

TRADING ON TRUMP'S TWEETS

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Table of contents

Executive summary 2

1. Introduction 3

2. Theoretical foundation 4

2.1 News traders 4

2.2 Market efficiency 4

2.3 Short and long position 5

2.4 Transaction cost 5

2.5 Benchmark and risk-adjusting 6

3. Analysis 7

3.1 Sources of data 7

3.2 Market impact 8

3.1.1 Evaluation of market impact 8

3.1.3 Comparing with the S&P-index 9

3.1.5 Sentiment and return 11

3.1.6 Isolating the effect 11

3.1.7 Market inefficiency 13

3.1.8 Part conclusion 14

3.3 Trading strategy 15

3.2.1 Trading rules 16

3.2.2 Historic performance 17

3.2.3 Part conclusion 22

4. Weaknesses 22

5. Conclusion 23

6. Bibliography 24

7. Appendix 26

7.1 Triggering events 26

7.2 Sensitivity analysis 28

7.3 Identification of tweets 28

7.4 Return each trade and indexed return 28

Executive summary

In this paper, we have examined President Donald Trump's impact on the stock market through his tweets targeting public traded companies of the Fortune 500 list. The purpose of this paper is to investigate the market impact of the tweets and unveil whether it is possible to make a profitable trading strategy based on the tweets or not. The research question for the paper is: "*Do the tweets of Donald Trump influence the stock price of targeted companies, and is it possible to design a trading strategy to profit from this information?"*

To reveal Trump's impact, we have selected a set of companies that have been mentioned in his tweets, and analysed the impact of the tweets on the associated stock prices. We found that Trump's tweets do have a significant impact on the stock market in the minutes following the tweet. The effect was found to peak within 30 minutes after publication, before converging towards initial level before the tweet at end of day.

Following our analysis, we made a trading strategy that sought to trade on Trump's tweets. Based on predefined criteria for going long or short and holding time, we made a bot that traded on companies mentioned in Trump's tweets. Compared to the S&P 500 index, our trading strategy yielded both lower returns and volatility. As presented in the paper, the strategy is thus not viable. However, the trading strategy is sensitive to the number of tweets and the transaction cost. Increasing the number of tweets or reducing the transaction costs, would therefore lead to a more competitive strategy.

1. Introduction

On the fifth of January this year the internet shopping giant, Amazon, experienced an immediate devaluation of 1 % of their stock price (Chapman,2017). Right before the devaluation, one of the most powerful men worldwide - the American President Donald Trump - was tweeting directly towards Amazon, stating: "*Amazon is doing great damage to tax paying retailers. Towns, cities and states throughout the U.S. are being hurt - many jobs being lost*!". This incident makes it interesting to examine whether there is a pattern in which the targeted stock experiences a price change following the tweet.

As Trump is actively targeting public traded companies through his tweets, in both a negative and positive manner, it is an ongoing discussion regarding the market impact of these tweets, and whether it is possible to exploit this as traders. Therefore, the research question in this paper is:

"Do the tweets of Donald Trump influence the stock price of targeted companies, and is it possible to design a trading strategy to profit from this information?"

To approach this subject, the paper will first introduce relevant theory to provide basis for our analysis and development of a trading strategy. Secondly, we will conduct an analysis based on our data to examine the market impact caused by Trump's tweets. Thirdly, a developed trading strategy based on the analysis and selected theory will be presented, together with its performance. Finally, we will present how the trading strategy are sensitive to changes in the number of tweets and transaction cost, and discuss possible weaknesses associated with the strategy. The paper will be confined to the average change, and thus exclude an analysis of volatility. This will allow a more comprehensive analysis of average change within the tasks limitations.

2. Theoretical foundation

To answer research question, a theoretical foundation is required. To successfully address Trump's impact, it is necessary to have knowledge regarding how news traders operate, market efficiency, and what different trading positions entails. Further we will present the impact of transaction costs and risks associated with event driven trading. Finally, we will present our measure of performance and benchmark for comparison.

2.1 News traders

News traders collect and act upon new information about instrument values (Harris, 2003). They try to predict how fundamental values will change based on the available information, and act if they think it will change significantly. Traders implicitly assume that the current price of the instrument is correct, and trade based on how the information should affect the fundamental value. When trading on public knowledge, like the president's tweets, one would naturally need to act quickly in order to make a profit, as the prices will adjust almost instantaneously to easily interpretable information.

Algorithmic trading is a trading system that makes quick decisions and transactions in the financial market based on a predefined set of rules (Fuglaas, 2017). By using a computer program, which for example identifies certain companies and loaded words in a tweet, the program could identify the tweet's sentiment and determine if a company is being slandered or praised. Based on the information, the algorithm can make a decision. In order to trade on tweets, immediate reaction is required, and an algorithm will therefore provide the best prerequisite to profit.

