The effect of Donald Trump his Twitter usage on the S&P 500

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Abstract

Since the 20th of January 2017, Donald Trump is President of the United States. Twitter is the only social medium he uses to share his opinions and comments. The aim of this research is to examine whether Donald Trump his Twitter usage has an effect on stock prices of S&P 500 companies. Tweets are divided by polarity, whereafter both abnormal and cumulative abnormal returns are calculated. This research does not provide any significant evidence that proves that Donald Trump his Twitter usage has a general effect on the daily stock prices of S&P 500 companies. This research does find significant evidence that prove that Donald Trump his tweets can have an effect on a single S&P 500 company their stock prices.

Keywords: Donald Trump, Twitter, S&P 500, Abnormal Returns

Contents

1. Introduction

On the 8th of November 2016, Donald Trump was elected as the 45th President of the United States. January 20th in 2017 marks the date that Donald Trump actually started his role as President of the United States. One can say that this was quite a surprise for both the nation and its investors. Despite the fact that none of the changes suggested by Trump had been implemented after the hundred-day mark, stock prices, in particular, the S&P 500 index, had already changed (Wagner, Zechkhauser, & Ziegler, 2018).

In contrast to his predecessors, Donald Trump can be seen as a real 'social media magnate'. Donald Trump is actively present on Twitter with his account @realDonaldTrump, on which he has over sixty million followers. By posting several tweets per day, his followers stay up to date on how he thinks about certain political matters. In this way, he influences the way millions of people think about international trade relations and American markets.

We are living in an era where social media is getting more and more attention, therefore it is deemed necessary that both investors and companies understand the potential economic benefits or costs of Donald Trump his social media usage. Stock prices not only tell how much a stock is worth but also show a glimpse of investors' expectations for the near future. Therefore, conducting research on Trump his social media usage and the related effects on stock prices will provide valuable insights for S&P500 companies who have to deal with the effects and put mitigation strategies in place.

The subject of whether social media influences stock prices is something that has increasingly been studied. Bollen, Mao, and Zeng (2011) examined whether Twitter content could be used to predict changes in the stock market. The research showed that with a high number of positive mood tweets the Dow Jones Index increased. Ranco et al. (2015) conducted similar research but tested for a specific effect on the stock market. In their research, they examined tweets from around thirty companies in the Dow Jones Index and made a distinction between positive tweets and negative tweets. The research revealed that after a positive tweet, there appeared to be a positive effect on the Dow Jones Index. Where a negative tweet turned out to have a negative effect on the Dow Jones Index.

Zhang, Fuehres, and Gloor (2011) tried to predict the Dow Jones Industrial Average, the S&P 500 index and the NASDAQ, via combining tweets with certain emotions. Their research demonstrates how one can make a distinction between positive and negative tweets. Furthermore, Kollias, Papadamou, and Stagiannis (2011) examine the effect of terrorist attacks on stock prices. The researchers conclude that there is a significant effect to be found on days with a terrorist attack, though the effect does not last. In contrast to already existing researches, this research will look at the tweets of a specific politician and whether these affect the stock prices of S&P 500 companies.

Donald Trump, as the 45th President of the United States, with over sixty million followers on Twitter, is a person that could influence the behaviour of investors. Therefore, the following research question has been formulated:

What is the effect of Donald Trump his tweets about S&P 500 companies on their daily stock prices?

This research aims to examine how the S&P 500 companies react after a tweet of Donald Trump that could possibly have an influence on the stock index. An example of a recent Twitter post on an S&P 500 company that is used: *"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?"*[1]. By using S&P 500 company their stock of that specific tweet as a dependent variable and Trump his tweets as the independent variable, this research will test if there is an actual effect to be found of Donald Trump his tweets on the daily S&P 500 stock prices. If it appears that there is a significant effect, this research could be the basis to start thinking about a strategy for investors on how to act upon Donald Trump his Twitter usage.

After an introduction and a literature review, in which the research question and hypothesis are introduced and substantiated, a data and methodology chapter followes. The dataset consists of tweets that are obtained from the official Twitter account of Donald Trump. Additionally, data from the companies' stock prices are obtained through Yahoo

[1] https://twitter.com/realdonaldtrump

Finance! Both of these data sources are considered to be reliable and freely available. Daily stock prices of S&P 500 companies are used to generalize an effect after. The used data is starting from 20 January 2017, the day that Donald Trump started as President of the United States. Time-series data is compared. A control period is used as an estimation window for normal returns and is not related to the tweet. Both event day abnormal returns, as five-day cumulative abnormal returns are tested. Excel and Stata are both used as tools to run the regressions required for this research. After the results, the discussion and conclusion of the research follow.

This research is novel because it does not only look at the tweets of a specific politician and its effects on stock prices of S&P 500 companies, but this research adds to the current literature by testing whether the shocks in the stock prices, that might be generated by Donald Trump his Twitter usage, recover within five days. The dataset is also completely new since Donald Trump only started as President of the United States a little over two years ago.

2. Theoretical framework

To determine the hypotheses, an extensive literature review is conducted. This review shows the academic basis for the research question. First, the connection between news and stocks is discussed. Second, the connection between social media and politics is going to be indicated. After, it will elaborate on the effect of Twitter on stock prices and different stock indexes, including the Dow Jones Industrial Average index, NASDAQ, and S&P 500. Then, researches show that celebrities on Twitter effect a company their stock price by one single tweet. Lastly, the four hypotheses to test the main research question are introduced.

A. News and stock prices

According to the Shorter Oxford English Dictionary (2014), news is defined as newly received information, commonly about recent events and published in traditional news sources. An example of a traditional news source a newspaper. Over the past, news has often been used to study finance topics, in this research, news and its effect on stock prices. Stock prices are defined as either stocks in the following indexes, Dow Jones Industrial Average Index, NASDAQ, S&P 500, or one of the three indexes as a whole. In existing research, news is often used as an 'event' which is then linked to the corresponding stock price, to examine whether the news that was published and thus became public information is influencing investors and thus stock prices. Current research of news and its effect on stock prices are mostly about negative events in the news, with war and terrorism as examples. War creates uncertainty among investors which results in investors being less willing to buy and hold stocks from companies or indexes located in war regions. Rigobon and Sack (2005) investigate whether news messages concerning the Iraq-war have an influence on the averages and standard deviations of treasury yields, equity prices, oil prices and dollar prices. By collecting 17 'war-related' messages from newspapers, they found that increased risk of war significantly affects the treasury yields, equity prices, oil prices and dollar prices in a negative way.

