co/5VtMfuY3PM	07/21/17
27	Amazon.com	AMZN	07/25/17	02:28	So many stories about me in the @washingtonpost are Fake News. They are as bad as ratings challenged @CNN. Lobbyist for **Amazon** and taxes?	07/25/17

	Amazon.com	AMZN	07/25/17	02:36	Is Fake News Washington Post being used as a lobbyist weapon against Congress to keep Politicians from looking into **Amazon** no-tax monopoly?	07/25/17
28	Toyota Motor Corporation	TM	08/04/17	10:02	**Toyota** & Mazda to build a new $1.6B plant here in the U.S.A. and create 4K new American jobs. A great investment in American manufacturing!	08/04/17
29	Merck	MRK	08/14/17	12:54	Now that Ken Frazier of **Merck Pharma** has resigned from President's Manufacturing Councilhe will have more time to LOWER RIPOFF DRUG PRICES!	08/14/17
30	Merck	MRK	08/14/17	22:09	.@**Merck Pharma** is a leader in higher & higher drug prices while at the same time taking jobs out of the U.S. Bring jobs back & LOWER PRICES!	08/15/17
31	Amazon.com	AMZN	08/16/17	10:12	**Amazon** is doing great damage to tax paying retailers. Towns cities and states throughout the U.S. are being hurt - many jobs being lost!	08/16/17
32	Amazon.com	AMZN	12/29/17	13:04	Why is the United States Post Office which is losing many billions of dollars a year while charging Amazon and others so little to deliver their packages making **Amazon** richer and the Post Office dumber and poorer? Should be charging MUCH MORE!	12/29/17
33	Toyota Motor Corporation	TM	01/10/18	23:37	Cutting taxes and simplifying regulations makes America the place to invest! Great news as **Toyota** and Mazda announce they are bringing 4000 JOBS and investing $1.6 BILLION in Alabama helping to further grow our economy! https://t.co/Kcg8IVH6iA	01/11/18
	Toyota Motor Corporation	TM	01/11/18	04:29	Good news: **Toyota** and Mazda announce giant new Huntsville Alabama plant which will produce over 300000 cars and SUV’s a year and employ 4000 people. Companies are coming back to the U.S. in a very big way. Congratulations Alabama!	01/11/18

34	Fiat Chrysler Automobiles	FCA	01/12/18	02:49	More great news as a result of historical Tax Cuts and Reform: **Fiat Chrysler** announces plan to invest more than $1 BILLION in Michigan plant relocating their heavy-truck production from Mexico to Michigan adding 2500 new jobs and paying $2000 bonus to U.S. employees! https://t.co/47azKD0l9B	01/12/18
35	Apple	AAPL	01/17/18	23:28	I promised that my policies would allow companies like **Apple** to bring massive amounts of money back to the United States. Great to see Apple follow through as a result of TAX CUTS. Huge win for American workers and the USA! https://t.co/OwXVUyLOb1	01/18/18
36	Amazon.com	AMZN	03/29/18	11:57	I have stated my concerns with **Amazon** long before the Election. Unlike others they pay little or no taxes to state & local governments use our Postal System as their Delivery Boy (causing tremendous loss to the U.S.) and are putting many thousands of retailers out of business!	03/29/18
37	Amazon.com	AMZN	03/31/18	12:45	While we are on the subject it is reported that the U.S. Post Office will lose $1.50 on average for each package it delivers for **Amazon**. That amounts to Billions of Dollars. The Failing N.Y. Times reports that "the size of the company's lobbying staff has ballooned" and that...	04/02/18
	Amazon.com	AMZN	03/31/18	12:52	...does not include the Fake Washington Post which is used as a "lobbyist" and should so REGISTER. If the P.O. "increased its parcel rates **Amazon's** shipping costs would rise by $2.6 Billion." This Post Office scam must stop. Amazon must pay real costs (and taxes) now!	04/02/18
	Amazon.com	AMZN	04/02/18	13:35	Only fools or worse are saying that our money losing Post Office makes money with **Amazon**. THEY LOSE A FORTUNE and this will be changed. Also our fully tax paying retailers are closing stores all over the country...not a level playing field!	04/02/18