2.2 Market efficiency

To profit from Trump's tweets we are dependent on an inefficient market, implying that share prices are not reflecting all available private and public information immediately as the tweet is published.

According to Eugene Fama's (1969) efficient market hypothesis (EMH), a market is efficient given three conditions. First, there must be minimal transaction cost trading stocks, so that traders are not prevented from trading. Secondly, all information must be available to the market participants at all time. The last condition states that there must be an agreement among

investors regarding the implication of current information on today's price and distribution of future prices.

Furthermore, Fama divides the markets into three forms, based on the efficiency of the markets. They are strong-form efficient when all the information is incorporated in the stock prices, semi-strong efficient when all public information is reflected and weak-form efficient when the price reflects all information in foregoing prices. Most empirical research states that markets are weak-form efficient (Harris, 2003) and thus breaks Fama's conditions of an efficient market. Here the future price follows a random walk process, and it creates an inefficient market if traders are exploiting this.

2.3 Short and long position

As news traders, we may choose to go long or short when trying to profit from Trump's tweets. Holding a long position indicates that traders have bought an asset, and it is therefore an asset that they own (Harris, 2003). Profit will be achieved when buying low and selling high. Short position on the other hand refers to when traders sell assets they do not have, and hope that the price will decrease. Short sellers cover their position when they repurchase the assets owed, and profits from selling high and buying low.

2.4 Transaction cost

Although it might be possible to exploit an inefficiency in the market caused by Trump's tweets, any potential profit from trading will be affected by transaction costs. Traders are concerned with transaction cost since it's one of the most significant determinants of their total returns, especially for traders that trade frequently or in large sizes (Harris, 2003). Transaction costs include all costs associated with trading, and is divided into three categories: explicit costs, implicit costs and missed trade opportunity cost. Explicit costs are easily identified costs, for example brokerage fees and interest paid on borrowed share or capital. Implicit costs arise because the trader generally have an impact upon prices. Missed trade opportunity cost occurs when traders fail to fill their order, or fail to fill in a timely manner. Explicit costs will be the most relevant for trading on Trump's tweets. With limited sized orders, the impact on prices should be minimal and remove implicit costs.

Short-sellers are investors who incur relatively large transaction costs as they must pay interest on borrowed shares or capital and a lending fee. The size of the transaction cost will however depend on whether the trader is trading intraday or not.

2.5 Benchmark and risk-adjusting

When evaluating the performance of our strategy, it's the relative result that is important. A benchmark is a standard which the performance of assets can be measured against (Harris, 2003). Since Trump's tweets affect several different industries, using a sector specific benchmark is not possible. We have decided to measure our performance to the S&P 500. This index tracks 500 large US companies (Bloomberg). The reason for our choice, in addition to the broad spectrum it covers, is the assumption that a company have to be of a certain size in order to get Trump's attention.

To further evaluate the results, they must be adjusted for the risk in each alternative (Prado, 2008). To risk-adjust the results we have decided to use the Sharpe ratio. The Sharpe ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk (Financial Times, n.d.). The higher sharpe-ratio you achieve, the more attractive is the investment since you receive higher returns per unit of risk.

$$S = \left(\frac{R_p - R_f}{\sigma_p} \right)$$

Figure 1 **The Sharp-ratio** Where R_p is the return of our strategy, R_f is the risk-free rate and σ_p is the standard deviation of the strategy. To estimate the risk-free rate, we use the rate of a 3-month US treasury bill. The weighted average risk-free rate is calculated to 0.73% for our analysis (US Treasury).

3. Analysis

As our research question implied, our analysis will be split in two parts. First, we will look if Trump is able to impact the market at all. In order to do this, we will observe the market's movement following his tweets, and attempt to isolate the effect by eliminating other sources. Afterwards, we will create a strategy to try to profit from any potential market impact. To do this, we will create an algorithmic bot with certain rules to execute the trades. We will analyse the bots performance by analysing its result over the last year and compare it with the S&P-index to decide if the strategy is viable.

3.1 Sources of data

Our analysis of the market impact and corresponding trading strategy, will be based on a total of 3000 tweets, with the majority from the last year. Using the Application Programming Interface of Twitter, the tweets were exported into an excel-model. Additionally, the excel-model consists of a list containing the companies on the Fortune 500. Our model then identified all the tweets that mentioned at least one of the companies from the list.