When information about terrorism, more specifically bombings, becomes published in the news and thus becomes public, this again results in uncertainty amongst investors followed by a decline in their willingness to buy and hold stocks located in regions of the bombings. Kollias, Papadamou, and Stagiannis (2011) investigated whether the Madrid and

London bombings affected the stock markets of respectively Spain and the United Kingdom. By computing abnormal returns, cumulative abnormal returns, and a GARCH model they found a significant negative effect on the day of the bombing. However, in the United Kingdom, the stock market recovered within one day. The stock market of Spain took a couple of days to recover.

Current research also showed that published financial news, affects stock prices. Financial news is defined as articles from newspapers, magazines or other media specializing in financial news, for example the Wall Street Journal. Schumaker and Chen (2009) created an S&P 500 prediction model based on financial news. By combining the news article and the stock price they came really close to predicting the future stock price. When information becomes public, investors can change strategy based on the new information. Tetlock (2007) investigated whether news from the Wall Street Journal is correlated with several stock indexes, such as the Dow Jones Industrial Average index and the New York Stock Exchange. In short, he found that media negativity has a decreasing effect on the indexes. Some investors trade based on non-public information. At the moment financial information comes public it can decrease information asymmetry, since then all investors have access to the financial information. This way investors can adapt their investment strategy based on the information that became public. Tetlock (2010) researched on whether public financial information predicts the Dow Jones Industrial Average index daily stock returns, and if it takes away asymmetric information. He found that public news indeed predicts the index, and that asymmetric information, for a large part, can be resolved by public news.

The above-mentioned studies show that news can indeed have a significant effect on stock prices. Where it is clear that negative events in the news, such as war and terrorism, affect stock indexes negatively. Secondly, financial news has an effect and is shown as a predictor of the stock indexes. These two findings are relevant for this research since Donald Trump his tweets can be seen as negative statements about financial matters and companies.

B. Social media and politics

According to Asur and Huberman (2010) social media is defined as online platforms where people can design content, share content, bookmark content and network. Examples include YouTube, Twitter and Facebook. Social media differs from news, defined in the previous section, due to the fact that almost every citizen can create content on social media, while in newspapers only journalist create the articles and columns. Ceron (2015) researched whether there is a difference in the policitical trust level of social media comparing with newswebsites. He concluded that newswebsites have a higher trust level, while social media has a lower level of trust. Social media has been used earlier to examine whether it is affecting politics. Most politicians have a social media account on which they create content and share their opnions, while at the same time possible voters have an opnion about policticians which is also often shared on social media. This way social media users are influenced by both the content of the politicians itself, and the possible voters' opnion about the polictiancs on social media. This can result in social media users changing there political preference, and even their vote.

Now, the size of social media in the United States, followed by researches that show the connection between social media and politics in general American. According to Statista, in 2019, over 3 billion people worldwide use media. In the United States, this percentage is 79%. Over 68 million Americans are monthly active on Twitter[2]. Newman et al. (2015) conducted research on this topic and found through a survey that 87% of American citizens used social media in the previous week. Within his research on social media, Facebook, YouTube, and Twitter are the biggest ones with, respectively, 1 billion, 1 billion, and 330 million active users.

Boulianne (2015) conducted research on whether the use of social media and political participation are connected. By doing a meta-analysis of 36 different studies, he found that over 80% of the tested variables showed a positive relationship between social media political participation. Parmelee and Bichard (2012) conducted a survey on how politicians and possible voters interact via Twitter. In specific, they discovered that over 40% of the people surveyed followed political leaders whose opinions differed. These three types of research show that social media plays an important role in America and that there is a strong connection with politics. Tumasjan et al. (2010) conducted research on whether microblogging has an effect on the German federal election. By analyzing over a hundred thousand messages about German politics, they found that microblogging indeed can be used as a predictor for the election result. This is because they found microblogging forums are

[2] https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/

used for political deliberation and as a view on political sentiment. Which proves opinions of politicians are shared, and thus possible voters can be influenced.

Together, the above-mentioned researches show the size of social media and that social media and politics are strongly connected. This lays the foundation to delve further into the effect of Twitter on stock prices and what effect politicians, who are active on social media, have on stock prices. Specifically, for this research, Donald Trump his Twitter usage on the S&P 500.

C. Twitter and stock prices

According to Kwak et al. (2010) Twitter is a microblogging platfrom that is launched in 2006, and is used as medium for sharing information. According to Statista, Twitter has 330 million monthly active users worldwide, of which 68 million are American citizens[3]. Almost every person in the world can create a profile, and become active on Twitter and then create their own content. At the same time, they are able to view and read the content of other people ative on Twitter. Twitters posts often contain information or a persons' opinion. Whether the information if real or fake is up to the reader to decide. The medium is often used by on the on hand well-known people, such as politicians, artist, sporters, but on the other hand the biggest group of Twitter-users are less known citizens. All investors can have access to Twitter and therefore read posts, and thus the informatin and opinions of others. This way investors can be influenced by the content of the postst, which can result in investors changing there investment strategy, and therefore Twitter postst influence the stock prices. Current research examined whether Twitter posts have predictive power of stock prices. This is often done by sentiment analysis, which scales tweets in either positive or negative.

One of the first researches was executed by Zhang, Feuhres, and Gloor (2011). They attempted to predict stock indexes, such as the Dow Jones Industrial Average index, the S&P 500 and the NASDAQ, on the basis of tweets. By linking specific emotions, among which hope, happy, fear and worry, to tweets, they examined if there was a correlation. With the Chicago Board Options Exchange Volatility Index as a benchmark, they linked these

[3] https://www.statista.com/statistics/274564/monthly-active-twitter-users-in-the-united-states/

emotions of the tweet to stock indexes of that day and tested if they these tweets had a significant effect on the stock index of the day after the tweet. They scaled the tweets per specific emotion as a percentage of the total amount of tweets containing an emotion that day. The research period is six months, and they conclude that negative tweets have a negative effect on the Dow Jones Industrial Average index, S&P 500 and de NASDAQ. And therefore they lay a basis for further research to examine the mood of tweets and its predictive power on the next day stock indexes.

