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Trump Twitter Behaviour Impact on US Companies

Event Studies

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PREFACE AND ACKNOWLEDGEMENTS

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ABSTRACT

This research studies the impact of Trump's twitter behaviour on US public companies by examining the relation between Trump's tweets and stock returns of the companies he mentions. Twitter data is collected from the day that Trump became president, on 1 January 2017 up to March 2019. S&P 500 data is used for the stock prices. The tweets are categorised into good, bad and neutral tweets. The results show that volatility increases due to Trump's tweets and that the stock price of positively (negatively) mentioned firms increase (decrease) after the tweet initially, but the abnormality disappears in the long haul.

Keywords: Trump, Twitter, Social Media, Stock Market Prediction, Sentiment Analysis
JEL Classification: G14, G41

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CHAPTER 1 INTRODUCTION

Twitter was founded in 2006. Since then it has gained enormous popularity and evolved into one of the most used social media platforms. Currently, Twitter has over 321 million active monthly users worldwide (Statista, 2019). Twitter is widely adopted as a channel to share information and communicate with others by individuals among other celebrities, CEOs and politicians.

President Trump, the president of the United States at this moment, is the first politician that actively uses Twitter to communicate with the outside world. He is even crowned as the ‘Twitter president’. His Twitter usage has become a daily habit and he usually posts several tweets a day. As he has the authority of the president, his tweets naturally receive a lot of attention. He currently has 46.7 million followers. Trump’s tweets do not only gain thousands of reactions (likes and retweets) on Twitter, but also even appear in the media, sometimes just within minutes after Trump posted the tweet. Trump is aware of this and has weaponized Twitter - he uses social media to control news cycle. His tweets are all placed strategically. Trump’s tweets often mention specific firms in his tweets, either positively or negatively.

Twitter is a form of social media. The effects of social media information shared on the financial markets have been researched for decades already. Mitchell and Mulherin (1994) state that the amount of news and market movement are dependent and have a similar pattern. News and market activities are significantly related. Kumar and Lee (2006) examine retail traders data and fnd that investor sentiment definitely influences investor’s behavior. They find that investor’s actions are in sync with other investors. That is to say they buy when other investors buy and sell when other investors sell. Zheludev et al. (2014) investigate the predictive power of the tweets through sentiment analysis. They find that financial information can be derived from sentiment caused by social media platforms. Sentiment from the tweets can provide new information on the future developments of the financial market.

As every type of social media collects data about individual’s behavior and is an outlet for sharing information, social media can provide us with important information about society’s interests and intentions with the stock market. Twitter is an especially important social media platform since it provides a very large amount of news and information on investor sentiment. Compared to other social media platforms such as Facebook and LinkedIn, Twitter can be considered the most direct and active social media platform as Twitter users can share their direct thoughts easily, as often as they want and even anonymously if preferred. Also, other social media such as Facebook focus more on personal use, whereas Twitter can be used for business. Stakeholders can for example use Twitter to gain information on the companies. Therefore, per second there are on average 6000 new tweets (Aslam, 2020). This adds up to more than 500 million tweets every day. Therefore, Twitter reaches a very large number of the public. Furthermore, Twitter caters more the retail investor and not so much the professional investor. We can expect that using Twitter will have positive relation with total share amount (the more shares a company has issued the more likely they are held by retail investors) and a negative relation with the share price (cheaper priced shares of a company are more likely held by the retail investor). So, it is to be expected that the sentiment of Trump's tweets will affect most the small investor in companies with many shares issued at a cheap price. For professional investor there exist other communication channels like conference calls.

Recently, research has demonstrated the impact of Twitter as an information medium for financial markets. Information from Twitter can significantly influence the stock prices. Schumaker and Chen (2009) show that Twitter data can forecast stock returns. Ranco et al. (2015) find significant results that show that stock prices are related to the sentiment in tweets that mention companies. Also, the accumulated Twitter sentiment can signify the course of the market movement. Yang, Mo and Liu (2015) state that groups of Tweeters form financial communities within Twitter and the influential Tweeters within the communities are representative for the relation between social sentiments and stock market activity. Talti et al. (2016) find that an increase in Tweets mentioning companies go ahead of unexpected changes in financial market trades for the mentioned company. This shows that Twitter movements support valuable knowledge on upcoming stock market developments.

A few investigations have been done on the effect of a tweet by Trump. Malaver-Vojvodic (2017) research the impact of the tweets on the Mexican peso and US dollar exchange rate and find that a negative tweet increases the volatility. Ge et al. (2017) find that Trump's tweets impact stock prices, trading volume and investor sentiment. They also find that tweets before he was president have a stronger impact. Juma'h and Alnsour (2018) research the impact of Trump's tweets on the performance of companies. Their results show that there is no significant effect of Trump's tweets on the stock market. However, now a larger sample of tweets can be collected for this research. Therefore, it should be investigated again.

Baker and Wurgler (2007) estimate the significance of investors' sentiment on the financial market. They find that stocks that are harder to be priced are influenced the most. Bollen and Mao (2011) collected Twitter data and investigate whether the sentiment derived from the tweets can forecast the market exchange. For the stock market data, they use the Dow Jones Industrial Average (DJIA) data. They state that Twitter moods can predict the financial market as by adding the element 'mood' the forecasts of the stock markets are significantly more accurate. Likewise, Kuleshov (2011) tries to make predictions of the stock market based on Twitter data and DJIA data. However, the results show that a low degree of accuracy is achieved. This led up to the conclusion that it is not possible to make predictions of the stock market with Twitter.

This impacts the stock market. Corea (2016) investigates how twitter can influence investors' sentiment. The findings show that the sentiment related to the tweets does not have a high predicting power, whereas the posting volume, the number of tweets, does. They find that pessimistic sentiment influences the stock price negatively. However, when the number of bad tweets increases to a certain amount it will still impact the stock price positively.

According to Fama et al. (1969), the financial market processes newly acquired knowledge extremely quickly and thus the stock prices should include every accessible info. This is called the efficient market hypothesis theory. Assuming this principle holds, it makes it possible to investigate the meaning of specific occurrences on the capital markets. In this research, an event study is conducted. The influence of president Trump's tweets on the stock prices of public US firms is investigated.

Studies show that important news causes stock prices to fluctuate over time. Chan (2003) finds that news causes stocks to drift, while no-news stocks on the other hand do not. Also, badly mentioned stocks in the public news move in an adverse direction. However, they find less momentum for stocks with favorable information. This is because bad news is processed into the stock prices with less intensity. This is called an underreaction. Since it is evident that stock prices will not react to news immediately, several event windows will be tried out for the event study in this paper. Therefore, firstly the influence of president Trump's tweets on the volatility in the stock prices of US public firms that are mentioned in his tweets is investigated. Furthermore, we explored whether negatively mentioned firms have a decline in stock prices and whether positively mentioned firms have a rise in stock price or no affect at all on stock price.

Also, a regression analysis will be done to measure the cumulative abnormal returns (CAR) and the cumulative abnormal volatility (CAV). The abnormal returns represent the impact of an event, the impact of a tweet from Trump. The CAR represents the complete effect of an event in a defined period, also called the event window. Most frequently, the event window is set for three days, from one day ahead of the event ($t = -1$) to one day following the event ($t = 1$). Several event windows will be used in this study to find the best fit. The CAV represents the total change in abnormal volatility of returns.

The main data obtained for this research is the tweets from president Trump from the first day of his presidency, 1 January 2017 to 1 March 2019. Data of the tweets by president Trump are collected from the Trump Twitter Archive (Brown, 2019). For analyzing the stock prices of public US firms, S&P 500 data with the market value and stock price is collected from Datastream, a reliable database with international economic and macro-economic information from Thomson Reuters. Brown & Warner (1985) research the impact of using stock returns for an event study and discover that daily stock price data cause little complications for an event study.

1.1 Research Question

The research question will be the following:

"What is the impact of Trump's tweets on the stock return of public US firms?"

Currently, President Trump is the number nine most followed Twitter account, whereas the previous president of the United States, Barack Obama, is on spot one (Social Blade, 2020). However, President Trump has more than three times the number of tweets as Obama, so more Twitter data is available for Trump. Moreover, Trump focuses on using Twitter, whereas Obama uses several social media platforms. Additionally, it is more interesting to study data of President Trump as he is the current president. He is well known for his tweets containing statements on specific companies, both positively as negatively.

Furthermore, tweets are found to create (temporary) volatility in the stock prices. Souza et al. (2015) found that Twitter sentiment is significantly correlated with stock returns and volatility. Furthermore, Cazzoli et al. (2016) show that important Twitter users contribute more to influencing the market. This suggests that president Trump, an important Twitter user, increases volatility in the stock price of companies he mentions in his tweets.

Therefore, my first hypothesis will be the following:

H_1 = Trump's tweets contribute to more volatility in the stock price of the mentioned companies.

Tetlock (2007) investigates how investor sentiment caused by media affects the stock market and discovers that negative news anticipates decreases in stock prices. Findings from Born, Myers and Clark (2017) show that good (bad) tweets impact the abnormal returns on the date of the tweet positively (negatively). However, they state that within five trading days the CARs are not significant anymore. Sprenger, Sandner, Tumasjan and Welpe (2014) state that stock market returns preceding positive news events are more pronounced than for negative news. Chan (2003) finds that no-news stocks do not drift, whereas stocks with news do and that bad news takes longer to translate into the stock prices. Nofer and Hinz (2015) researched whether positive sentiment caused by tweets can increase stock market returns, but they didn't find significant results. Therefore, our prediction is that we will accordingly find that the stock price of postively mentioned companies in Trump's tweets do not increase after the tweet.