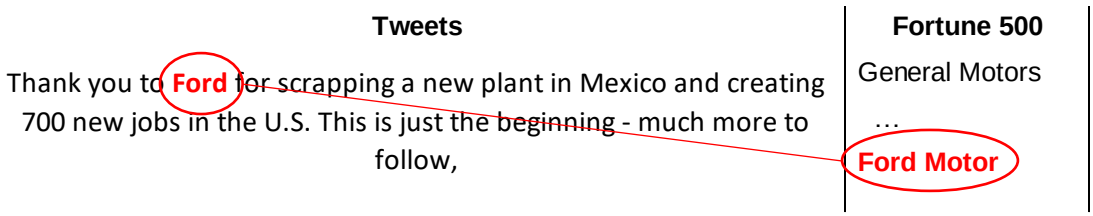


Figure 2 **Excel-model** The excel-model identified those tweets where at least one of the companies at the Fortune 500-list where mentioned.

However, tweets in which some people in the close circuit of Trump are mentioned, such as Hillary Clinton, Tiffany Trump or others, were excluded from the list. This also applies if the tweet consists of the phrase «fake news». This delimitation is justified by the idea that Trump loses some of his credibility and objectivity when this is mentioned in a tweet, and thus lower the market impact of the targeted company. After excluding some tweets, we are left with a total of 41 tweets which will be used in the analysis.

For each identified tweet we have tracked the stock price movement for the company in question the time after the tweet. Due to limitations in the Bloomberg-terminal, we have chosen ten different points of time which varies between 10 minutes after the tweet to EoD of day 7, as shown in figure 1. Since Trump often tweets outside opening hours, we will register prices that are available in the real market.

In order to analyse the market impact, we will compute the percentage change in the stock price from the last available price before the tweet. If Trump tweets within opening hours, the basis for the analysis will be the current price at the time of the tweet. However, when Donald Trump's tweets in the closing hours of the exchanges, the last available price will be the last EoD-price.

Last available price before the tweet	From the first available price after the tweet				
Basis	10 min 5 hours	30 min EoD	1 hour EoD 2	2 hours EoD 4	3 hours EoD 7

Figure 3 **Points of time** We have tracked the stock price movement at ten different points of time after the tweet.

3.2 Market impact

Before designing a trading strategy based on Trump's tweets, it is necessary to evaluate if the tweets have an impact on the market at all, and if so, to what extent. If we are to make a strategy based on these tweets, we have to prove that the impact of these tweets causes an inefficiency in the market that is possible to exploit. Our hypothesis is that a negative tweet about a company will decrease the stock price, while a positively loaded tweet will increase the price.

3.1.1 Evaluation of market impact

The analysis on the market impact of Trump's tweets, will be based on 41 of Trump's tweets, that in total are targeting 61 listed companies in either a negative or positive manner. The figure below illustrates the effect of Trump's tweets based on the data we have gathered. Both the average return and success-rate change over time.

	10 min	30 min	1 hour	2 hours	3 hours	5 hours	EoD	EoD 2	EoD 4	EoD 7
Average change	0,51 %	0,55 %	0,51 %	0,46 %	0,38 %	0,15 %	0,11 %	0,06 %	-0,31 %	-0,62 %
Success-rate	65 %	64 %	64 %	61 %	61 %	58 %	58 %	52 %	55 %	51 %

Figure 4 **Market impact** Illustrates the average change in line with our hypothesis and success-rate of our hypothesis. The change calculation throughout the paper is positive if the stock price correlate with the tweet's sentiment, and negative if the correlation is negative. The average of these values gives the average change.

The success-rate represents the proportion of tweets resulting in a price change in line with our hypothesis. This means the company's share price increases as a consequence to a positive loaded tweet, and decreases because of a negative loaded tweet.