Bollen, Mao, and Zeng (2011) researched whether Twitter posts affect the Dow Jones Industrial Average index. For their research, they used a sample of almost 10 million tweets, posted by over 2,7 million Twitter users. By using OpinionFinder to asses whether the tweets used have a positive versus a negative mood. By looking at the mood of the tweets, the predictions of the Dow Jones Industrial Average index will be significantly better and it is possible to predict the index level of the next day. They found that for a day with a high number of tweets concerning a good mood, the Dow Jones Industrial index shows a more positive development. Pagolu et al. (2016) examine how the changes, both increases and decreases, in the Dow Jones Industrial Average companies' stock prices, are uttered in the tweets about those companies. They found a strong correlation between a company their stock price and the mood of tweets used on in the sample of tweets. Tweets that entail positive emotions about the company show increasing progress its stock price, while tweets that entail negative emotions show decreasing progress of the company their stock price. Ranco et al. (2015) investigate if the volume of tweets concerning 30 companies, affect the Dow Jones Industrial Average index. To examine this, they first decide the polarity of events, the sentiment/mood, via Support Vector Machine (SVM) classifiers. In case SVM did not distribute the tweet towards positive or negative, its defined neutral. With an estimation window of 120 days, abnormal and cumulative abnormal returns (CAR) were computed. They conclude that if the number of positive tweets increases, the CAR raised along. As the number of negative tweets increased, the CAR falls along. The 10-day CAR results are significant at the 1% level, for both positive and negative. Neutral tweets did not show significant CAR result at the 1% level.

Corea and Cervellati (2015) conducted research on whether tweets are a suitable approach to forecast the NASDAQ-100. Tweets were filtered based on English speaking users, with existing financial expertise, and the company their ticker. They ended up with a two-month period dataset consisting out of tweets from Apple, Facebook, and Google. DataSift was hired to download the data and appoint a sentiment score, and thus decide if the tweet was positive or negative. The conclusions were that the model increased explanatory power comparing the existing benchmark, and thus was able to predict the NASDAQ-100 better. The paper does not give separate conclusions depending on the mood of the tweet.

Mao et al. (2012) examined whether the S&P 500 stock index is connected to the number of daily tweets. They test for three different levels, namely the stock market, industry sector, and individual company stocks. Companies were divided into sectors by the Global Industry Classification Standard, a standard developed by S&P and MSCI which subdivides companies into ten sectors. As individual company stock Apple is used, since its the company most mentioned in tweets. By using Twitter API, the dataset consisted of almost 560 000 tweets, spread out over a period of 56 days. By using a basic linear regression model they assessed whether there is a relation between Twitter and the three different levels. They conclude that Twitter has predictive power over the S&P 500. On the stock market level, is most strongly correlated with the closing price, while on sector level they observe different results per sector. The sectors which are tweeted most about, show a significant relation, at the same time sectors whit limited tweets do no show any significant relation. Lastly, Apple their individual stock level is mostly correlated with the absolute price change, price change, and traded volume. There was no significant relation between Apple their stock price and the closing price.

The abovementioned researches show that Twitter is strongly connected to several stock indexes. The biggest similarity between the discussed researches and this research is that it focuses on tweets and its predictive power on stock indexes. Next to that, current research makes use the sentiment/mood, defined as either positive, negative, or neutral. This split will also be made in this research. Yet, one of the main differences is that most of the current researches look at tweets from firms or a random set of tweets regarding emotion words, while this research will focus on the tweets of one specific person, namely Donald Trump. Besides that, current research focused on multiple stock indexes. Just as Mao et al. (2012), this research will only investigate the S&P 500. Another difference lays in the methodology. Following the approach of Ranco et al. (2015), this research will use abnormal returns and cumulative abnormal returns in combination with an estimation window to answer the main research question.

D. Twitter celebrities & Stock prices

Previous research of Meeder et al. (2011) defined a special group of Twitter users, namely Twitter celebrities. According to Meeder et al. (2011) Twitter celebrities are the 1000 most followed Twitter users. Whether Twitter celebrities have an effect on stock prices, has already been researched and proven. Previous research examined whether one tweet, posted by a Twitter celebrity, effected the stock price of the company mentioned. The Twitter celebrities researched have a varity of different professions, and most of the show a negative effect. In essence, a celebrity talks negatively about a company on Twitter results in the decrease in stock prices of that company.

One example was in 2016 by Elon Musk, CEO of Tesla. Elon Musk has over 27 million followers, and tweeted that Tesla would exclusively work with Panasonic for their Model 3 cells, while other news articles claimed that Tesla would work with Samsung. These two facts together resulted in a decrease of 8% of Samsung their stock price[4]. Kylie Jenner, a television celebrity with her own reality show, with almost 28 million followers. She tweeted that she stopped using the Snapchat application on her phone. This resulted in Snapchat their closing price, on that specific day, being 6,1 % lower as right before the moment of the tweet (Vasquez, 2018). Ge, Kurov, and Wolfe (2017) conducted research whether Donald Trump his tweets have an impact on stock prices. They used 27 tweets from the 9th of November 2016 until the 28th of February 2017, which specifically naming a publicly traded company. Via OLS they calculate the expected return and after they calculate the abnormal returns. They find that positive tweets create a positive effect on the company their stock price, while negative tweets create a negative effect on the company their stock price.

The abovementioned studies prove that Twitter celebrities can affect a company their stock price by posting one single tweet. Similar to the study of Ge, Kurov, and Wolfe (2017), this research will look at abnormal returns. Contrary to the research of Ge, Kurov, and Wolfe (2017), this research will use a bigger dataset with longer time span of tweets. Moreover, this research will add to the current literature by testing whether the shocks in the stock prices, that might be generated by Donald Trump his Twitter usage, recover within five days.