Therefore, my second hypothesis will be the following:

H_2 = The share prices of negatively cited firms in a tweet by Trump decrease after the tweet.

Accordingly, my third hypothesis will be:

H_3 = The share prices of positively cited firms in a tweet by Trump increase after the tweet.

Furthermore, if Trump's tweets in fact have an impact on the financial market, it is interesting to investigate whether this abnormality disappears in the long run. Not much research has been done on the lasting effects of Trump's tweets. Ingram (2017) states that the financial market restores on the same day already.

H_4 = The abnormality caused by Trump's tweets disappears in the long run.

1.2 Relevance

This research will add value by investigating the consequences information provided by social media platforms, specifically Twitter, has on the financial market. Most research conducted on this topic investigates the effect of social media in general instead of focusing on a specific person. This research contributes by investigating the impact of only one individual. The influence of a tweet by president Trump on stock prices and the volatility will be investigated. The focus of this research is the influence of a tweet by Trump on the mentioned public US firms.

For this research Twitter data is analyzed and a sentiment analysis is performed on the collected data. By combining this with the S&P500 stock returns, an event study has been done. The main findings of this research show that Trump's tweets increase the volatility of the stock prices of mentioned firms. Initially, the stock price of positively mentioned firms increases after the tweet whereas stock prices of negatively mentioned firms decrease after the tweet. However, this abnormality disappears in the long run.

1.3 Outline

This research starts with an introduction of the research topic in chapter 1. In chapter 2 a literature review is conducted. Next, in chapter 3 the methodology is explained including research design, data collection and data analysis. Next, the findings will be discussed in chapter 4. The paper ends with conclusions and limitations in chapter 5.

CHAPTER 2 LITERATURE REVIEW

2.1 Investor Sentiment on stocks

Market forces, the change of supply and demand, causes stock prices to adjust daily. When the demand grows, the prices would rise and the other way around, if the demand for a stock shrinks, the price would reduce. Rationally, investors make choices based on the valuation of a company, such as earnings. However, choices also depend on other factors. Delong et al. (1990) find that there are also irritational investors, stockholders who react to sentiment. Investor sentiment has no general definition. Baker and Wurgler (2006) explain it as the tendency to make speculations. In other words, it is the mood of investors towards the financial markets or individual securities. It is evident that investors' sentiments influence the financial market. One approach to explain investors' sentiments is through behavioural finance. However, the theory of behavioural finance is not enough to clarify how investors' sentiments affect the financial market in social networks.

Li et al. (2014) state that financial news impacts stock price returns because it provides information and information impacts investors' sentiments. Social media are also a source of information and therefore it impacts investors' sentiments. Zheludev et al. (2014) state that social media sentiments hold news on the financial market. As Twitter is a form of social media, information from Twitter could be capable of forcefully affecting the stock prices. Schumaker and Chen (2009) show that Twitter has predictive power over stock returns.

Baker and Wurgler (2006) show that smaller stocks make bigger earnings when the sentiment low. However, the size effect does not exist at the time that sentiment is large. Also, lower sentiment generates higher returns for new, higher volatility, unprofitable stocks and non-dividend stocks. The same vice versa. Stambaugh et al. (2012) study whether sentiment effects exist. The results show that anomalies caused by mispricing is stronger and have higher profits when sentiment is high. Furthermore, they find that long term returns, and investor sentiment are not dependent on each other. Baker and Wurgler (2007) research how investor sentiment affects stock prices by investigating empirical effects of investor sentiment. They find investor sentiment to be measurable. Investor sentiment has the highest impact on hard to arbitrage or hard to value stocks. Stocks with higher sensitivity to investor sentiment are those younger, smaller, higher volatility, not profitable, non-dividend paying, troubled firms or firms with expected positive development.

Tetlock (2007) finds that news media content can be a predictor for the shifts in various indices of the financial market. Guo et al. (2017) assert that investor sentiment is valuable for predicting the economy, but only when stocks are watched by many investors. Brown and Cliff (2002) investigated the dependency of investor sentiment and the short-term market return. They discover historic market returns are also a significant explanation of sentiment. They also find that sentiment has a similar movement as the market, but small forecasting capability for near-term stock returns. Li et al. (2013) created predicting frameworks to investigate the impact of news on stock price return and concluded that sentiment analysis improves the prediction accuracy.

2.2 Financial Text Mining

There are large sets of data that contain information on economic performance. Text mining is an approach used to extract information from huge pieces of text such as news articles. This could be a big challenge due to for example different formats, spelling and languages. However, there are databases that can be used for this such as Factiva. Also, several mining techniques have been developed to analyze data and lots of research has been done on which technique is the best to gather valuable information from text containing financial information.

A lot of studies have been done on predicting market movements with text mining. Schumaker and Chen (2006) investigated predictive artificial intelligence methods for analysing economic news items. Their model that used words from the articles along with the stock prices during the publication of the article was the most accurate in forecasting. Sun et al. (2016) use text information from blogs make predictions for the stock market. Mahajan et al. (2008) propose a method to analyze financial news in order to determine how big events impact the market. They find an approach to identify major events and make forecasts on how this will impact the stock market. Kloptchenko et al. (2004) combine a text- and data mining approach for analyzing fiscal papers to predict the financial performances of companies in the future. They find that text mining is more accurate than just looking at the numbers. Joseph et al. (2011) research the affect of online searches on the economic market to try to predict abnormal returns and trading volumes. Their results show that online searches are a reliable predictor.

Zhai et al. (2007) try to improve predicting daily stock price trends by investigating the impact of mass media by combining news and technical indicators. Their results show higher prediction performance and profitability. Kim et al. (2014) investigate an approach for analyzing the link between news and stock exchange movements. They created their own lexicon and model for text mining and showed that news sentiment has an explanatory power for stock price developments.

CHAPTER 3 METHODOLOGY

3.1 Research Design

3.1.1 Event Study

In order to investigate how Trump's tweets can influence the financial market, an event study will be performed. By working with financial information, the effect a specific event has on a company's finance can be assessed in an event study (MacKinlay, 1997). Here the event of interest will be Trump's tweets on specific firms. As mentioned in the introduction, usually, event studies set the event window to three days, from one day ahead of the event (t = -1) to one day following the event (t = 1). Several event windows will be used to find the best fit. If we assume that a tweet does not leak out before being placed, we can take day 0, the day the tweet is placed, as the start date. Since most research show that it takes one or two days before the reaction of investors and that the abnormality disappears after several days, it is best to take 1 or 2 as the end date. Therefore, we will try (0,1) and (0,2). We also do (0,5) to confirm that abnormality disappears in the long term, just as other researches suggest.

We use different time windows. To measure the impact on a short period we use (0,1), (0,2) and (0,5) for the long term. The tweets are probably close in time. Therefore, to prevent overlap between event window and estimation period the mean adjusted method with a short estimation period is applied. According to MacKinlay (1997), an overlap would cause a bias in our results, because the studied event would influence the normality of the estimation period. Therefore, the estimation window will be -20 to -12, which is a total of 10 days (date 0 to 9). The timeline for this research is depicted in figure 1.

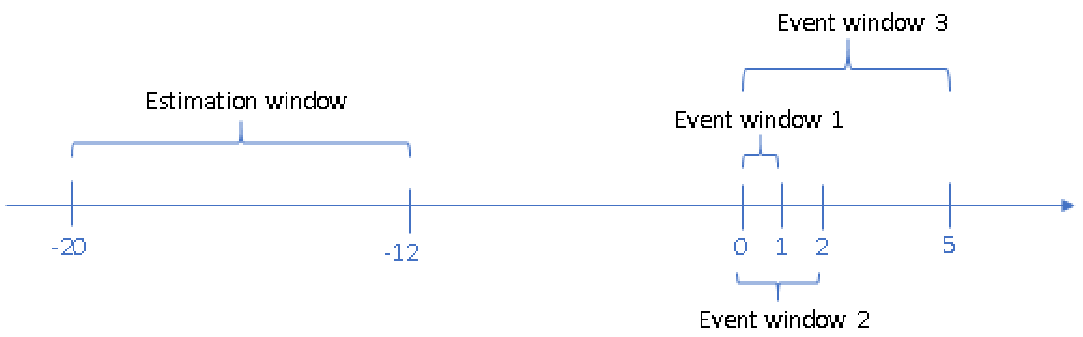

Figure 1 Timeline

3.1.2 Sentiment Analysis

With text mining we assign each tweet a sentiment. The “bag-of-words” method will be used to extract parts of text for the analysis. A lexicon package created by Tidyverse is used to assign each word a positive, negative or neutral value. For more detail refer to section 3.3 data analysis. With this method we can classify each tweet as either positive, negative or neutral. There is no distinguishing between positiveness or negativeness level of the tweet.

With the data consisting of Trump’s tweets and data of S&P 500, an analysis can be performed to investigate the power of a tweet by Trump. This will be done by performing time series. As the S&P 500 data has been collected from Datastream, the Datastream Event Study tool can be applied to do the Event Study. This tool has been developed to do an event study with stock prices.

The market model will be applied first to quantify the quantify both the cumulative abnormal returns and cumulative abnormal volatility. Then the same is done with the mean adjusted return model to perform the robustness check.