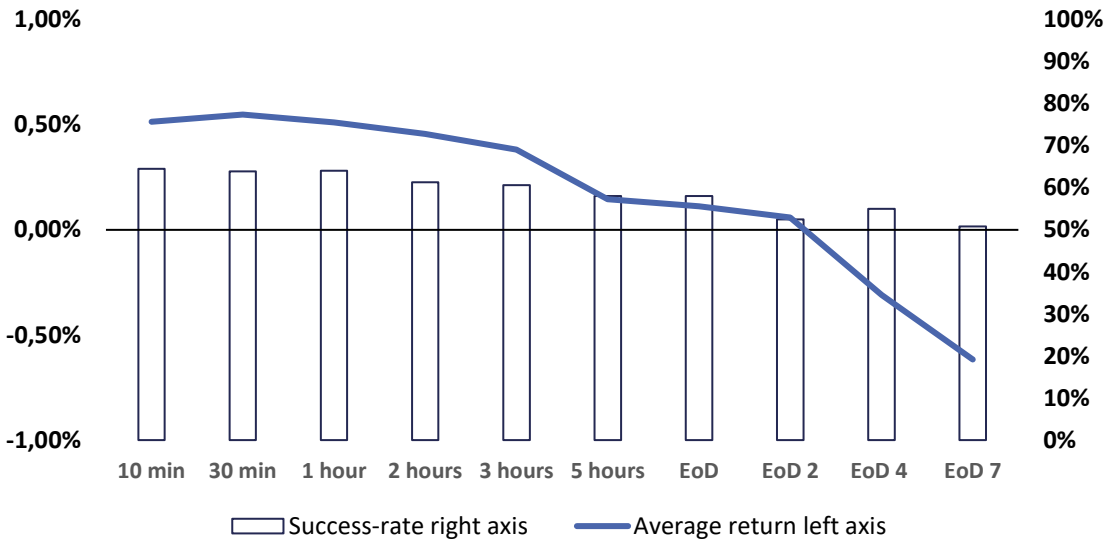


Figure 5 **Market impact of Trump's tweets** The figure illustrates how the average change in stock price peaks within 30 minutes, before gradually converging against zero and below. Additionally, the success rate of our hypothesis are reduced with time.

Figure 5 above shows the success-rate and the average return calculated based on the 61 different events. Until the blue line intersects with the black line, at EoD 2, the average return is positive. The presented data indicates that Trump's tweets have some impact on the market. The data indicates a trend, where the magnitude of success-rate and average return is negatively correlated with time, meaning that the tweets have a greater impact right after Trump has published them. It is also worth mentioning that over time the stock price becomes more of a random walk, and dependent upon other companies or industries specific matters. This result is supported by other studies made on Trump's tweets, which points out that companies usually rebound from their losses within the same day as they are mentioned in a negative tweet (Ingram, 2017).

3.1.3 Comparing with the S&P-index

Our results show that the stock price changes with an average of 0,52 % in the ten-minute period following the tweet. To examine whether this is a coincidence or a representation of the market return in the same period, we will compare this number with the movement in the S&P 500-index. By studying movement in the S&P-index within the same ten minutes periods after the tweets, we find that the index achieves an average increase of 0,06 %.

To determine whether there is a significant difference between the two rates of change, we will compute a two-tail t-test with unequal variance. The resulting p-value of 0,009 reveals that the difference between the means would be the observed 0,457 % (0,515 - 0,057) or larger only 0,9 % of the time, assuming that the means are the same. Therefore, we reject the null hypothesis

that the sample means are the same. The observed difference between the sample means is thus convincing enough to conclude that the average change in the stocks and index differ significantly.

	Index	Trump
Mean	0,057 %	0,515 %
Variance	0,001 %	0,016 %
Observations	41	60
t Stat	-2,704	
P(T<=t) two-tail	0,009	
t Critical two-tail	1,995	

Figure 6 **Comparing with the S&P-index** The figure shows a t-test which examines the difference between the average change in S&P-index and the targeted companies in the ten-minute period following the tweets.

This relationship can be more closely examined by the graph below, which illustrates the distribution of returns of the index and targeted companies. Since the index consists of many stocks, we would expect that the changes are less volatile than a single stock. This expectation is supported by the graph, which shows that the index return is normally distributed around zero and has few extreme values. On the other side, the price change of targeted companies is more volatile, and consists of larger values in both positive and negative direction. It is clear, however, that most of the tweets results in a price change in line with our hypothesis. Since movements in one single stock in nature is more volatile than an index consisting of 500 stocks, this analysis can not answer whether the tweets create volatility in the market (which is not the scope of this paper). However, since the means are differing with high significance, we can conclude that the tweets have a market impact related to average return.