[4] https://eu.usatoday.com/story/money/cars/2016/06/08/tesla-batteries-panasonic-samsung/85590834/

E. Hypotheses

From previous sections, it can be concluded that a lot of research on Twitter and its predictive power on stock indexes is already completed. Therefore, the goal of this research is to identify whether a celebrity his or her tweets have an effect on companies in the S&P 500. The research will focus on Donald Trump his statements, in the form of tweets. To answer this, the following first hypothesis is formulated:

H1: Donald Trump his tweets about S&P 500 companies have a negative effect on the daily stock prices.

The answer to this hypothesis will show if the tweets have an effect on the S&P 500, however, no difference in the mood or sentiment in the tweet is made. Existing research show that this difference in tweets can lead to different influences on a stock index. Therefore, the following two hypotheses are formulated:

H2: A 'negative' tweet of Donald Trump about S&P 500 companies has a negative effect on the daily stock prices.

H3: A 'positive' tweet of Donald Trump about S&P 500 companies has a positive effect on the daily stock prices.

Kollias, Papadamou, and Stagiannis (2011) concluded that after bombings, the stock markets of Spain and the United Kingdom recovered within a few days. To test how lasting the effect of Donald Trump' tweets on the S&P 500 is, the fourth and last hypothesis is formulated:

H4: S&P 500 companies recover within five days from the shocks created by Donald Trump his tweets.

3. Data & Methodology

In this section, the selection of the dataset and the methodology is explained. First, a precise description of how the dataset was computed is provided. Afterwards, the methodology is discussed and linked to the corresponding hypotheses.

A. Data

The first step in the analytical process is to determine which Twitter account should be used to obtain the tweets from. As discussed in the introduction, the tweets are retrieved from @realDonaldTrump, the only Twitter account that is truly used by Donald Trump himself. Secondly, the research period needs to be determined in order to be able to download the right set of tweets. Donald Trump has been the President of the United States since the 20th of January, 2017. Previous research shows that there is no fixed research period, since some researchers use a six month research period (Zhang, Feuhres, and Gloor, 2011), whilst other take 56 days only (Mao et al., 2012). In order to obtain the most accurate conclusions, the biggest possible dataset is chosen for this research. Since Donald Trump has only been President for a little over two years and five months, a lack of research on the topic exists. Moreover, Donald Trump is not naming S&P 500 companies in his tweets on a daily basis, the used research period is from the 20th of January 2017 until the 20th of May 2019.

Thus, the tweets from @realDonaldTrump starting on the 20th of January 2017 and ending on the 20th of May 2019 are used. The API of Twitter grants access to the last 3200 tweets of a specific account, meaning access is provided only to the the tweets posted until the 28th of April 2018. To download the right set of tweets, an existing Python library 'twint' is used. Via Python and several lines of codes, which can be found in the Appendix code 1, the tweets are downloaded. The first line of the quote, import Twint, can be seen as an external library. This is an application that manually scrapes data, which is indicated in the code. All lines that start with c. are the inputs, thus the variables one intends to download. C.custom and c.output format the data into one document. This application resulted in scraping 6231 tweets from @realDonaldTrump Twitter account into an Excel document.

After the tweets are downloaded, the following step is to learn which companies are a part of the S&P 500 on the 20th of May. This data was downloaded from suredividend, a website that contains a weekly updated list of the S&P 500 including the ticker, the company name and the sector, amongst other things[5]. The used list was updated on Wednesday the 22nd of May 2019. The list was added in the Excel file that contained the scaped tweets. Since Donald Trump not always uses a full name of the company, for example Amazon instead of Amazon.com, all company names were copied and adjusted. Adjustments, such as deleting Inc., .com, corporation, Class A, Class B, Class C, NV, were made to get more hits while searching for the S&P 500 companies named in his tweets. In addition, all capitals were removed from both the tweets and the S&P 500 companies, since Excel would otherwise miss a certain number of hits.

Afterwards, a formula was generated in Excel to show all tweets in the downloaded set that contained either the full company name, the adjusted company name or the ticker of one of the S&P 500 companies. Within the results, a correction for URLs from Facebook and Twitter was made. These tweets were not specifically stating an opinion regarding the company, but were just pointing at the company. An example: "*Thank you Arizona. Beautiful turnout of 15,000 in Phoenix tonight! Full coverage of rally via my Facebook at: https://www.facebook.com/DonaldTrump/videos/10159709733805725/* ...". After this correction, 105 tweets were left, divided over 16 S&P 500 companies. The last check to verify if the tweet truly concerns the S&P 500 company or if the name of the company is used for a different purpose, is executed manually. This resulted in a final number of 68 tweets, divided over 14 S&P 500 companies. The companies and distribution of the tweets amongst them can be viewed in Table 1:

[5] https://www.suredividend.com/sp-500-stocks/

Table 1: Companies that Donald Trump directly mentioned in his tweets with the corresponding number of tweets per company. Amazon and Facebook are by far the biggest two and together represent more than half of the tweets in the dataset.

Company	**Number of tweets**
Amazon.com	24
Facebook Inc.	11
General Motors	7
NASDAQ	7
Harley-Davidson	6
Apple Inc.	6
Nike Inc.	2
Wells Fargo	2
Broadcom	2
Charter Communications	1
Nordstrom	1
Southwest Airlines	1
Andeavor	1
Boeing	1

The S&P 500 is not open for trade on a daily basis. Therefore, when a tweet in the dataset was posted on a non-trading day, the first subsequent trading day is used to calculate the event-day abnormal returns. In other words, t=0 is the first trading day after the tweet. On trading days, the S&P 500 opens at 9.30 and closes 16.00. When a tweet is posted after 16.00, the stock return of the next day, for both the company and the S&P 500 as a whole, was used to calculate the event-day abnormal returns. In other words t=0 is the day after the tweet was posted.