3.2 Data Collection

Firstly, Twitter data consisting of the tweets from president Trump since the first day of his presidency, 1st of January 2017 till 1st of March 2019 is needed. This is collected from the Trump Twitter Archive. From this data only tweets that include companies from the S&P 500 are relevant for this research. Therefore, we filter on only the tweets mentioning S&P 500 companies. Eventually, there are only 22 companies from the S&P 500 that are mentioned in Trump’s tweets. The results are shown in table 1.

Table 1 Mentioned companies and the number of tweets

No.	Name	Industry Group	# of Tweets
1	AMAZON.COM	BDRET	10
2	AMGEN	BIOTC	1
3	COMCAST A	BRDEN	3
4	APPLE	COMPH	5
5	BOEING	AEROS	3
6	JP MORGAN CHASE & CO.	BANKS	1
7	CINCINNATI FINL.	PCINS	1
8	CONSOLIDATED EDISON	CNVEL	1
9	CORNING	TELEQ	1
10	TARGET	BDRET	1
11	EXXON MOBIL	OILIN	3
12	HARLEY-DAVIDSON	AUTOS	6

13	HUMANA	HCPRO	1
14	LOCKHEED MARTIN	DEFEN	2
15	FORD MOTOR	AUTOS	6
16	NORDSTROM	APRET	1
17	EDISON INTL.	CNVEL	1
18	WALMART	BDRET	1
19	DELTA AIR LINES	AIRLN	1
20	GENERAL MOTORS	AUTOS	7
21	AMERICAN AIRLINES GROUP	AIRLN	1
22	BROADCOM	SEMIC	2

The collected data from Twitter includes the tweet date and time. However, the stock market is not permanently open. S&P 500 is open for trading from Sunday night to Friday night. Therefore, we adjusted the event dates to this so that we can more accurately predict the impact of Trump's tweets. Furthermore, tweet dates that took place on a S&P 500 holiday according to the US stock market holiday schedule also have an adjusted event date. Refer to appendix A figure 1 for an overview of each tweet with their corresponding event date.

Secondly, market data consisting of S&P 500 data with stock price is collected from Datastream. With the help of the Datastream Event Study tool, the abnormal returns are calculated with both the market model and the mean adjusted model.

3.3 Data Analysis

To understand the collected tweets from Trump, a sentiment analysis is performed in R. This way the tweets can be categorised into positive, negative and neutral texts. The R Package for Sentiment Analysis developed by MonkeyLearn is installed and used for the sentiment analysis. After installing the package, the texts that must be analysed are defined. This is done by assigning each tweet a value. Then the texts can be analysed with the sentiment analysis model. MonkeyLearn R package uses the lexicon created by Tidyverse to analyse the texts. The result will be that the tweets will each be labelled as positive, negative or neutral. The model also gives a prediction confidence for every result. For example, the first tweet is labelled as Negative by the sentiment analysis model with a prediction confidence of 72.8%. Detailed results are included in Appendix B.

Also, a regression analysis is performed to quantify the CAR and the CAV. The abnormal returns represent the impact of an event, the impact of a tweet from Trump. The CAR represents the affect of an event over the event window.

3.3.1 Abnormal Returns

In the market model the stock return is adjusted for the overall trend in the market.
The market model adjusted return can be calculated as follows:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t}$$

$R_{i,t}$: the return of the stock of the *i*th company at time *t*

$R_{m,t}$: the return of the market index *m* at time *t*

$\epsilon_{i,t}$: the error

For firm *i* and event date t the abnormal return is the error $\epsilon_{i,t}$ and can be calculated as follows:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t})$$

where

$AR_{i,t}$: abnormal returns for time period t

$R_{m,t}$: actual returns for time period t

In a perfect situation, in the efficient market mentioned by Fama (1970), when all the information is processed in the market, our error should be zero. Therefore, when the abnormal returns differ from zero, there is an abnormal return present.

t = 0 is event date

The Cumulative Abnormal Returns is the sum of all the Abnormal Returns over the period.

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

3.3.2 CAR t-statistics

A t-test is performed for the CAR for every firm at point t to see if the results are significant.
We will test our null hypothesis:

$$H_0: CAR = 0$$

$$t_{CAR} = \frac{CAR_i}{S_{CAR}}$$

where $S_{CAR}^2 = L_2 \, S_{AR_i}^2$

$S_{AR_i}^2$ is the standard deviation of the abnormal returns in the estimation window and is calculated with the following formula:

$$S_{AR_i}^2 = \frac{1}{M_i - 2} \sum_{t=t_0}^{t_1} (AR_{it})^2$$

$$L_2 = T_2 - T_1$$

Where

T_1 : the event day

T_2 : the ‘latest’ day of the event window

3.3.3 Historical Volatility

For calculating the volatility, we will take a week of S&P 500 stock returns, so a seven-day time frame will be used.

The standard deviation is calculated with the following formula:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (r_i - m)^2}{n - 1}}$$

where

σ : standard deviation

r_i : interday Returns

m: mean of data points

n: number of data points

The mean is calculated by taking the average of all data points:

$$m = \frac{\sum_{i=1}^{n} r_i}{n}$$

The interday returns are calculated by using the daily closing stock prices. This is calculated with the following formula:

$$r_i = \frac{P_{i+1} - P_i}{P_i}$$

Next, the Standard Deviation needs to be annualized to get the Historical Volatility. There are 252 trading days in a year.

$$HV = \sigma * \sqrt{252}$$

The total volatility consists of systematic and nonsystematic risk.

$$\sigma_{total}^2 = \sigma_{system}^2 + \sigma_{firm}^2$$

The systematic risk accounts for market movement, while the nonsystematic risk is firm specific. For our research we are interested in the nonsystematic risk, also called the idiosyncratic risk.

The firm specific risk, also known as the error term ϵ, can also be calculated with the R^2, the fit of the model.

$$\epsilon = 1 - R^2$$

3.3.4 Forecasting Volatility with GARCH (1,1) model

The volatility is calculated with the (GARCH) model to calculate the CAV. Hansen & Lunde (2005) investigate different ARCH-type models and conclude that more advanced models are not better than the GARCH (1,1) model. Therefore, in this research GARCH (1,1) will be used. The GARCH model is constructed as the following:

$$r_t = \mu + \epsilon_t$$

$$\epsilon_t = \sqrt{h_t} z_t$$

$$h_t = \varpi + \sum_{i=1}^{p} \beta_i h_{t-1} + \sum_{j=1}^{q} \alpha_j \, \epsilon_{t-j}^2$$

where r_t : return at time t

μ : mean return

ϵ_t: mean return

z_t ~ $iid\ N(0,1)$: normally distributed random variable

ϖ , $\alpha_1, \alpha_2, \ldots \alpha_q, \beta_1, \beta_2, \ldots \beta_p$: parameters of the model

The parameters $\varpi > 0$, $\alpha_j \geq 0$, $\beta_j \geq 0$ are positive. The variance h_t is positive and can be easily computed.

3.3.5 Abnormal Volatility Calculations

With our GARCH model, the forecasted volatility can be obtained. To quantify the abnormal volatility, the difference between the forecasted volatility and the volatility that was calculated with the returns is taken.

$$Abnormal\ Volatility = |Forecasted\ volatility - Historical\ volatility|$$

The formula for cumulative abnormal volatility is as follows:

$$CAV(n_1, n_2) = \left(\sum_{t\,=\,n_1}^{n_2} AV \right)$$

CHAPTER 4 RESULTS

Our first hypothesis investigates whether a tweet by Trump would increase the of the mentioned companies. Firstly, the volatility is calculated with our stock prices calculated returns. The outcome is shown in table 2. Unfortunately, it shows that the results are not significant with a 95% confidence level. This indicates that there is a non-significant trend that Trump's tweets can influence the volatility of companies he tweets about.

Table 2 Volatility per tweet
* are significant results tested with a 95% confidence level

Tweet No.	Company	Event Date	Volatility	Annualized Volatility	t-statistics
1	AMAZON.COM	28-6-2017	0.006809	0.108082374	2.162185
2	AMAZON.COM	25-7-2017	0.011915	0.189142552	-2.20294
3	AMAZON.COM	8-8-2017	0.008212	0.130361908	-2.01634
4	AMAZON.COM	16-8-2017	0.006553	0.104031927	2.985158
5	AMAZON.COM	29-12-2017	0.01343	0.213190627	6.87787
6	AMAZON.COM	2-4-2018	0.005439	0.086345204	-0.1335
7	AMAZON.COM	3-4-2018	0.008157	0.129493869	0.164152
8	AMAZON.COM	29-3-2018	0.009336	0.148199631	-1.5167
9	AMAZON.COM	4-1-2018	0.004654	0.073882861	7.005065
10	AMAZON.COM	4-1-2018	0.004654	0.073882861	7.005065
11	AMGEN	20-5-2018	0.01571	0.249381742	3.866455
12	COMCAST A	29-11-2017	0.017321	0.274961104	-0.03074
13	COMCAST A	25-7-2018	0.009751	0.154792301	1.770459
14	COMCAST A	11-12-2018	0.018108	0.28745158	-0.27749
15	APPLE	17-1-2018	0.010722	0.170209638	-5.49834
16	APPLE	25-4-2018	0.011252	0.178618361	3.534784
17	APPLE	27-5-2018	0.016914	0.268497214	-8.92054
18	APPLE	8-9-2018	0.010335	0.164065349	-1.32104
19	APPLE	10-8-2018	0.004695	0.074538671	2.615362
20	BOEING	17-2-2017	0.019516	0.309803897	1.200701
21	BOEING	3-8-2018	0.014646	0.232494524	-5.1833
22	BOEING	23-12-2018	0.016887	0.26807774	-3.09285
23	JP MORGAN CHASE & CO.	24-1-2018	0.005802	0.092097011	3.735568
24	CINCINNATI FINL.	7-6-2017	0.006368	0.101094206	5.963576
25	CORNING	21-7-2017	0.011059	0.175552352	-4.60464
26	TARGET	24-8-2018	0.015652	0.248473408	-3.20517
27	EXXON MOBIL	6-3-2017	0.009037	0.143455897	3.164476
28	EXXON MOBIL	7-3-2017	0.009018	0.143155039	4.119117
29	EXXON MOBIL	7-3-2017	0.009018	0.143155039	4.119117
30	HARLEY-DAVIDSON	3-7-2018	0.015053	0.238960607	-5.67839
31	HARLEY-DAVIDSON	25-6-2018	0.011616	0.184402048	2.705628
32	HARLEY-DAVIDSON	26-6-2018	0.012479	0.198097074	4.311019
33	HARLEY-DAVIDSON	26-6-2018	0.012479	0.198097074	4.311019
34	HARLEY-DAVIDSON	26-6-2018	0.012479	0.198097074	4.311019
35	HARLEY-DAVIDSON	27-6-2018	0.020309	0.322392565	2.000992
36	HUMANA	14-2-2017	0.019607	0.311258802	0.972434
37	LOCKHEED MARTIN	18-1-2017	0.006204	0.098488014	0.405439