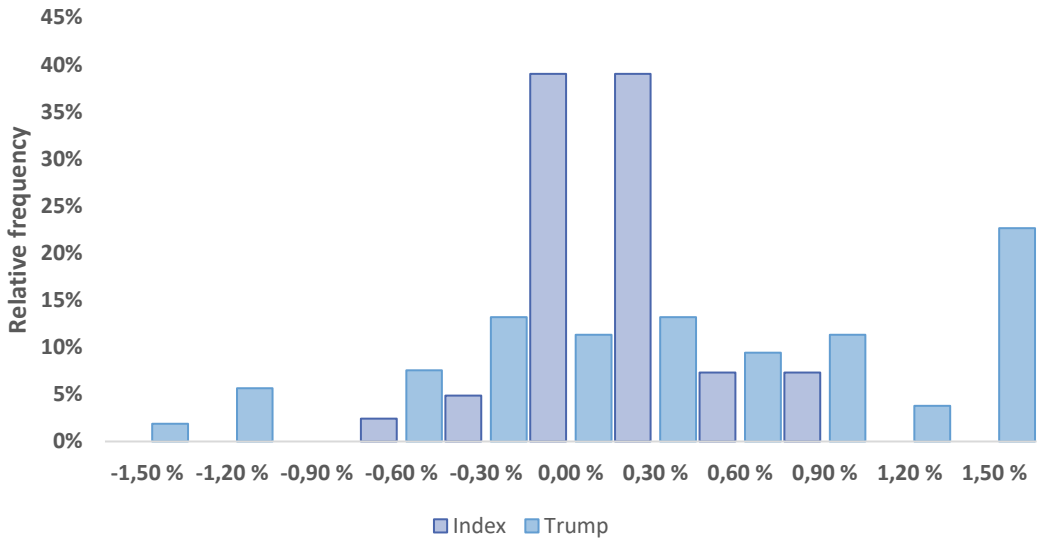


Figure 7 **Distribution of return** The graph illustrates the difference in the distribution of return in the index compared to the targeted companies. As expected, the average change of the targeted companies are more volatile, but also more positive.

3.1.5 Sentiment and return

To further analyse the effects of the tweets, we will examine if there are differences in market impact related to the strength of the sentiment. Figure 6 illustrates the percentage change in stock price at 10, 30 and 60 minutes for different levels of sentiments. Tweets with a sentiment of -0,5 have a more limited market impact than the cases with -1 and 1. This indicates that the effect is larger the more strength in the sentiment, regardless if the sentiment is positive or negative. This pattern is thus supporting our hypothesis that the tweets have a market impact. In addition, the figure illustrates a potential trend in which the return of a negatively loaded tweet (-1) decreases with time, while the return of a positively loaded tweet (+1) increases with time. Due to limited number of observations (around 20), we will be careful to claim the consistency of this trend, but it would be interesting to look at in future research on the area.

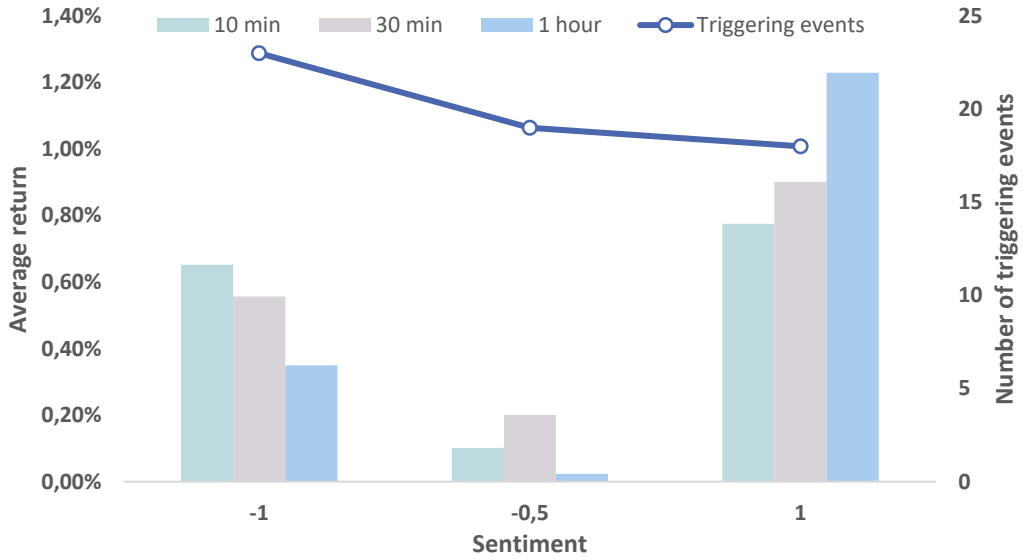


Figure 8 **Average change with different sentiment** The figure shows how the return are connected to sentiment. A sentiment of low level, meaning 0,5, delivers a lower rate of change than a sentiment with higher level.

3.1.6 Isolating the effect

The foregoing part concludes that the tweets are resulting in an immediate price movement in the targeted stocks. However, since most of Trump's tweets lies outside the market opening hours, difficulties arise regarding isolating the pure effect of the tweet. In the period between the tweet and the market opens, there are other variables that can affect the stock price. Due to the short time frame, such variables mainly include other news about the stock. When the tweets occur within opening hours, it is easier to isolate the Trump-effect since one can look at the

immediate price movement and reduce the problem related to other news. By examining two different tweets, one within opening hours and one outside, we will try to analyse this problem.