As the dataset is established, the next step is to determine the polarity per tweet. To determine the polarity, OpinionFinder is used as a tool (Bollen, Mao & Zeng, 2011). OpinionFinder is a system that looks for subjectivity within sentences, in this case tweets, and is developed by researchers from the University of Pittsburgh, Cornell University, and the University of Utah[6]. The system uses certain terms to determine the subjectivity, and thus the polarity of tweets. Examples are ‘violent’, ‘tension’, ‘struggle’, ‘high’, ‘generous’ and ‘benefit’. After OpinionFinder located these terms in Donald Trump his tweets, the polarity

[6] https://mpqa.cs.pitt.edu/opinionfinder/

of the tweets is determined. In this paper the polarity of tweets is approximated with an ordinal scale with two values: negative (-) and positive (+). The dataset consists out of 50 tweets with negative polarity and 18 with positive polarity.

Then, the stock prices of the 14 companies, which were obtained via Yahoo Finance!, were converted into Excel. The historical data of all 14 companies was downloaded up and until 120 trading days before the 20th of January 2017, as to make sure that the estimation window, the event itself and the event window would be in the file. The downloaded file shows the daily open, high, low, close and adjusted close price. The formula used to calculate the returns is discussed in the methodology section. Then lastly, the right returns, estimation window, the event itself and the event window are linked to the tweet manually. For the tweet about Nordstrom (*"My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person -- always pushing me to do the right thing! Terrible!"*) with the event date of the 8th of February 2017, the returns of 120 trading days before the event and five days after the event are linked as respectively, the estimation window and event window. The abovementioned steps collectively created the dataset used for this research.

B. Methodology

This research uses an event study methodology, with tweets of Donald Trump as the event. From event day returns as a basis, abnormal returns are calculated, followed by cumulative abnormal returns. This section covers the determination of these returns.

First, the daily returns. With the extracted data from Yahoo Finance!, the daily returns, R_d, are calculated as follows:

$$R_d = \frac{P_d - P_{d-1}}{P_{d-1}}$$

P_d is defined as the closing price of that S&P 500 company their stock on day d, with P_{d-1} being the closing price on the day before. The raw-returns are utilized (MacKinlay, 1997). MacKinlay (1997) wrote a detailed overview containing the steps that need to be taken when analyzing returns, on the basis of specific events. MacKinlay (1997) claims isolating the event-specific effect by calculating abnormal returns is essential. Abnormal returns of stock i, on date t, are defined as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

The first part expresses the stock return, and the second part the normal return. MacKinlay (1997) compares the constant mean return model with the market model, and concludes that the market model has an advantage. It eliminates the market fluctuations that result in lower variances of the abnormal returns. Ranco et al. (2015) used the same market model that MacKinlay describes. The market model is a linear relationship including the return on the market portfolio and expresses the return of stock i, on date t, as follows:

$$E[R_{i,d}] = \hat{\alpha}_i + \widehat{\beta}_\iota R_{m,t} + \varepsilon_{i,t}$$

$R_{i,d}$expresses the returns of the stock i, $R_{m,t}$ the market portfolio returns and $\varepsilon_{i,t}$ the error term. The constant $\hat{\alpha}_i$ and the coefficient $\widehat{\beta}_\iota$ are estimated via OLS- regressions in STATA. Two choices are required to determine the final formula for the normal returns, namely which index is used as market portfolio and the estimation period. MacKinlay (1997) recommends one index, the S&P 500, which is also in line with the research that Ranco et al. (2015) conducted. They investigated whether tweets are influencing the stock of 30 Dow Jones Average Index companies and used the Dow Jones Average Index as market portfolio. The market index used as market portfolio in research will therefore be the S&P 500. Then the estimation period, which can be seen as the control period on which normal returns is estimated, and is unrelated to the event. In this research the estimation period is 200 days. Current research often uses a shorter estimation period. Van der Sar (2015) strongly recommends 100 trading days, while Ranco et al. (2015) make use of an estimation period of 120 days, in their study. In this research only one $\widehat{\beta_\iota}$ per company is calculated. This is done because otherwise, the possible effect of the first tweet about that company would already be visible in the $\widehat{\beta}_\iota$ of the next tweet about that company. Since the $\widehat{\beta}_\iota$ are used for multiple tweets within a longer time period, the estimation period in this research is 200 days as to reduce the risk of estimation error.

This results in the final formula for abnormal returns:

$$AR_{i,t} = R_{i,t} - \hat{\alpha}_i + \widehat{\beta}_\iota R_{m,t}$$

Hypothesis 1

The first hypothesis tests whether the tweets of Donald Trump regarding specific S&P 500 companies have a negative effect on the daily stock returns of these companies. This is done by testing if the average abnormal return is equal to zero. According to Malkiel and Fama (1970) this is achieved through aggregating all the stocks and taking the average. The average abnormal return of all tweets is calculated as follows:

$$AAR_{tot} = (\frac{1}{N})\sum_{i=1}^{N} AR_{i,t}$$

N refers to the number of tweets in the dataset. To test the significance of the average abnormal returns a 'one-sample' student t-test is conducted (van der Sar, 2015). The t-statistic is calculated as follows:

$$TAAR_i = \frac{AAR_t}{{S_i}^2/\sqrt{N}}$$

${S_i}^2$, for stock i, is calculated as follows:

$${S_i}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{i,t} - AAR_i)^2$$

with N-1 degrees of freedom. This t-statistic can be compared with the different significance levels 1%, 5% and 10%. The null- and alternative hypothesis are:

H_0: There are no abnormal returns($AAR\ = 0$).

H_a: There are negative abnormal returns($AAR < 0$).

When testing the first hypothesis, both the negative and positive tweets are averaged. Based on existing literature positive tweets have a positive effect on the stock returns, whilst negative tweets have a negative effect. Averaging positive and negative tweets can therefore lead to negative tweets evening out the abnormal returns generated by positive tweets, and vice versa($AAR \approx 0$). To correct this, there is a split in the next two hypotheses. Positive tweets and negative tweets are tested separately.

Hypothesis 2

To test the second hypothesis, two dummy variables are created. D_{Pos} and D_{neg}, which respectively stand for all positive tweets and all negative tweets. The method of hypothesis 1 is almost completely duplicated, except for the fact that the average abnormal return consists out of the average of abnormal returns generated by negative tweets only. This results in the following null- and alternative hypothesis:

H_0: There are no abnormal returns$(AAR_{\ neg} = 0)$.