38	LOCKHEED MARTIN	24-7-2018	0.008567	0.135989357	1.466022
39	FORD MOTOR	25-1-2017	0.024894	0.395181432	-1.75949
40	FORD MOTOR	3-1-2017	0.021884	0.347402974	0.838475
41	FORD MOTOR	28-3-2017	0.00851	0.135090344	-3.82867
42	FORD MOTOR	4-2-2017	0.011287	0.179179843	4.634652
43	FORD MOTOR	9-1-2017	0.013111	0.208127579	3.452419
44	FORD MOTOR	9-9-2018	0.015789	0.250650046	2.410589
45	NORDSTROM	8-2-2017	0.010024	0.159132308	-2.04096
46	EDISON INTL.	17-9-2018	0.005722	0.090833561	1.613043
47	WALMART	17-1-2017	0.010034	0.159285806	-2.21533
48	DELTA AIR LINES	30-1-2017	0.014078	0.223487473	-1.2704
49	GENERAL MOTORS	17-1-2017	0.00879	0.139530341	1.675314
50	GENERAL MOTORS	25-1-2017	0.024461	0.388307196	-6.25984
51	GENERAL MOTORS	3-1-2017	0.01953	0.310034983	3.359885
52	GENERAL MOTORS	27-11-2018	0.037383	0.59343831	-0.44057
53	GENERAL MOTORS	27-11-2018	0.037383	0.59343831	-0.44057
54	GENERAL MOTORS	29-11-2018	0.009279	0.147298195	-0.92414
55	GENERAL MOTORS	29-11-2018	0.009279	0.147298195	-0.92414
56	AMERICAN AIRLINES GROUP	24-9-2017	0.008944	0.14198128	1.915348
57	BROADCOM	2-12-2017	0.015335	0.243442738	-3.07946
58	BROADCOM	2-12-2017	0.015335	0.243442738	-3.07946
	Total		0.750817	11.91885516	

However, the volatility calculated above is the total volatility. Total volatility is only a good proxy for firm-specific risk if investors do not diversify. The total volatility is the sum of the systematic and non systematic risk. The first risk is explained by the market factor. The non systematic risk is firm specific and unexplained by the market factor. This is also called the idiosyncratic risk. Therefore, it is more meaningful to calculate the firm specific risk to find the real impact of a tweet by Trump. This can be calculated with the following formula:

$$Idosyncratic\ risk = 1 - R^2$$

The results over the event window are shown in table 3. We see that the idiosyncratic risk is larger than the total volatility. The total volatility is small. This shows that the impact on the overall financial market is small as the systematic risk is caused by external factors not related to the firm itself. Trump's tweet has a large impact on the specific firm's risk. However, the firm specific unsystematic risks can be mitigated or even eliminated through diversification. Therefore, we expect the volatility to return to normal in the long run.

Table 3 Idiosyncratic risk

Tweet No.	Company	Volatility	R^2	Idosyncratic risk
1	AMAZON.COM	0.00680855	0.0858780	0.9141220
2	AMAZON.COM	0.011914861	0.0158710	0.9841290
3	AMAZON.COM	0.008212028	-0.2089400	1.2089400
4	AMAZON.COM	0.006553395	0.0534870	0.9465130
5	AMAZON.COM	0.013429747	0.1103420	0.8896580
6	AMAZON.COM	0.005439237	-0.0331960	1.0331960
7	AMAZON.COM	0.008157347	-0.1205410	1.1205410
8	AMAZON.COM	0.009335699	0.0885710	0.9114290
9	AMAZON.COM	0.004654183	-0.2672970	1.2672970
10	AMAZON.COM	0.004654183	-0.2672970	1.2672970
11	AMGEN	0.015709573	-0.0001530	1.0001530
12	COMCAST A	0.017320921	-0.0855430	1.0855430
13	COMCAST A	0.009750998	0.0414920	0.9585080
14	COMCAST A	0.018107747	-0.2682820	1.2682820
15	APPLE	0.010722199	0.0072830	0.9927170
16	APPLE	0.011251899	-0.1729840	1.1729840
17	APPLE	0.016913735	0.0642430	0.9357570
18	APPLE	0.010335146	0.1204140	0.8795860
19	APPLE	0.004695495	-0.2291470	1.2291470
20	BOEING	0.019515811	0.4672130	0.5327870
21	BOEING	0.014645778	-0.0585620	1.0585620
22	BOEING	0.01688731	-0.0407460	1.0407460
23	JP MORGAN CHASE & CO.	0.005801566	0.0133630	0.9866370
24	CINCINNATI FINL.	0.006368336	-0.0894350	1.0894350
25	CORNING	0.011058759	-0.0388880	1.0388880
26	TARGET	0.015652353	-0.0902060	1.0902060
27	EXXON MOBIL	0.009036872	-0.0902060	1.0902060
28	EXXON MOBIL	0.00901792	0.099422	0.9005780
29	EXXON MOBIL	0.00901792	0.099422	0.9005780
30	HARLEY-DAVIDSON	0.015053103	-0.0211050	1.0211050
31	HARLEY-DAVIDSON	0.011616237	-0.2752700	1.2752700
32	HARLEY-DAVIDSON	0.012478943	0.2173090	0.7826910
33	HARLEY-DAVIDSON	0.012478943	0.2173090	0.7826910
34	HARLEY-DAVIDSON	0.012478943	0.2173090	0.7826910
35	HARLEY-DAVIDSON	0.020308823	-0.0409870	1.0409870
36	HUMANA	0.019607462	0.0729270	0.9270730
37	LOCKHEED MARTIN	0.006204162	-0.0602540	1.0602540
38	LOCKHEED MARTIN	0.008566524	0.1848600	0.8151400
39	FORD MOTOR	0.02489409	0.0311640	0.9688360
40	FORD MOTOR	0.02188433	-0.5377600	1.5377600
41	FORD MOTOR	0.008509892	-0.0767810	1.0767810
42	FORD MOTOR	0.011287269	-0.0140450	1.0140450
43	FORD MOTOR	0.013110805	0.2682890	0.7317110
44	FORD MOTOR	0.015789469	0.2489020	0.7510980
45	NORDSTROM	0.010024393	-0.1785870	1.1785870
46	EDISON INTL.	0.005721977	-0.2870570	1.2870570
47	WALMART	0.010034063	-0.0690790	1.0690790
48	DELTA AIR LINES	0.014078388	0.1914930	0.8085070
49	GENERAL MOTORS	0.008789585	0.0605370	0.9394630
50	GENERAL MOTORS	0.024461054	-0.2386380	1.2386380

51	GENERAL MOTORS	0.019530368	-0.2528450	1.2528450
52	GENERAL MOTORS	0.0373831	0.0512780	0.9487220
53	GENERAL MOTORS	0.0373831	0.0512780	0.9487220
54	GENERAL MOTORS	0.009278914	-0.0868360	1.0868360
55	GENERAL MOTORS	0.009278914	-0.0868360	1.0868360
56	AMERICAN AIRLINES GROUP	0.00894398	-0.0123260	1.0123260
57	BROADCOM	0.015335451	0.0384330	0.9615670
58	BROADCOM	0.015335451	0.0384330	0.9615670
	Total	**0.750817302**		**59.3421510**

In order to find more accurate results on the impact of volatility, we forecast the predicted volatility of the companies in our scope with the GARCH (1,1) model. With our predicted volatility and our previously obtained volatility actuals, the abnormal volatility is the difference of these two volatility measures.

If CAV is higher than 0, it means that the tweets influence the volatility of the mentioned firms. The results are shown in table 4. All tweets except one tweet have an impact on the volatility as the CAV > 0. Therefore, our null hypothesis is rejected. It can be concluded that Trump's tweets contribute to more volatility in the share price of the mentioned companies.