38	Amazon.com	AMZN	04/03/18	13:55	I am right about **Amazon** costing the United States Post Office massive amounts of money for being their Delivery Boy. Amazon should pay these costs (plus) and not have them bourne by the American Taxpayer. Many billions of dollars. P.O. leaders don't have a clue (or do they?)!	04/03/18
39	Apple	AAPL	04/25/18	14:11	Looking forward to my meeting with Tim Cook of **Apple**. We will be talking about many things including how the U.S. has been treated unfairly for many years by many countries on trade.	04/25/18
40	Harley Davidson	HOG	06/25/18	21:28	Surprised that **Harley-Davidson** of all companies would be the first to wave the White Flag. I fought hard for them and ultimately they will not pay tariffs selling into the E.U. which has hurt us badly on trade down $151 Billion. Taxes just a Harley excuse - be patient! #MAGA	06/26/18
	Harley Davidson	HOG	06/26/18	11:16	Early this year **Harley-Davidson** said they would move much of their plant operations in Kansas City to Thailand. That was long before Tariffs were announced. Hence they were just using Tariffs/Trade War as an excuse. Shows how unbalanced & unfair trade is but we will fix it.....	06/26/18
	Harley Davidson	HOG	06/26/18	11:37	....When I had **Harley-Davidson** officials over to the White House I chided them about tariffs in other countries like India being too high. Companies are now coming back to America. Harley must know that they won't be able to sell back into U.S. without paying a big tax!	06/26/18
	Harley Davidson	HOG	06/26/18	12:17	A **Harley-Davidson** should never be built in another country-never! Their employees and customers are already very angry at them. If they move watch it will be the beginning of the end - they surrendered they quit! The Aura will be gone and they will be taxed like never before!	06/26/18

41	Harley Davidson	HOG	06/27/18	15:26	**Harley-Davidson** should stay 100% in America with the people that got you your success. I've done so much for you and then this. Other companies are coming back where they belong! We won't forget and neither will your customers or your now very HAPPY competitors!	06/27/18
42	Harley Davidson	HOG	07/03/18	14:00	Now that **Harley-Davidson** is moving part of its operation out of the U.S. my Administration is working with other Motor Cycle companies who want to move into the U.S. Harley customers are not happy with their move - sales are down 7% in 2017. The U.S. is where the Action is!	07/03/18
43	Pfizer	PFE	07/09/18	17:08	**Pfizer** & others should be ashamed that they have raised drug prices for no reason. They are merely taking advantage of the poor & others unable to defend themselves while at the same time giving bargain basement prices to other countries in Europe & elsewhere. We will respond!	07/10/18
44	Pfizer	PFE	07/10/18	22:37	Just talked with **Pfizer** CEO and @SecAzar on our drug pricing blueprint. Pfizer is rolling back price hikes so American patients don't pay more. We applaud Pfizer for this decision and hope other companies do the same. Great news for the American people!	07/11/18
45	Novartis	NOVN	07/19/18	10:23	Thank you to **Novartis** for not increasing your prices on prescription drugs. Likewise to Pfizer. We are making a big push to actually reduce the prices maybe substantially on prescription drugs.	07/19/18
46	Pfizer	PFE	07/19/18	10:23	Thank you to Novartis for not increasing your prices on prescription drugs. Likewise to **Pfizer**. We are making a big push to actually reduce the prices maybe substantially on prescription drugs.	07/19/18
47	Ford Motor Company	F	07/25/18	22:45	Sergio Marchionne who passed away today was one of the most brilliant & successful car executives since the days of the legendary Henry **Ford**. It was a great honor for me to get to know Sergio as POTUS he loved the car industry and fought hard for it. He will be truly missed!	07/26/18