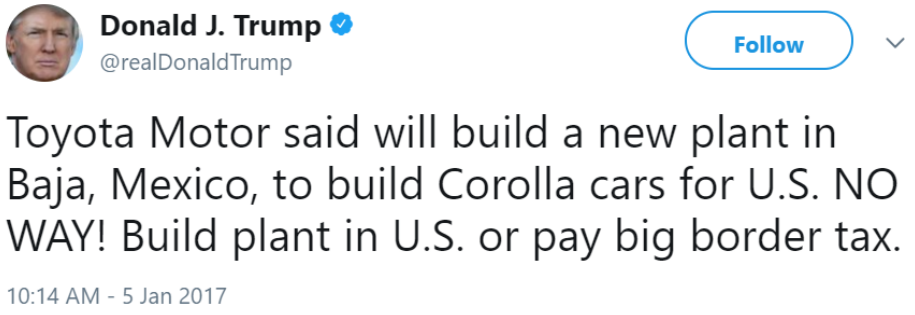


Figure 9 **Trump targeting Toyota** The tweet in which Trump directly target Toyota (RealDonaldTrump, 2017).

Case 1: Tweet intraday

The first example concerns the negatively loaded tweet against Toyota in January 2017, as mentioned in the introduction. The tweet was published 1.14 pm local time and Toyota's share price dropped immediately after the tweet, as shown in the graph below. The tweet about Toyota was based on previous news regarding the company, which was reported by the media in the days before (Ge, Kurov, & Wolfe, 2017). Although the tweet was based on publicly available information, Trump's statement generated a reaction in the market. According to Google Finance (Google Finance) no other news occurred in the ten minutes period following the tweet, which support that the 1 % decrease was a pure Trump-effect.

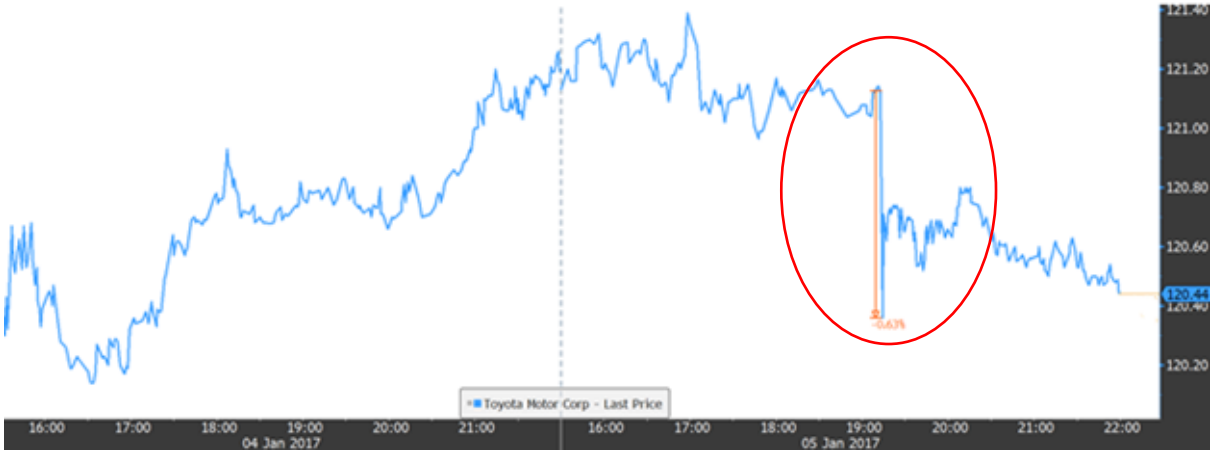


Figure 10 **Stock price of Toyota** As an immediate reaction to the tweet, the stock price fell by almost 1 percent.

Case 2: Tweet outside market hours

The second example concerns a positively loaded tweet, that recognized American Airlines' fantastic response related to Hurricane Maria. Since the tweet was published on a Saturday,

outside market hours, difficulties arise related to measuring the pure Trump-effect. From the tweet on Saturday to the market opens Monday morning, other variables such as news or other company specific matters can influence the stock price. In addition, before Trump appreciated the company, they already had received recognition for their effort in the news (Charles, 2017). If Trump consistently tweets as a reaction to existing news, there may be the underlying news that creates the market impact. When the market is closed it is difficult to distinguish between the Trump-effect and the effect of the underlying news. This makes it difficult to claim that the tweet was the actual cause of the change in stock price, meaning that there is a correlation rather than a causal relationship.