H_a: There are negative abnormal returns$(AAR_{\ neg} < 0)$.

Hypothesis 3

The method of hypothesis 2 is, again, almost completely duplicated, except for the fact that the average abnormal return consists out of the average of abnormal returns generated by positive tweets only. This results in the following null- and alternative hypothesis:

H_0: There are no abnormal returns$(AAR_{\ pos} = 0)$.

H_a: There are positive abnormal returns$(AAR_{\ pos} > 0)$.

Hypothesis 4

The first three hypotheses test whether there is an instant effect on daily stock returns generated by the tweets of Donald Trump. However, it does not provide any evidence on whether this effect is lasting for more than one day. To test the lastingness of the potential effect generated by Donald Trump, the five-day cumulative abnormal returns are calculated as follows (van der Sar, 2015):

$$CAR_{KL} = \sum_{t=K}^{L} AR_{i,t}$$

CAR_{KL} is the cumulative abnormal return of stock I of time interval [K,L]. In this case K is always 1, and K always 5.

The t-statistic iscalculated as follows:

$$t_{i,KL} = \frac{CAR_{KL}}{s(CAR_{KL})}$$

$t_{i,KL}$ is the t-statistic for stock i of time interval [K,l], and $s(CAR_{KL})$ is calculated as follows:

$$s(CAR_{KL}) = \sqrt{((T_2 - T_1 + 1)\sigma^2(AR_{i,t}))}$$

where T_1 the start of the event window is, and T_2 the end of the event window. This results in the null- and alternative hypothesis:

H_0: There are no five-day cumulative abnormal returns($CAR\ = 0$).

H_a: There are five-day cumulative abnormal returns($CAR\ \neq 0$).

4. Results

In this section, the results generated by using the above-mentioned dataset and methodology are discussed. First, a short overview of the descriptive statistics is displayed, which summarize the structure and division of the dataset. Next, the results per hypothesis are discussed, which result in either accepting or rejecting the hypothesis.

A. Descriptive statistics

Table 2 is an overview of the descriptive statistics regarding the abnormal returns. In Table 2 no division is made per company, since this research aims to find an overall effect of Donald Trump his Twitter usage on the S&P 500 companies and their stock prices.

Table 2: descriptive statistics of the abnormal returns based on three datasets, divided by polarity. For every dataset, five key numbers are displayed.

		Abnormal Returns	
Statistic	**All tweets**	**Postive tweets**	**Negative tweets**
Minimum	-0.04982	-0.01052	-0.04982
Average	-0.00486	0.00489	-0.00837
Maximum	0.02325	0.02325	0.02189
Standard deviation	0.01474	0.00908	0.01480
Observations	68	18	50

When observing Table 2, the first thing that stands out is that the average abnormal return of tweets with a positive polarity is positive and the average of tweets with a negative polarity is negative. Due to fact that the dataset contains more tweets with a negative polarity in comparison to a postive polarity, the average of all abnormal returns is negative. Whether these three effects are significant, is observed in the following sections.

B. Event-day abnormal returns

To answer the first three hypotheses, three different t-test are performed. The first t-test is executed in order to test whether there is a significant negative effect on stock prices of S&P 500 companies for all tweets in the dataset. A second t-test is used to assess whether only tweets with a negative polarity affect the stock prices of S&P 500 companies negatively. Lastly, to test whether tweets with a postive polarity affect the stock prices of S&P 500 companies positively, a third t-test is performed. Table 3 provides an summarized overview of the t-tests results.

*Table 3: T-test results for abnormal returns divided in three categories, all tweets, tweets with a positive polarity and tweets with a negative polarity. Tested at three significance levels (α): *significant at 10%, ** at 5%, *** at 1%.*

		One-sample t-test	
Statistic	**All tweets**	**Postive tweets**	**Negative tweets**
Average	-0.00486	0.00488	-0.00837
Standard deviation	0.01474	0.00908	0.01480
T-statistic	-0.32999	0.53815	-0.56565

The first three hypothesis are as follows:

H1: Donald Trump his tweets about S&P 500 companies have a negative effect on the daily stock prices.

H2: A 'negative' tweet of Donald Trump about S&P 500 companies has a negative effect on the daily stock prices.

H3: A 'positive' tweet of Donald Trump about S&P 500 companies has a positive effect on the daily stock prices

All three hypotheses are tested by performing a one-sample student t-test. For H1, it is tested whether the average abnormal returns of all tweets used in the dataset is lower than zero. In Table 3, it can be seen that the average effect of Donald Trump his tweets on the daily stock prices of S&P 500 companies is -0.486%. However, this effect is not significant. Based on this, the null-hypothesis cannot be rejected. Thus, there are no significant average abnormal returns. For H2, it is tested whether the average abnormal returns, of tweets with a positive polarity only, is higher than zero. In Table 3, it can be found that even though the effect is 0.489% and thus indeed positive. This effect is not significant. Based on this, the null-hypothesis cannot be rejected. There are no significant abnormal returns for positive tweets posted by Donald Trump. For H3, it is tested whether the average abnormal returns, of tweets with a positve polarity only, is higher than zero. In Table 3, it can be found that even though the effect found is 0.489% and thus positive. This effect is not significant. Based on this, the null-hypothesis cannot be rejected, meaning there are no significant abnormal returns for positive tweets.

When combining the three above-mentioned findings, one can say that there is no significant effect of Donald Trump his Twitter usage on stock prices of S&P 500 companies. In order to recommend valuable insights and recommendations for future research, all tweets were tested individually. From the 68 tweets tested, seven tweets with a negative polarity show a significant effect. Table 4 gives an overview of the seven significant tweets, including the company names, post date, post time, abnormal return, standard deviation and T-statistic. The full tweet texts of the seven tweets can be found in the Appendix, Table 7.