48	Boeing	BA	08/03/18	22:43	NASA which is making a BIG comeback under the Trump Administration has just named 9 astronauts for **Boeing** and Spacex space flights. We have the greatest facilities in the world and we are now letting the private sector pay to use them. Exciting things happening. Space Force!	08/06/18
49	Apple	AAPL	08/10/18	22:47	Had a very good phone call with @EmmanuelMacron President of France. Discussed various subjects in particular Security and Trade. Many other calls and conversations today. Looking forward to dinner tonight with Tim Cook of **Apple.** He is investing big dollars in U.S.A.	08/13/18
50	Harley Davidson	HOG	08/12/18	12:57	Many **@harleydavidson** owners plan to boycott the company if manufacturing moves overseas. Great! Most other companies are coming in our direction including Harley competitors. A really bad move! U.S. will soon have a level playing field or better.	08/13/18
51	Nike	NKE	09/05/18	13:39	Just like the NFL whose ratings have gone WAY DOWN **Nike** is getting absolutely killed with anger and boycotts. I wonder if they had any idea that it would be this way? As far as the NFL is concerned I just find it hard to watch and always will until they stand for the FLAG!	09/05/18
52	Nike	NKE	09/07/18	10:56	What was **Nike** thinking?	09/07/18
53	Apple	AAPL	09/08/18	15:45	**Apple** prices may increase because of the massive Tariffs we may be imposing on China - but there is an easy solution where there would be ZERO tax and indeed a tax incentive. Make your products in the United States instead of China. Start building new plants now. Exciting! #MAGA	09/10/18
54	General Motors	GM	11/27/18	19:05	Very disappointed with **General Motors** and their CEO Mary Barra for closing plants in Ohio Michigan and Maryland. Nothing being closed in Mexico & China. The U.S. saved General Motors and this is the THANKS we get! We are now looking at cutting all @GM subsidies including....	11/28/18

	General Motors	GM	11/27/18	19:05	....for electric cars. **General Motors** made a big China bet years ago when they built plants there (and in Mexico) - don't think that bet is going to pay off. I am here to protect America's Workers!	11/28/18
55	General Motors	GM	11/29/18	11:37	**General Motors** is very counter to what other auto and other companies are doing. Big Steel is opening and renovating plants all over the country. Auto companies are pouring into the U.S. including BMW which just announced a major new plant. The U.S.A. is booming!	11/29/18
56	Fiat Chrysler Automobiles	FCA	02/27/19	09:20	**Fiat Chrysle**r will be adding more than 6500 JOBS in Michigan (Detroit area) doubling its hourly workforce as part of a 4.5 Billion Dollar investment. Thank you Fiat Chrysler. They are all coming back to the USA it's where the action is!	02/27/19
57	Toyota Motor Corporation	TM	03/14/19	16:18	Congratulations **@Toyota**! BIG NEWS for U.S. Auto Workers! The USMCA is already fixing the broken NAFTA deal. https://t.co/f9iHprPk5B	03/15/19
58	General Motors	GM	03/16/19	21:01	Because the economy is so good **General Motors** must get their Lordstown Ohio plant open maybe in a different form or with a new owner FAST! Toyota is investing 13.5 $Billion in U.S. others likewise. G.M. MUST ACT QUICKLY. Time is of the essence!	03/18/19
	General Motors	GM	03/17/19	22:27	Just spoke to Mary Barra CEO of General Motors about the Lordstown Ohio plant. I am not happy that it is closed when everything else in our Country is BOOMING. I asked her to sell it or do something quickly. She blamed the UAW Union — I don't care I just want it open!	03/18/19
	General Motors	GM	03/18/19	11:37	**General Motors** and the UAW are going to start "talks" in September/October. Why wait start them now! I want jobs to stay in the U.S.A. and want Lordstown (Ohio) in one of the best economies in our history opened or sold to a company who will open it up fast! Car companies.....	03/18/19