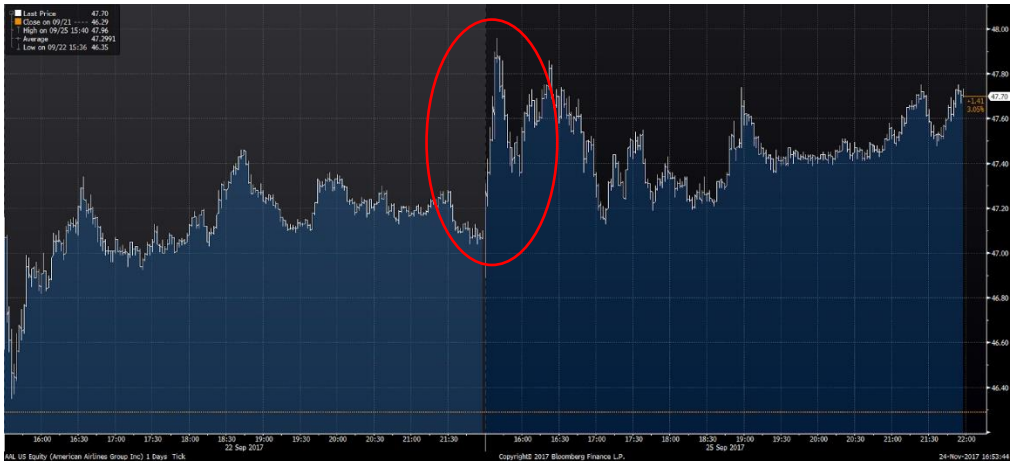


Figure 11 **Stock price of American Airlines** When the market opened Monday the stock price increased almost two percent. However, it is unclear whether the effect is due to the tweet at Saturday or other company spesific news.

This discussion illustrates the difference between the tweets published within market hours and those outside. It highlights the complexity associated with evaluating and analysing the market impact of Trump's tweets, as well as difficulties with establishing a causal relationship between a tweet and a change in stock price. However, based on our analysis it is possible to claim that Trump's tweets do have a temporarily market impact.

3.1.7 Market inefficiency

By stating that Trump's tweets do have short term market impact, we are indirectly implying the existence on an inefficient market that is possible to exploit. The inefficiency can be a result of several different variables that are in opposition to the EMH's three conditions (Fama, 1969).

One reason is that traders may perceive the effect of a tweet differently, thus breaking Fama's condition that traders must have the same view on current information. Since Trump's tweets are causing high volatility, which especially concern tweets containing individual names such

as companies (Forex Capital Markets, 2017), it might be possible to trade upon these uncertain events.

Also, it may be implied that Trump's use of Twitter as a channel to target companies can resemble market manipulation. Many of Trump's claims and accusations are difficult to be proven correctly, and therefore his behaviour can be categorized as tortious interference of business (Respawned, 2017). Because many traders believe there is a predictable impact of Trump twitter rants, several daily traders and investment firms trade on this (Peltz, 2017). It may be possible to trade upon this inefficiency due to an increase in discrepancy between the fundamental value and the stock price caused by the tweet. This opportunity however, may be the result of a disagreement between the market participants regarding the tweet's impact on the market.

3.1.8 Part conclusion

Based on the analysis performed in this part of paper, we are able to conclude that Trump's tweets do have a short-term market impact which decreases with time. Our data indicates that the greatest impact is within 30 minutes after the tweet is published. Trump's tweets may also cause inefficiency in the market that is possible to exploit as a result of different perception of current information among traders.

3.3 Trading strategy

The foregoing section discussed how Trump's tweets have a market impact, especially in the short run. In this part, we will explore whether it is possible to make a profitable trading strategy based on this information.

There is one main difference between examining the market impact of the tweets, and to actually be able to make money on it. Since Trump mostly is tweeting at times the stock market is closed, our trading bot is in these cases unable to trade before the SoD next morning. Due to the opening auction the stock price of SoD can differ from the EoD the foregoing day. Therefore, if the tweets have an immediate influence on the stock price, we would expect that the effect to some degree already is reflected in the SoD-price. Our hypothesis is that this will limit our opportunity to profit compared to the average change presented in the part about market impact.

This hypothesis is supported by the graph below, which shows a continuous discrepancy between the market impact (as presented in the foregoing part) and the possible trading return, which reduces the trading return. The difference between the two lines remains stable at 0,23 percentage points throughout the time frame, which indicates the discrepancy is caused by the opening auction of the first possible trading day after Trump's tweet.