Table 4 CAV per tweet

Tweet No.	Name	Volatility	CAV
1	AMAZON.COM	0.00680855	0.064927144
2	AMAZON.COM	0.011914861	0.0685
3	AMAZON.COM	0.008212028	0.029961243
4	AMAZON.COM	0.006553395	0.026411754
5	AMAZON.COM	0.013429747	0.015848993
6	AMAZON.COM	0.005439237	0.161651138
7	AMAZON.COM	0.008157347	0.094101881
8	AMAZON.COM	0.009335699	0.107261586
9	AMAZON.COM	0.004654183	0.016010727
10	AMAZON.COM	0.004654183	0.016010727
11	AMGEN	0.015709573	0.013896613
12	COMCAST A	0.017320921	0.035874448
13	COMCAST A	0.009750998	0.03908115
14	COMCAST A	0.018107747	0.023248887
15	APPLE	0.010722199	0.016747616
16	APPLE	0.011251899	0.042187712
17	APPLE	0.016913735	0.006640239
18	APPLE	0.010335146	0.030283843
19	APPLE	0.004695495	0.022894933
20	BOEING	0.019515811	0.016393563
21	BOEING	0.014645778	0.022170526
22	BOEING	0.01688731	0.037071027
23	JP MORGAN CHASE & CO.	0.005801566	0.004348122
24	CINCINNATI FINL.	0.006368336	0.007468586
25	CORNING	0.011058759	0.034567478
26	TARGET	0.015652353	0.031742361

27	EXXON MOBIL	0.009036872	0.081874841
28	EXXON MOBIL	0.00901792	0.076975447
29	EXXON MOBIL	0.00901792	0.076975447
30	HARLEY-DAVIDSON	0.015053103	0.042193459
31	HARLEY-DAVIDSON	0.011616237	0.069465814
32	HARLEY-DAVIDSON	0.012478943	0.060041688
33	HARLEY-DAVIDSON	0.012478943	0.060041688
34	HARLEY-DAVIDSON	0.012478943	0.060041688
35	HARLEY-DAVIDSON	0.020308823	0.072572473
36	HUMANA	0.019607462	0.02756165
37	LOCKHEED MARTIN	0.006204162	-0.004367871
38	LOCKHEED MARTIN	0.008566524	0.003704348
39	FORD MOTOR	0.02489409	0.023841054
40	FORD MOTOR	0.02188433	0.055373071
41	FORD MOTOR	0.008509892	0.02716264
42	FORD MOTOR	0.011287269	0.024928634
43	FORD MOTOR	0.013110805	0.027497332
44	FORD MOTOR	0.015789469	0.02484775
45	NORDSTROM	0.010024393	0.076235876
46	EDISON INTL.	0.005721977	0.012725538
47	WALMART	0.010034063	0.013637525
48	DELTA AIR LINES	0.014078388	0.041357769
49	GENERAL MOTORS	0.008789585	0.027501059
50	GENERAL MOTORS	0.024461054	0.040532455
51	GENERAL MOTORS	0.019530368	0.053315702
52	GENERAL MOTORS	0.0373831	0.053658274
53	GENERAL MOTORS	0.0373831	0.053658274
54	GENERAL MOTORS	0.009278914	0.056126605
55	GENERAL MOTORS	0.009278914	0.056126605
56	AMERICAN AIRLINES GROUP	0.00894398	0.059001174
57	BROADCOM	0.015335451	0.051128324
58	BROADCOM	0.015335451	0.051128324

Next, to test the second and third hypothesis, the impact of the tweets by Trump on the stock prices of mentioned companies is investigated. The output of the event study shows the abnormal return and the CAR for good, neutral and bad news and the total. The CARs demonstrate the effect of Trump's tweets. This is outlined in table 5.

Table 5 CAR per tweet

t-statistics are significant for t <-1.96 or t > 1.96 for at the 95% confidence level.

Tweet No.	Company	CAR	t-statistic
1	AMAZON.COM	0.026915	0.84935367
2	AMAZON.COM	-0.03809	-1.1166798
3	AMAZON.COM	-0.02034	-1.1888689
4	AMAZON.COM	0.027161	0.72743924
5	AMAZON.COM	0.045243	1.68476197
6	AMAZON.COM	-0.00181	-0.0866668
7	AMAZON.COM	0.002515	0.11928647

8	AMAZON.COM	-0.03507	-0.0426731
9	AMAZON.COM	0.054015	4.57335157
10	AMAZON.COM	0.054015	4.57335157
11	AMGEN	0.03006	0.70846328
12	COMCAST A	-0.00091	-0.0257331
13	COMCAST A	0.041926	1.94146858
14	COMCAST A	-0.0035	-0.0859289
15	APPLE	-0.06124	-2.7103101
16	APPLE	0.075519	2.26322145
17	APPLE	-0.08188	-2.1989671
18	APPLE	-0.02661	-1.2335685
19	APPLE	0.026181	2.08640715
20	BOEING	0.005836	0.1315275
21	BOEING	-0.04314	-3.1870649
22	BOEING	-0.02974	-0.816635
23	JP MORGAN CHASE & CO.	0.015621	1.06218862
24	CINCINNATI FINL.	0.055334	3.90472008
25	CORNING	-0.10391	-4.5115678
26	TARGET	-0.02027	-0.6624359
27	EXXON MOBIL	0.023845	1.20807168
28	EXXON MOBIL	0.034036	1.6899012
29	EXXON MOBIL	0.034036	1.6899012
30	HARLEY-DAVIDSON	-0.06811	-1.6586527
31	HARLEY-DAVIDSON	0.019706	0.48770926
32	HARLEY-DAVIDSON	0.026488	0.65533885
33	HARLEY-DAVIDSON	0.026488	0.65533885
34	HARLEY-DAVIDSON	0.026488	0.65533885
35	HARLEY-DAVIDSON	0.014043	0.34720999
36	HUMANA	0.010345	0.25737447
37	LOCKHEED MARTIN	0.005468	0.41146194
38	LOCKHEED MARTIN	0.014078	0.74102199
39	FORD MOTOR	-0.02745	-0.4606912
40	FORD MOTOR	0.018309	0.39433316
41	FORD MOTOR	-0.02392	-1.3242108
42	FORD MOTOR	0.041694	1.66469755
43	FORD MOTOR	0.039879	1.28185689
44	FORD MOTOR	0.021346	0.58457695
45	NORDSTROM	-0.04985	-1.0243825
46	EDISON INTL.	0.014527	1.11879948
47	WALMART	-0.01728	-0.8740865
48	DELTA AIR LINES	0.043679	-0.1809858
49	GENERAL MOTORS	0.028612	1.53517272
50	GENERAL MOTORS	-0.06102	-1.1473721
51	GENERAL MOTORS	0.078826	1.44119044
52	GENERAL MOTORS	-0.01197	-0.1479462
53	GENERAL MOTORS	-0.01197	-0.1479462
54	GENERAL MOTORS	-0.0222	-0.8077761
55	GENERAL MOTORS	-0.0222	-0.8077761
56	AMERICAN AIRLINES GROUP	0.053534	1.63644831
57	BROADCOM	-0.03895	-0.9907969
58	BROADCOM	-0.03895	-0.9907969

To analyse the findings, we calculated CAR per tweet category: positive, negative or neutral and studied the results for event windows (0,1), (0,2) and (0,5). This is summarized in table 6.

Table 6 Market Model CAR's per category per event day

	Market Model			
	Good News	Neutral News	Bad News	Total
Event Day	CAR	CAR	CAR	CAR
0	0.054	0.038	0.081	0.188
1	-0.044	-0.030	0.033	-0.038
2	0.040	-0.070	-0.038	-0.067
3	-0.014	-0.051	0.001	-0.083
4	-0.028	0.066	0.140	0.169
5	0.025	-0.056	-0.030	-0.043

The results of the short-term windows (0,1) and (0,2) window are depicted in figures 2 and 3.

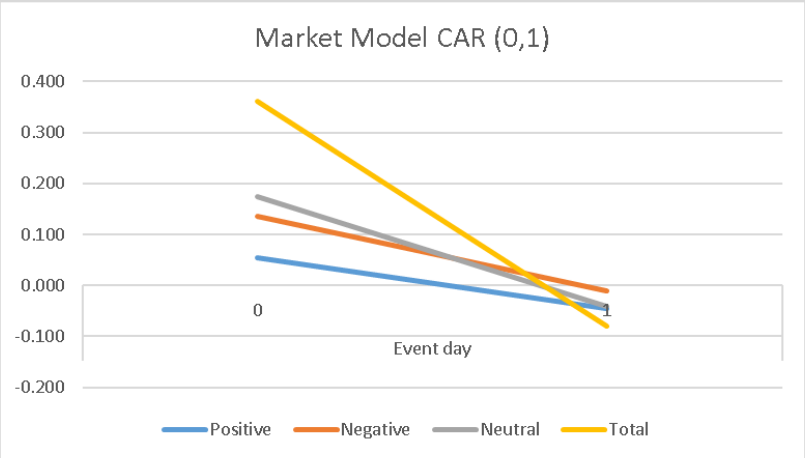

Figure 2 Market Model CAR event window (0,1)

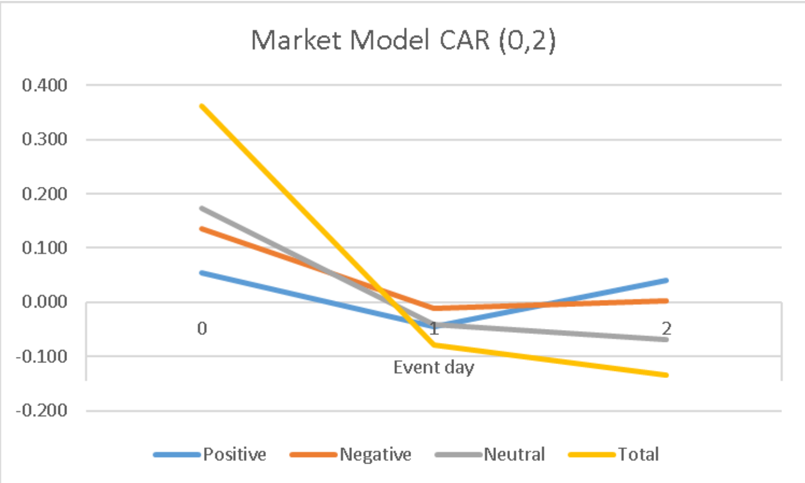

Figure 3 Market Model CAR event window (0,2)

The results show that the short term abnormal returns indeed increases with a positive tweet and decreases with a negative tweet. Therefore, our null hypothesis can be rejected and we can conclude that Trump's tweets do have an impact. For the second hypothesis on negatively cited firms, it can be concluded that the share prices of negatively cited firms in Trump's tweets decrease after the tweet.