59	Toyota Motor Corporation	TM	03/16/19	21:01	Because the economy is so good General Motors must get their Lordstown Ohio plant open maybe in a different form or with a new owner FAST! **Toyota** is investing 13.5 $Billion in U.S. others likewise. G.M. MUST ACT QUICKLY. Time is of the essence!	03/18/19
60	Google	GOOG L	03/16/19	21:07	**Google** is helping China and their military but not the U.S. Terrible! The good news is that they helped Crooked Hillary Clinton and not Trump....and how did that turn out?	03/18/19
61	Ford Motor Company	F	03/20/19	20:51	Great news from **@Ford**! They are investing nearly $1 BILLION in Flat Rock Michigan for auto production on top of a $1 BILLION investment last month in a facility outside of Chicago. Companies are pouring back into the United States - they want to be where the action is!	03/21/19
62	Google	GOOG L	03/27/19	19:38	Just met with @SundarPichai President of **@Google** who is obviously doing quite well. He stated strongly that he is totally committed to the U.S. Military not the Chinese Military....	03/28/19
			03/27/19	19:38	....Also discussed political fairness and various things that **@Google** can do for our Country. Meeting ended very well!	03/28/19
63	Boeing	BA	04/15/19	10:29	What do I know about branding maybe nothing (but I did become President!) but if I were **Boeing** I would FIX the Boeing 737 MAX add some additional great features & REBRAND the plane with a new name.No product has suffered like this one. But again what the hell do I know?	04/15/19
64	Harley Davidson	HOG	04/23/19	11:04	“**Harley Davidson** has struggled with Tariffs with the EU currently paying 31%. They’ve had to move production overseas to try and offset some of that Tariff that they’ve been hit with which will rise to 66% in June of 2021.” @MariaBartiromo So unfair to U.S. We will Reciprocate!	04/23/19

65	Twitter	TWTR	04/23/19	20:54	Great meeting this afternoon at the @WhiteHouse with @Jack from **@Twitter**. Lots of subjects discussed regarding their platform and the world of social media in general. Look forward to keeping an open dialogue! https://t.co/QnZi579eFb	04/24/19
66	General Motors	GM	05/08/19	15:18	GREAT NEWS FOR OHIO! Just spoke to Mary Barra CEO of **General Motors w**ho informed me that subject to a UAW agreement etc. GM will be selling their beautiful Lordstown Plant to Workhorse where they plan to build Electric Trucks. GM will also be spending $700000000 in Ohio...	05/08/19
	General Motors	GM	05/08/19	15:18	....in 3 separate locations creating another 450 jobs. I have been working nicely with GM to get this done. Thank you to Mary B your GREAT Governor and Senator Rob Portman. With all the car companies coming back and much more THE USA IS BOOMING!	05/08/19
67	Lockheed Martin	LMT	07/11/19	00:06	I was just informed by Marillyn Hewson CEO of **Lockheed Martin** of her decision to keep the Sikorsky Helicopter Plant in Coatesville Pennsylvania open and humming! We are very proud of Pennsylvania and the people who work there....	07/11/19
			07/11/19	00:06	....Thank you to **Lockheed Martin** one of the USA's truly great companies!	07/11/19
68	Facebook	FB	07/12/19	00:15	I am not a fan of Bitcoin and other Cryptocurrencies which are not money and whose value is highly volatile and based on thin air. Unregulated Crypto Assets can facilitate unlawful behavior including drug trade and other illegal activity....	07/12/19
	Facebook	FB	07/12/19	00:15	....Similarly **Facebook** Libra's "virtual currency" will have little standing or dependability. If Facebook and other companies want to become a bank they must seek a new Banking Charter and become subject to all Banking Regulations just like other Banks both National...	07/12/19