*Table 4: companies, mentioned by Donald Trump on Twitter, that showed significant abnormal return. Tested at three significance levels (α): *significant at 10%, ** at 5%, *** at 1%.*

Company	Tweet date	Time	Abnormal return	Standard deviation	T-statistic
Harley-Davidson	25-06-2018	23:28	-0.04982	0.01541	-3.23***
Amazon.com	02-04-2018	15:35	-0.03262	0.01637	-1.99**
Amazon.com	31-03-2018	14:52	-0.03262	0.01637	-1.99**
Amazon.com	31-03-2018	14:45	-0.03262	0.01637	-1.99**
Nordstrom	08-02-2017	16:51	-0.03961	0.02213	-1.79*
Facebook Inc.	21-10-2017	23:21	-0.01926	0.01152	-1.67*
Facebook Inc.	21-10-2017	22:06	-0.01926	0.01152	-1.67*

What stands out when looking at Table 4, is that all seven tweets have a significant negative abnormal return. They were all posted after 14:44 and during the first one-and-a-half year of Donald Trump his presidency. Also, the significant tweets about Amazon.com and Facebook Inc. have the same abnormal returns, standard deviation and thus T-statistic. For Amazon.com, this is because the 2nd of April 2018 was the first trading day after the tweets were posted on the 31st of March 2018. Since this research only looks at daily returns on trading days, it seems like the tweets are posted on the same date, which results in the same abnormal returns. Moreover, the tweets about Facebook Inc. are both posted on the same day. Looking at the Appendix Table 7, it can be seen that six out of the seven significant tweets revolve around money-related issues such as taxes, losses on trade and expenses on Facebook. The other signicant tweet is about Donald Trump his daughter not being fairly treated in the eyes of Trump himself. Appendix Table 8 shows the Global Industry Classification Standard (GICS) from the four significant companies. Amazon.com, Nordstrom and Harley-Davidson are in the same sector called consumer discretionary. Only Facebook Inc. is in the sector communication services.

C. Five-day cumulative abnormal returns

The fourth and final hypothesis aimed to test whether the shocks in stock prices, created by Donald Trump his Twitter usage, are lasting or recover within five days. First, the average five-day cumulative abnormal returns are calculated, followed by with the five-day cumulative abnormal for the seven tweets with an significant event-day abnormal return. The hypothesis is as follows:

H4: S&P 500 companies recover within five days from the shocks created by Donald Trump his tweets.

The hypothesis is tested by executing a one-sample student t-test. The hypothesis tests whether the five-day cumulative abnormal returns are equal to zero. In Table 5, it can be seen that the average five-day cumulative abnormal return of all tweets in the dataset is -1.126%. For positive tweets only, the average five-day cumulative abnormal returns is -0.377% and for negative tweets only the average is -1.747%. However, all three averages are not significant.

*Table 5: T-test results for five-day cumulative abnormal returns divided in three categories, all tweets, tweets with a positive polarity and tweets with a negative polarity. Tested at three significance levels (α): *significant at 10%, ** at 5%, *** at 1%.*

		One-sample t-test	
Statistic	**All tweets**	**Postive tweets**	**Negative tweets**
Average	-0.01264	-0.00377	-0.01747
Standard deviation	0.047651	0.049033	0.046924
T-statistic	-0.26525	-0.07683	-0.37224

Since the first three hypotheses resulted in seven significant tweets, the five-day cumulative abnormal returns, standard deviation and the T-statistic of these seven tweets were calculated.

This, to test whether the effect on the stock prices of S&P 500 companies created by Donald Trump his Twitter usage recover within five days. Table 6 provides a summarized overview of the performed analysis.

*Table 6: five-day cumulative abnormal returns of tweets with an significant event-day abnormal return. Tested at three significance levels (α): *significant at 10%, ** at 5%, *** at 1%.*

Company	Tweet date	CAR	Standard deviation	T-statistic
Harley-Davidson	25-06-2018	-0.03982	0.05955	-0.668
Amazon.com	02-04-2018	0.01496	0.07403	0.202
Amazon.com	31-03-2018	0.01496	0.07403	0.202
Amazon.com	31-03-2018	0.01496	0.07403	0.202
Nordstrom	08-02-2017	-0.05809	0.05256	-1.105
Facebook Inc.	21-10-2017	-0.00878	0.02200	-0.398
Facebook Inc.	21-10-2017	-0.00878	0.02200	-0.398

Table 6 shows that all seven tweets do not give a significant T-statistic, thus there are no significant abnormal returns. This combined with the insignificant averages concludes that the null-hypothesis cannot be rejected.

5. Discussion

In this section, the results are further elaborated on and discussed. The results are compared with current acedemic findings, and similarities and differences are addressed. First, the event-day abnormal returns results are discussed, followed by the 5-day cumulative abnormal returns.

A. Event-day abnormal returns

The event-day abnormal returns, as can be found in Table 3, on average are decreasing with 0.49%. When exploring current research, Ge, Kurov, and Wolfe (2017) found that tweets posted by Donald Trump move stock prices, with a change of 0.78% in abnormal returns, this meaning an increased stock price for positive tweets and a decreased stock price for negative tweets. The slope of the effect found in this research is in line with the research Ge, Kurov, and Wolfe (2017) conducted. The problem is that the effect of Ge, Kurov, and Wolfe (2017) is significant at a 1% level, whilst the effect found in this research is not significant, meaning this research does not provide evidence that Donald Trump his Twitter usage affects stock prices of S&P 500 companies. One reason for this difference could be the fact that Ge, Kurov, and Wolfe (2017) use hourly returns. They use 27 tweets, specifically naming publicly traded companies, over a period of 75 days. This resulted in 1125 observation points. In this research, an estimation period of 200 days is used, combined with daily returns instead of hourly returns. With more observation points, the expected returns are more accurate, which results in the abnormal returns being more precise. This resulted in significant T-statistics for Ge, Kurov, and Wolfe (2017).