Accordingly, for the third hypothesis on positively mentioned companies, it can be concluded that the share prices of positively cited firms in Trump's tweets increase after the tweet.

Furthermore, the results of the (0,5) window are shown in figure 4.

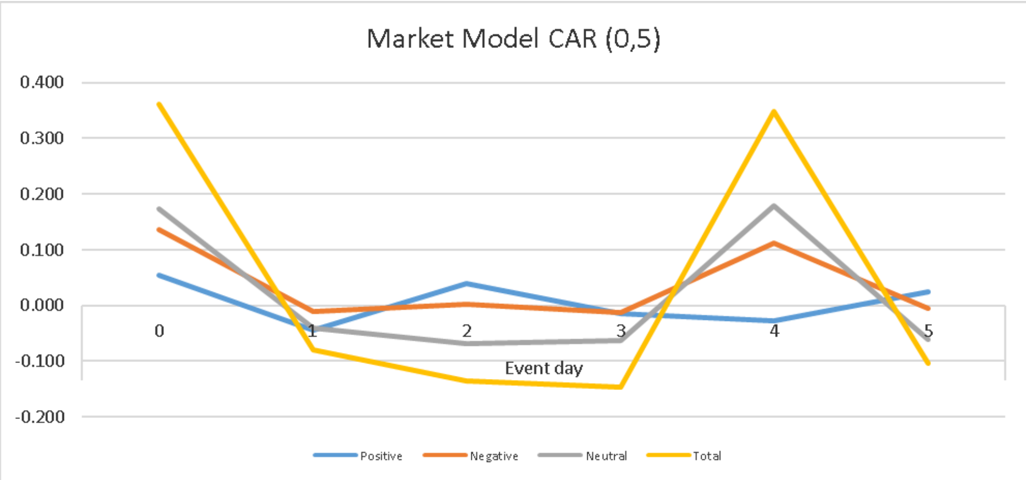

Figure 4 Market Model CAR event window (0,5)

In figure 4, we can see that at day 5 the CAR moves back to the starting point of day 1. It can be concluded that the abnormality disappears in the long run. Therefore, the null hypothesis of the fourth hypothesis is also rejected.

Next, to check for robustness, we perform the same analysis but this time with the mean adjusted return model instead of the market model. The results for this are summarized in table 7. The results are in line with the previous results using the market model.

Table 7 Mean Adjusted CAR's per category per event day

Mean Adjusted Return Model				
	Good News	Neutral News	Bad News	Total
Event Day	CAR	CAR	CAR	CAR
0	0.043	0.057	0.062	0.176
1	0.077	-0.063	0.005	0.023
2	-0.025	-0.040	-0.039	-0.103
3	-0.022	-0.062	0.011	-0.090
4	-0.025	-0.015	0.061	0.014
5	-0.009	-0.052	-0.077	-0.120

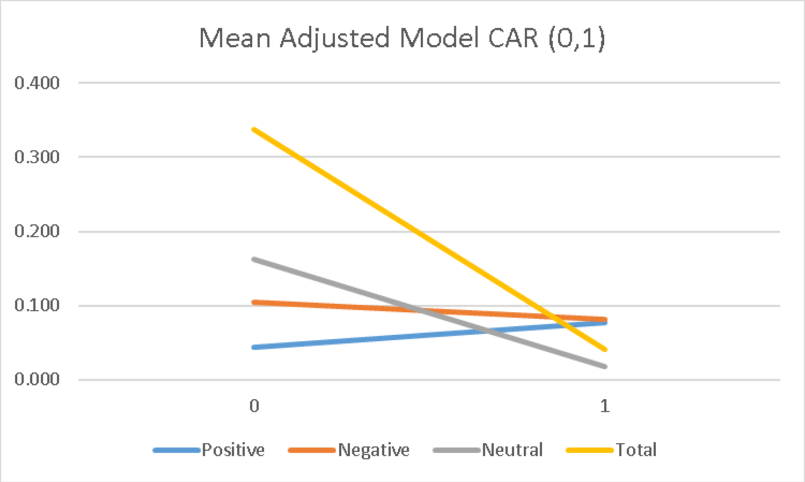

Figure 5 Mean Adjusted Model CAR event window (0,1)

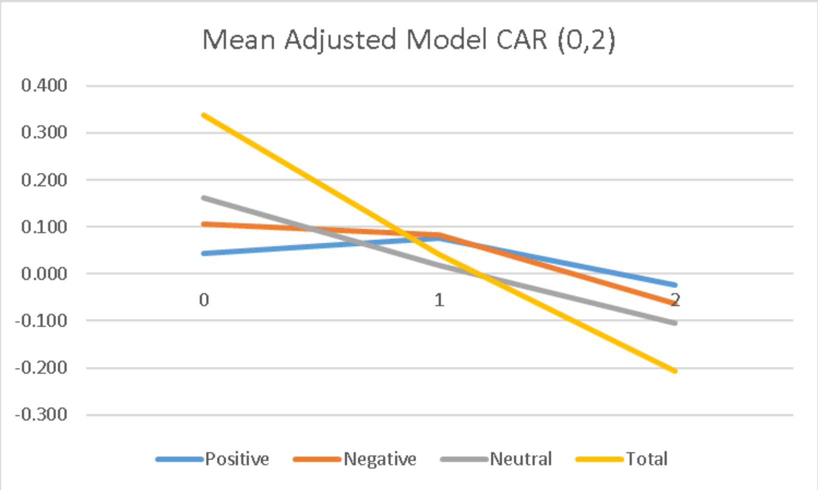

Figure 6 Mean Adjusted Model CAR event window (0,2)

The results show that in line with the market model results, the short term abnormal returns increases with a positive tweet and decreases with a negative tweet. However ,the effect of a positive tweet has a shorter impact as we see here that the CAR increases after a day, but decreases again after 2 days. Whereas, with the market model the CAR increases after 2 days. Furthermore, the results of the (0,5) window are shown in figure 7. Also, in the long run the abnormality disappears just like in our market model results. Therefore, we can conclude that our resultsa re robust.

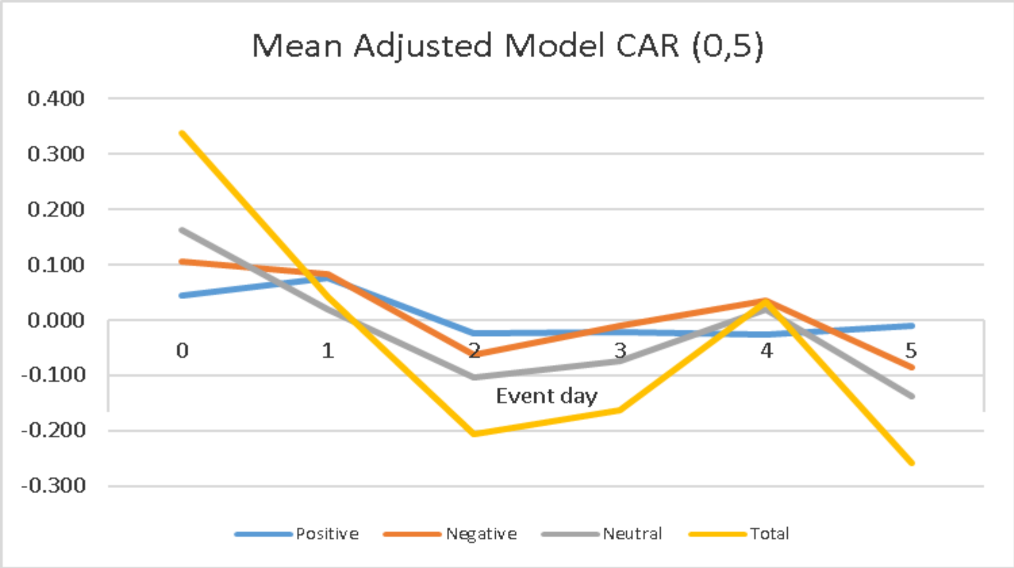

Figure 7 Mean Adjusted Model CAR event window (0,5)

CHAPTER 5 CONCLUSION & DISCUSSION

5.1 Conclusion

The research question: "*What is the impact of Trump's tweets on the stock return of public US firms?"* can now be answered. To conclude, this study shows that social media activity of president Trump, can have a big influence in the financial market since social media influences investor sentiment. Our event study results show that companies have increased abnormal volatility after being mentioned in a tweet by Trump. Furthermore, we find that Trump's tweets impact the mentioned companies either negatively or positively. The negatively mentioned companies have decreased stock prices whereas positively mentioned companies have increased stock prices. The results show that this impact only stays short-term (one or two days). In the long-run (approximately five days) the effect disappears. Refer to Table 8 for an overview of each hypothesis and the corresponding results.