	Facebook	FB	07/12/19	00:15	...and International. We have only one real currency in the USA and it is stronger than ever both dependable and reliable. It is by far the most dominant currency anywhere in the World and it will always stay that way. It is called the United States Dollar!	07/12/19
69	Google	GOOG L	07/26/19	14:02	There may or may not be National Security concerns with regard to **Google** and their relationship with China. If there is a problem we will find out about it. I sincerely hope there is not!!!	07/26/19
70	Apple	AAPL	07/26/19	15:25	**Apple** will not be given Tariff waiver or relief for Mac Pro parts that are made in China. Make them in the USA no Tariffs!	07/26/19
71	Boeing	BA	08/08/19	14:38	As your President one would think that I would be thrilled with our very strong dollar. I am not! The Fed's high interest rate level in comparison to other countries is keeping the dollar high making it more difficult for our great manufacturers like Caterpillar **Boeing**.....	08/08/19
	Boeing	BA	08/08/19	14:38	....John Deere our car companies & others to compete on a level playing field. With substantial Fed Cuts (there is no inflation) and no quantitative tightening the dollar will make it possible for our companies to win against any competition. We have the greatest companies...	08/08/19
	Boeing	BA	08/08/19	14:38	....in the world there is nobody even close but unfortunately the same cannot be said about our Federal Reserve. They have called it wrong at every step of the way and we are still winning. Can you imagine what would happen if they actually called it right?	08/08/19
72	John Deere	DE	08/08/19	14:38	As your President one would think that I would be thrilled with our very strong dollar. I am not! The Fed's high interest rate level in comparison to other countries is keeping the dollar high making it more difficult for our great manufacturers like Caterpillar Boeing.....	08/08/19

	John Deere	DE	08/08/19	14:38	....John Deere our car companies & others to compete on a level playing field. With substantial Fed Cuts (there is no inflation) and no quantitative tightening the dollar will make it possible for our companies to win against any competition. We have the greatest companies...	08/08/19
	John Deere	DE	08/08/19	14:38	....in the world there is nobody even close but unfortunately the same cannot be said about our Federal Reserve. They have called it wrong at every step of the way and we are still winning. Can you imagine what would happen if they actually called it right?	08/08/19
73	Caterpillar	CAT	08/08/19	14:38	As your President one would think that I would be thrilled with our very strong dollar. I am not! The Fed's high interest rate level in comparison to other countries is keeping the dollar high making it more difficult for our great manufacturers like Caterpillar Boeing.....	08/08/19
	Caterpillar	CAT	08/08/19	14:38	....John Deere our car companies & others to compete on a level playing field. With substantial Fed Cuts (there is no inflation) and no quantitative tightening the dollar will make it possible for our companies to win against any competition. We have the greatest companies...	08/08/19
	Caterpillar	CAT	08/08/19	14:38	....in the world there is nobody even close but unfortunately the same cannot be said about our Federal Reserve. They have called it wrong at every step of the way and we are still winning. Can you imagine what would happen if they actually called it right?	08/08/19
74	Walmart	WMT	08/15/19	20:18	**Walmart** a great indicator as to how the U.S. is doing just released outstanding numbers. Our Country unlike others is doing great! Don't let the Fake News convince you otherwise.	08/16/19
75	Apple	AAPL	08/16/19	23:04	Having dinner tonight with Tim Cook of **Apple**. They will be spending vast sums of money in the U.S. Great!	08/19/19