In Table, it 3 can be found that even though the findings show a decreasing return of 0.83% for negative tweets and a 0.48% increase for positive tweets, both the findings are not significant. Thus, this research does not provide empirical evidence that Donald Trump his negative tweets affect stock prices of S&P 500 companies in a negative manner. In contradiction to this research, Zhang, Fuehres, and Gloor (2011) did show that negative tweets have a significant effect on stock prices. Zhang, Fuehres, and Gloor (2011) used almost 30.000 tweets a day, for a period of six months. They downloaded tweets based on emotional keywords such as fear, hope and happy. In contrast, in this research, all tweets of one person are downloaded first, and then only after applying certain criteria, the polarity of the tweet is defined based on these emotional key words. The amount of tweets in the dataset of Zhang, Fuehres, and Gloor (2011) is just over 53 million, which can provide a more accurate link between negative tweets and stock prices, than only 50 tweets from one user. Next to that, Zhang, Fuehres, and Gloor (2011) used the VIX, Chicago Board Options Exchange Volatility Index, as a benchmark, which was highly negatively correlated with the stock indexes researched. In this research, the whole S&P 500 index returns are used to estimate the expected returns. Since all companies in the dataset are S&P 500 companies, the index is positvely correlated with most of the individual stock prices.

In contradiction to Ranco et al. (2015), this research does not provide empirical evidence that Donald Trump his positive tweets affect stock prices of S&P 500 companies positively. Ranco et al. (2015) used the market model, with an estimation period of 120 days, to estimate their beta's. Even though this research used an estimation period of 200 days to decrease the estimation error, the company-specific beta's are only calculated prior to the earliest tweet in the dataset. Nine out of the 15 companies researched, had more than one tweet in the dataset, which can result in the outdated beta's being used to calculate the expected normal returns of the tweets later than the first company-specific tweet. Ranco et al. (2015) calculated the beta per single tweet. Again Ranco et al. (2015) used over one-and-a-half million tweets, from any user on Twitter, whilst this research only used 18 positive tweets.

B. *Five-day cumulative abnormal returns*

Ranco et al. (2015) prove that for positive tweets, there are significant cumulative abnormal returns up until four days, while for negative tweets the cumulative abnormal returns are significant up until eight days. This research computed five-day cumulative abnormal returns for the seven negative tweets that showed a significant event-day abnormal return and found that none of the tweets showed a significant five-day cumulative abnormal return. Possibly, this difference can be attributed to the fact that this research uses single tweets as events, whilst Ranco et al. (2015) use Twitter peaks as events. Out of 1.555.770 tweets, 260 peaks are identified. Peaks containing a large number of tweets, often lead to more significant results. On the other hand, Kollias, Papadamou, and Stagiannis (2011) found that for bombings the stock market recovers within five days. This is in line with this research.

6. Conclusion

This research examined whether Donald Trump his Twitter usage has an effect on the daily stock prices of S&P 500 companies. The overall effect of the tweets was examined, whereafter a division based on polarity was made. Lastly, this research tested whether the shocks in stock prices of S&P 500, created by Donald Trump his Twitter usage, are lasting, or recover within five days. The main research question goed as follows:

What is the effect of Donald Trump his tweets about S&P 500 companies on their daily stock prices?

In an attempt to answer this question, abnormal returns were calculated and one-sample t-tests were performed to examine whether the abnormal returns give a significant effect. In answering this main research question, this research does not provide any significant results that prove an effect of Donald Trump his Twitter usage on daily stock prices of S&P 500 companies. For further research, it is recommended to use intraday returns instead of daily returns. By using intraday returns, the estimated beta's can be based on more oberservation points, resulting in a lower estimation error, thus more accurate beta's. Also, instead of only measuring the event-day abnormal returns, the hourly abnormal returns can be calculated. This can provide a different insight into subject and is not tested in existing literature. One problem is that a part of the tweets are not posted during trading hours. Intraday data can only be used when there is a valid method that tackles this problem.

After testing for a general effect on daily stock prices of S&P 500 companies, this research examined whether Donald Trump his Twitter usage can affect the stock price of a single company in the S&P 500. For this, seven tweets, distributed over four companies gave a significant negative effect. All, except for one, are money-related. Next to that, all seven tweets were posted before the 1st of July 2018. In further research, it could be interesting to investigate whether Donald Trump his tweets about money-, trade- and economy-related issues have an influence on stock prices. Next to that, it would also be useful for investors, when the existing data is available and extensive enough, to examine whether the shocks created by Donald Trump on Twitter disappear after him being President for one-and-a-half years. Three out of the four companies with significant abnormal returns are divided in the same sector by GICS. In the future, it would be recommended to follow the approach of Mao et al (2012) and test the effect of Donald Trump his Twitter usage on different sector levels.

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8. Appendix

Code 1: Most important part of the Phyton code that was used to scrape all tweets including tweet date and time from @realDonaldTrump. The tweets selected with the code were downloaded in an Excel document.

```
Import Twint
        c = twint.Config()
        c.Username = "realdonaldtrump"
        c.Store_json = True
        c.Since = "2017-01-20"
        c.Until = "2019-05-20"
        # CSV Fieldnames
        c.Custom["tweet"] = ["id", "date", "time", "username", "tweet", "replies_count",
"retweets_count", "likes_count"]
        # Name of the directory
c.Output = "RDTtweets.JSON
```

Table 7: Tweets with significant abnormal returns, all with negative polarity and negave abnormal return. All tweets retrieved from the Twitter account @RealDonaldTrump.

Company	Tweet date	Tweet
Harley-Davidson	25-06-2018	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
Amazon.com	02-04-2018	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!
Amazon.com	31-03-2018	….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!
Amazon.com	31-03-2018	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…
Nordstrom	08-02-2017	My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person -- always pushing me to do the right thing! Terrible!
Facebook Inc.	21-10-2017	Crooked Hillary Clinton spent hundreds of millions of dollars more on Presidential Election than I did. Facebook was on her side, not mine!
Facebook Inc.	21-10-2017	Keep hearing about "tiny" amount of money spent on Facebook ads. What about the billions of dollars of Fake News on CNN, ABC, NBC & CBS?

Table 8: Global Industry Classification Standard (GICS) sector from companies with significant abnormal returns. Retrieved from Compustat.

Company	GICS Sector	GICS Sub-industry
Harley-Davidson	Consumer Discretionary	Motorcycle Manufacturers
Amazon.com	Consumer Discretionary	Internet & Direct Marketing Retail
Nordstrom	Consumer Discretionary	Department Stores
Facebook Inc.	Communication services	Interactive Media & Services