Table 8 Hypothesis Results

	Hypothesis	Result (Accepted/Rejected)
H_1	Trump's tweets contribute to more volatility in the stock price of the mentioned companies.	Accepted.
H_2	The stock prices of negatively cited firms in a tweet by Trump decrease after the tweet.	Accepted.
H_3	The stock prices of positively cited firms in a tweet by Trump increase after the tweet.	Accepted.
H_4	The abnormality caused by Trump's tweets disappears in the long run.	Accepted.

5.2 Limitations and Future Research

The results of this study are limited because the impact of only one person with power's twitter activity is investigated. Therefore, we cannot generalize and conclude whether all people with power can impact the financial market through tweets. Further research could investigate the impact of other influential people's activity on Twitter on the stock market to see if similar results are obtained.

Moreover, in this research we only selected companies included in the S&P 500 for our scope as S&P 500 financial data is used. However, this means our data consists of solely large American companies which are considered more reliable and steadier. Other smaller companies could be interesting to analyse too.

Furthermore, it would be meaningful to include other factors such as size for our regressions. However, since we use data from S&P 500, we did not find this necessary as it contains larger American companies only.

Future research can be conducted by performing a similar approach, but with more data as Trump will continue making more tweets during his presidency. It is interesting to investigate whether the results stay the same.

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APPENDIX A Tweets + Event dates

Company	Date	Event date
AMAZON.COM	06-28-2017 13:06:14	28-6-2017
AMAZON.COM	07-25-2017 02:36:17	25-7-2017
AMAZON.COM	08-08-2017 18:00:30	8-8-2017
AMAZON.COM	08-16-2017 10:12:45	16-8-2017
AMAZON.COM	12-29-2017 13:04:09	29-12-2017
AMAZON.COM	02-04-2018 13:35:03	4-2-2018
AMAZON.COM	03-04-2018 13:55:37	3-4-2018
AMAZON.COM	03-29-2018 11:57:38	29-3-2018
AMAZON.COM	03-31-2018 12:45:41	4-1-2018
AMAZON.COM	03-31-2018 12:52:59	4-1-2018
AMGEN	05-18-2018 20:02:49	20-5-2018
COMCAST A	11-29-2017 12:16:21	29-11-2017
COMCAST A	07-25-2018 00:39:16	25-7-2018
COMCAST A	11-12-2018 18:13:10	11-12-2018
APPLE	01-17-2018 23:28:30	17-1-2018
APPLE	04-25-2018 14:11:57	25-4-2018
APPLE	05-27-2018 20:32:33	27-5-2018
APPLE	08-09-2018 15:45:28	8-9-2018
APPLE	10-08-2018 22:47:45	10-8-2018
BOEING	02-17-2017 11:38:20	17-2-2017
BOEING	03-08-2018 22:43:03	8-3-2018
BOEING	12-23-2018 16:46:47	23-12-2018
JP MORGAN CHASE & CO	01-24-2018 11:58:58	24-1-2018
CINCINNATI FINL.	07-06-2017 12:17:13	7-6-2017
CORNING	07-21-2017 03:31:45	21-7-2017
TARGET	08-24-2018 09:57:15	24-8-2018
EXXON MOBIL	06-03-2017 21:19:04	6-3-2017
EXXON MOBIL	07-03-2017 03:49:54	7-3-2017
EXXON MOBIL	07-03-2017 03:50:49	7-3-2017
HARLEY-DAVIDSON	03-07-2018 14:00:22	4-7-2018
HARLEY-DAVIDSON	06-25-2018 21:28:06	25-6-2018
HARLEY-DAVIDSON	06-26-2018 11:16:36	26-6-2018
HARLEY-DAVIDSON	06-26-2018 11:37:51	26-6-2018
HARLEY-DAVIDSON	06-26-2018 12:17:49	26-6-2018
HARLEY-DAVIDSON	06-27-2018 15:26:24	27-6-2018
HUMANA	02-14-2017 22:50:33	14-2-2017
LOCKHEED MARTIN	01-18-2017 12:34:09	18-1-2017
LOCKHEED MARTIN	07-24-2018 11:01:13	24-7-2018
FORD MOTOR	01-25-2017 00:46:57	25-1-2017
FORD MOTOR	03-01-2017 16:44:13	3-1-2017
FORD MOTOR	03-28-2017 10:36:02	28-3-2017
FORD MOTOR	04-01-2017 13:19:09	4-2-2017
FORD MOTOR	09-01-2017 14:16:34	9-1-2017
FORD MOTOR	09-09-2018 13:49:20	9-9-2018
NORDSTROM	08-02-2017 15:51:01	8-2-2017
EDISON INTL.	09-17-2018 09:46:51	17-9-2018
WALMART	01-17-2017 17:55:38	17-1-2017
DELTA AIR LINES	01-30-2017 12:16:30	30-1-2017
GENERAL MOTORS	01-17-2017 17:55:38	17-1-2017
GENERAL MOTORS	01-25-2017 00:46:57	25-1-2017
GENERAL MOTORS	03-01-2017 12:30:05	3-1-2017
GENERAL MOTORS	11-27-2018 19:05:39	27-11-2018
GENERAL MOTORS	11-27-2018 19:05:39	27-11-2018
GENERAL MOTORS	11-29-2018 11:37:14	29-11-2018

GENERAL MOTORS	11-29-2018 11:37:14	29-11-2018
AMERICAN AIRLINES GROUP	09-22-2017 17:54:59	24-9-2017
BROADCOM	2-11-2017 19:58:56	2-12-2017
BROADCOM	2-11-2017 20:33:18	2-12-2017

Appendix B: Results Sentiment Analysis in R

	req	confidence	probability	label
1	Tweet 1	0.728	0.728	Negat~
2	"E-mails show that the AmazonWashin~	0.665	0.665	Negat~
3	Only fools or worse are saying that~	0.96	0.96	Negat~
4	"I am right about Amazon costing th~	0.956	0.956	Negat~
5	"I have stated my concerns with Ama~	0.824	0.824	Negat~
6	" While we are on the subject it is~	0.567	0.567	Negat~
7	" ...does not include the Fake Wash~	0.916	0.916	Negat~
8	"The #AmazonWashingtonPost sometime~	0.949	0.949	Negat~
9	"Is Fake News Washington Post being~	0.589	0.589	Negat~
10	"Amazon is doing great damage to ta~	0.73	0.73	Negat~
11	"Why is the United States Post Offi~	0.933	0.933	Negat~
12	" RT @SteveForbesCEO: .@realDonaldTr~	0.666	0.666	Negat~
13	"American Cable Association has big~	0.974	0.974	Negat~
14	So sad and unfair that the FCC would~	0.995	0.995	Negat~
15	"Wow Matt Lauer was just fired from ~	0.725	0.725	Posit~
16	Apple prices may increase because of~	0.841	0.841	Posit~
17	Had a very good phone call with @Emm~	0.892	0.892	Posit~
18	Why didn’t President Obama do someth~	0.952	0.952	Negat~
19	Looking forward to my meeting with T~	0.683	0.683	Posit~
20	I promised that my policies would al~	0.454	0.454	Posit~
21	I am pleased to announce that our v~	0.882	0.882	Posit~
22	NASA which is making a BIG comeback~	0.677	0.677	Posit~
23	Going to Charleston South Carolina ~	0.794	0.794	Posit~
24	Tremendous investment by companies ~	0.972	0.972	Posit~
25	Getting ready to leave for Cincinna~	0.395	0.395	Posit~
26	RT @Edison_Electric: While customer~	0.501	0.501	Neutr~
27	Billions of dollars in investments ~	0.877	0.877	Neutr~
28	Target CEO raves about the Economy.~	0.546	0.546	Posit~
29	Buy American & hire American ar~	0.518	0.518	Negat~
30	Thank you to @exxonmobil for your $~	0.63	0.63	Neutr~
31	'President Trump Congratulates Exxo~	0.469	0.469	Posit~
32	Now that Harley-Davidson is moving ~	0.562	0.562	Neutr~
33	Harley-Davidson should stay 100% in~	0.614	0.614	Negat~
34	A Harley-Davidson should never be b~	0.973	0.973	Negat~
35	....When I had Harley-Davidson offi~	0.857	0.857	Negat~
36	Early this year Harley-Davidson sai~	0.608	0.608	Negat~
37	Surprised that Harley-Davidson of a~	0.792	0.792	Negat~
38	Obamacare continues to fail. Humana~	0.674	0.674	Negat~
39	Totally biased @NBCNews went out of~	0.725	0.725	Negat~
40	RT @DanScavino: “Lockheed Martin wi~	0.658	0.658	Neutr~
41	Ford has abruptly killed a plan to ~	0.61	0.61	Negat~
42	Big announcement by Ford today. Maj~	0.497	0.497	Negat~
43	Great meeting with Ford CEO Mark Fi~	0.616	0.616	Posit~
44	Ford said last week that it will ex~	0.642	0.642	Posit~
45	Thank you to Ford for scrapping a n~	0.638	0.638	Posit~
46	@DanScavino: Ford to scrap Mexico p~	0.588	0.588	Neutr~
47	My daughter Ivanka has been treated~	0.931	0.931	Negat~
48	RT @Edison_Electric: While customer~	0.501	0.501	Neutr~
49	Only 109 people out of 325000 were ~	0.883	0.883	Negat~
50	General Motors is sending Mexican m~	0.772	0.772	Neutr~