76	Google	GOOG L	08/19/19	15:52	Wow Report Just Out! **Google** manipulated from 2.6 million to 16 million votes for Hillary Clinton in 2016 Election! This was put out by a Clinton supporter not a Trump Supporter! Google should be sued. My victory was even bigger than thought! @JudicialWatch	08/19/19
77	Ford Motor Company	F	08/21/19	22:50	The Legendary Henry Ford and Alfred P. Sloan the Founders of **Ford Motor Company** and General Motors are "rolling over" at the weakness of current car company executives willing to spend more money on a car that is not as safe or good and cost $3000 more to consumers. Crazy!	08/22/19
	Ford Motor Company	F	08/21/19	23:01	Henry Ford would be very disappointed if he saw his modern-day descendants wanting to build a much more expensive car that is far less safe and doesn't work as well because execs don't want to fight California regulators. Car companies should know....	08/22/19
78	General Motors	GM	08/21/19	22:50	The Legendary Henry Ford and Alfred P. Sloan the Founders of Ford Motor Company and **General Motors** are "rolling over" at the weakness of current car company executives willing to spend more money on a car that is not as safe or good and cost $3000 more to consumers. Crazy!	08/22/19
79	General Motors	GM	08/30/19	12:06	**General Motors** which was once the Giant of Detroit is now one of the smallest auto manufacturers there. They moved major plants to China BEFORE I CAME INTO OFFICE. This was done despite the saving help given them by the USA. Now they should start moving back to America again?	08/30/19
80	General Motors	GM	09/15/19	22:54	Here we go again with **General Motors** and the United Auto Workers. Get together and make a deal!	09/16/19
81	Facebook	FB	09/20/19	00:03	Nice meeting with Mark Zuckerberg of @Facebook in the Oval Office today. https://t.co/k5ofQREfOc https://t.co/jNt93F2BsG	09/20/19

82	Apple	AAPL	09/30/19	19:04	Great news! **@Apple** announced that it is building its new Mac Pro in Texas. This means hundreds of American jobs in Austin and for suppliers across the Country. Congratulations to the Apple team and their workers! https://t.co/FMrWFq9wcz	10/01/19
	Fiat Chrysler Automobiles	FCA	10/30/19	17:19	Thank you @GM **@FiatChrysler_NA** @Toyota and @GloblAutomkrs for standing with us for Better Cheaper Safer Cars for Americans. California has treated the Auto Industry very poorly for many years harming Workers and Consumers. We are fixing this problem! https://t.co/cf6I1e0yjQ	10/31/19
84	General Motors	GM	10/30/19	17:19	Thank you **@GM** @FiatChrysler_NA @Toyota and @GloblAutomkrs for standing with us for Better Cheaper Safer Cars for Americans. California has treated the Auto Industry very poorly for many years harming Workers and Consumers. We are fixing this problem! https://t.co/cf6I1e0yjQ	10/31/19
85	Toyota Motor Corporation	TM	10/30/19	17:19	Thank you @GM @FiatChrysler_NA **@Toyota** and @GloblAutomkrs for standing with us for Better Cheaper Safer Cars for Americans. California has treated the Auto Industry very poorly for many years harming Workers and Consumers. We are fixing this problem! https://t.co/cf6I1e0yjQ	10/31/19
86	General Motors	GM	11/01/19	12:52	Wow a blowout JOBS number just out adjusted for revisions and the General Motors strike 303000. This is far greater than expectations. USA ROCKS!	11/01/19
87	Walmart	WMT	11/14/19	14:32	**Walmart** announces great numbers. No impact from Tariffs (which are contributing $Billions to our Treasury). Inflation low (do you hear that Powell?)!	11/14/19
88	Apple	AAPL	11/20/19	23:18	Today I opened a major **Apple** Manufacturing plant in Texas that will bring high paying jobs back to America. Today Nancy Pelosi closed Congress because she doesn't care about American Workers!	11/21/19

	Apple	AAPL	11/21/19	12:31	During my visit yesterday to Austin Texas for the startup of the new Mac Pro & the discussion of a new one $billion campus also in Texas I asked Tim Cook to see if he could get **Apple** involved in building 5G in the U.S. They have it all - Money Technology Vision & Cook!l	11/21/19
89	Apple	AAPL	11/24/19	04:53	Pushed hard to have **Apple** build in USA! https://t.co/BRfXBkJdc2	11/25/19