51	General Motors is very counter to w~	0.429	0.429	Posit~
52	Very disappointed with General Moto~	0.362	0.362	Neutr~
53	....for electric cars. General Moto~	0.505	0.505	Negat~
54	General Motors is very counter to w~	0.429	0.429	Posit~
55	Great meeting with Ford CEO Mark Fi~	0.616	0.616	Posit~
56	Thank you to General Motors and Wal~	0.747	0.747	Posit~
57	Thank you to Doug Parker and Americ~	0.999	0.999	Posit~
58	Broadcom's move to America=$20 BILL~	0.619	0.619	Neutr~
59	Today we are thrilled to welcome @B~	0.834	0.834	Neutr~
60	Thank you to General Motors and Wal~	0.747	0.747	Posit~

Appendix C: Tweets overview + corresponding label

Company	Tweet	Date	Sentiment
AMAZON.COM	So sorry to hear the news about Jeff Bozo being taken down by a competitor whose reporting I understand is far more accurate than the reporting in his lobbyist newspaper the Amazon Washington Post. Hopefully the paper will soon be placed in better & more responsible hands!	01-14-2019	Negat~
AMAZON.COM	E-mails show that the AmazonWashingtonPost and the FailingNewYorkTimes were reluctant to cover the Clinton/Lynch secret meeting in plane..	8-8-2017	Negat~
AMAZON.COM	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!	4-2-2018	Negat~
AMAZON.COM	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?)!	4-3-2018	Negat~
AMAZON.COM	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!	03-29-2018	Negat~
AMAZON.COM	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...	03-31-2018	Negat~
AMAZON.COM	...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!	03-31-2018	Negat~
AMAZON.COM	The #AmazonWashingtonPost sometimes referred to as the guardian of Amazon not paying internet taxes (which they should) is FAKE NEWS!	06-28-2017	Negat~
AMAZON.COM	Is Fake News Washington Post being used as a lobbyist weapon against Congress to keep Politicians from looking into Amazon no-tax monopoly?	07-25-2017	Negat~
AMAZON.COM	Amazon is doing great damage to tax paying retailers. Towns cities and states throughout the U.S. are being hurt - many jobs being lost!	08-16-2017	Negat~
AMAZON.COM	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!	12-29-2017	Negat~
AMGEN	RT @SteveForbesCEO: .@realDonaldTrump speech on drug costs pays immediate dividends. New @Amgen drug lists at 30% less than expected. Middl…	05-18-2018	Negat~
COMCAST A	American Cable Association has big problems with Comcast. They say that Comcast routinely violates Antitrust Laws. “These guys are acting much worse and have much more potential for damage to consumers than anything AT&T-Time Warner would do.” Charlie Gasparino	11-12-2018	Negat~
COMCAST A	So sad and unfair that the FCC wouldn’t approve the Sinclair Broadcast merger with Tribune. This would have been a great and much needed Conservative voice for and of the People. Liberal Fake News NBC and Comcast gets approved much bigger but not Sinclair. Disgraceful!	07-25-2018	Negat~
COMCAST A	Wow Matt Lauer was just fired from NBC for “inappropriate sexual behavior in the workplace.” But when will the top executives at NBC & Comcast be fired for putting out so much Fake News. Check out Andy Lack’s past!	11-29-2017	Posit~
APPLE	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	9-8-2018	Posit~
APPLE	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.	8-10-2018	Posit~
APPLE	Why didn’t President Obama do something about the so-called Russian Meddling when he was told about it by the FBI before the Election? Because he thought Crooked Hillary was going to win and he didn’t want to upset the apple cart! He was in charge not me and did nothing.	05-27-2018	Negat~

APPLE	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.	04-25-2018	Posit~
APPLE	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	01-17-2018	Posit~
BOEING	I am pleased to announce that our very talented Deputy Secretary of Defense Patrick Shanahan will assume the title of Acting Secretary of Defense starting January 1 2019. Patrick has a long list of accomplishments while serving as Deputy & previously Boeing. He will be great!	12-23-2018	Posit~
BOEING	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!	8-3-2018	Posit~
BOEING	Going to Charleston South Carolina in order to spend time with Boeing and talk jobs! Look forward to it.	02-17-2017	Posit~
JP MORGAN CHASE & CO.	Tremendous investment by companies from all over the world being made in America. There has never been anything like it. Now Disney J.P. Morgan Chase and many others. Massive Regulation Reduction and Tax Cuts are making us a powerhouse again. Long way to go! Jobs Jobs Jobs!	01-24-2018	Posit~
CINCINNATI FINL.	Getting ready to leave for Cincinnati in the GREAT STATE of OHIO to meet with ObamaCare victims and talk Healthcare & also Infrastructure!	6-7-2017	Posit~
CONSOLIDATED EDISON	RT @Edison_Electric: While customers may not see electric company personnel in their neighborhoods the energy grid is heavily interconnect…	09-17-2018	Neutr~
CORNING	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	07-21-2017	Neutr~
TARGET	Target CEO raves about the Economy. “This is the best consumer environment I’ve seen in my career.” A big statement from a top executive. But virtually everybody is saying this & when our Trade Deals are made & cost cutting done you haven’t seen anything yet! @DRUDGE_REPORT	08-24-2018	Posit~
EXXON MOBIL	Buy American & hire American are the principles at the core of my agenda which is: JOBSJOBS JOBS! Thank you @exxonmobil.	3-7-2017	Negat~
EXXON MOBIL	Thank you to @exxonmobil for your $20 billion investment that is creating more than 45000 manufacturing & construction jobs in the USA!	3-7-2017	Neutr~
EXXON MOBIL	'President Trump Congratulates Exxon Mobil for Job-Creating Investment Program'https://t.co/adBzWhtq8S	3-6-2017	Posit~
HARLEY-DAVIDSON	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!	7-3-2018	Neutr~
HARLEY-DAVIDSON	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!	06-27-2018	Negat~
HARLEY-DAVIDSON	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!	06-26-2018	Negat~
HARLEY-DAVIDSON	....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!	06-26-2018	Negat~
HARLEY-DAVIDSON	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.....	06-26-2018	Negat~
HARLEY-DAVIDSON	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	06-25-2018	Negat~
HUMANA	Obamacare continues to fail. Humana to pull out in 2018. Will repeal replace & save healthcare for ALL Americans. https://t.co/glWEQ0lNR4	02-14-2017	Negat~

LOCKHEED MARTIN	Totally biased @NBCNews went out of its way to say that the big announcement from Ford G.M. Lockheed & others that jobs are coming back...	01-18-2017	Negat~
LOCKHEED MARTIN	RT @DanScavino: “Lockheed Martin will add 400 workers to boost production of the F-35 fighter jet the most expensive in U.S. history afte…	07-24-2018	Neutr~
FORD MOTOR	“Ford has abruptly killed a plan to sell a Chinese-made small vehicle in the U.S. because of the prospect of higher U.S. Tariffs.” CNBC. This is just the beginning. This car can now be BUILT IN THE U.S.A. and Ford will pay no tariffs!	9-9-2018	Negat~
FORD MOTOR	Big announcement by Ford today. Major investment to be made in three Michigan plants. Car companies coming back to U.S. JOBS! JOBS! JOBS!	03-28-2017	Negat~
FORD MOTOR	Great meeting with Ford CEO Mark Fields and General Motors CEO Mary Barra at the @WhiteHouse today. https://t.co/T0eIgO6LP8	01-25-2017	Posit~
FORD MOTOR	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!	1-9-2017	Posit~
FORD MOTOR	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	1-4-2017	Posit~
FORD MOTOR	@DanScavino: Ford to scrap Mexico plant invest in Michigan due to Trump policieshttps://t.co/137nUo03Gl	1-3-2017	Neutr~
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!	2-8-2017	Negat~
EDISON INTL.	RT @Edison_Electric: While customers may not see electric company personnel in their neighborhoods the energy grid is heavily interconnect…	09-17-2018	Neutr~
DELTA AIR LINES	Only 109 people out of 325000 were detained and held for questioning. Big problems at airports were caused by Delta computer outage.....	01-30-2017	Negat~
GENERAL MOTORS	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!	1-3-2017	Neutr~
GENERAL MOTORS	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!	11-29-2018	Posit~
GENERAL MOTORS	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....	11-27-2018	Neutr~
GENERAL MOTORS	....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!	11-27-2018	Negat~
GENERAL MOTORS	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!	11-29-2018	Posit~
GENERAL MOTORS	Great meeting with Ford CEO Mark Fields and General Motors CEO Mary Barra at the @WhiteHouse today. https://t.co/T0eIgO6LP8	01-25-2017	Posit~
GENERAL MOTORS	Thank you to General Motors and Walmart for starting the big jobs push back into the U.S.!	01-17-2017	Posit~
AMERICAN AIRLINES GROUP	Thank you to Doug Parker and American Airlines for all of the help you have given to the U.S. with Hurricane flights. Fantastic job!	09-22-2017	Posit~
BROADCOM	Broadcom's move to America=$20 BILLION of annual rev into U.S.A. $3+ BILLION/yr. in research/engineering & $6 BILLION/yr. in manufacturing. https://t.co/NsJ4PtVTtl	11-2-2017	Neutr~
BROADCOM	Today we are thrilled to welcome @Broadcom CEO Hock Tan to the WH to announce he is moving their HQ’s from Singapore back to the U.S.A..... https://t.co/WrqUXBndyZ	11-2-2017	Neutr~
WALMART	Thank you to General Motors and Walmart for starting the big jobs push back into the U.S.!	01-17-2017	Posit~