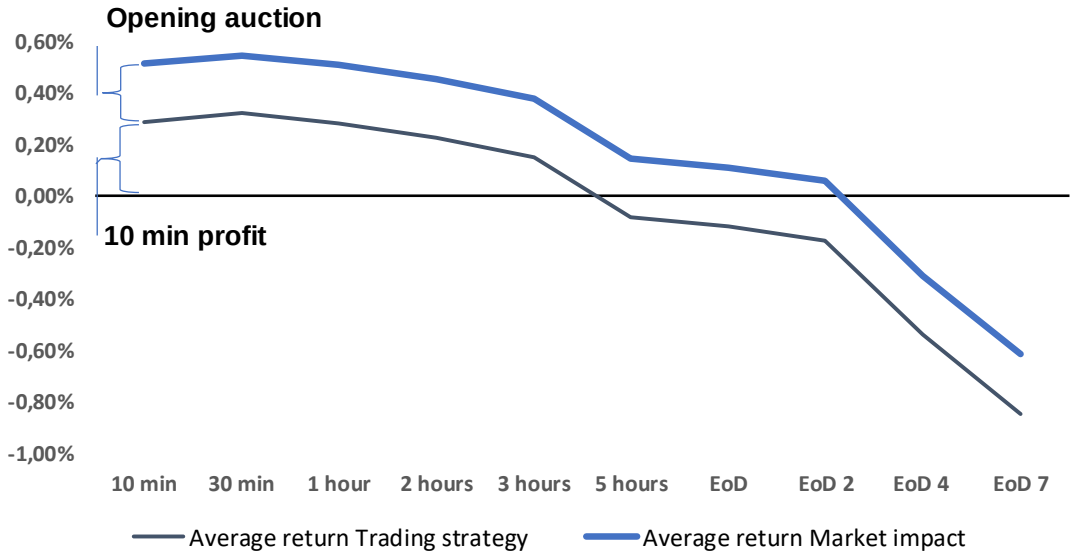


Figure 12 **Market impact vs trading return** Since most of tweets are outside market hours, some of the effect of the tweet are already reflected in the opening auction, thus lowe|r the opportunity to profit.

3.2.1 Trading rules

Before trading we are required to make a trading strategy which will be presented in the following. The trading strategy will be based upon previous research on the area, combined with our analysis in the part above. A prerequisite for the strategy is the ability to constantly monitor Trump's twitter account. To trade with immediacy when Trump tweets about a stock, we are dependent upon making a trading bot. We aim to make a bot that is able to identify tweets consisting of listed companies, and as fast as possible facilitate a trade in the corresponding stock based on the sentiment of the tweet. The bot will be constrained by specific rules. These rules are divided into four parts: the trigger criteria, analysing of sentiment, the trade and holding time.

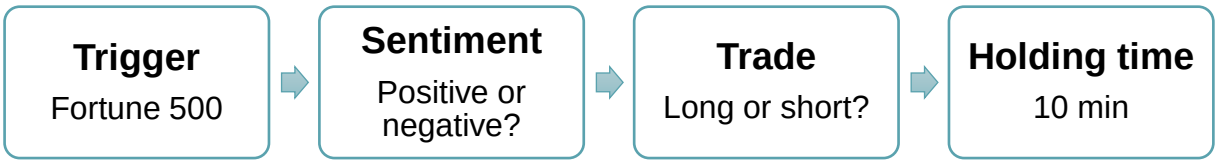


Figure 13 **Trading rules** The trading bot is given a set of rules to follow, divided into trigger criterias, evaluation of sentiment, type of trade and when to close the position.

Trigger criteria

Since Trump exceptionally tweets about listed companies, the bot requires a trigger that identifies when this happen. In this paper, the trading bot will be based upon the Fortune 500 list of US companies, and a trigger will be activated when at least one of the companies on this list is explicitly mentioned in a tweet.

Analysing sentiment

When the trigger activates, the trading bot immediately starts analysing the sentiment of the tweet. The bot will rate the sentiment of the tweet on a 0,5-unit-scale between -1 and 1. Negative sentiments corresponds to bad news for the company, while a positive sentiment corresponds to good news. The rating will be based upon an overall analysis of the tweet, including an evaluation of positively and negatively loaded words.

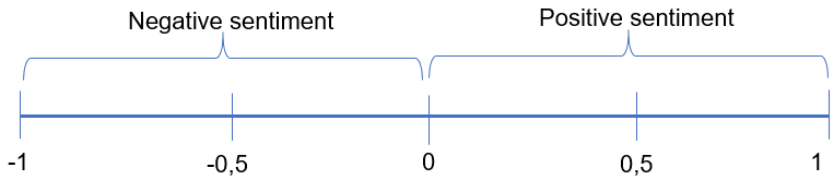


Figure 14 **Scale on sentiment** Based on an analysis of how positive or negative loaded the tweet is, the trading bot rank the sentiment on a 0,5-unit scale from -1 to 1.

Long or short position

At this stage, the trading bot has identified a stock and rated the sentiment in the interval between -1 and 1. From this moment, the bot will automatically start trading in the corresponding instrument. If the sentiment is positive, the bot will immediately buy the related stock. If the sentiment is negative, the stock will be shorted. When Trump tweets about a couple of companies in the same tweet, the trading volume will be divided by the number of companies mentioned. This is due to capital constraint, and also to reduce risk associated with one single tweet.

Holding period

When designing the trading strategy, we also need to establish rules regarding the holding period. Since trading based on tweets is a relatively new form for news trading, there are some uncertainty related to deciding what is the optimal holding period. Previous analyses of Trump's tweets indicate that shares of companies that were criticized rebounded from their losses on the same day they were mentioned (Ingram, 2017). It is worth mentioning that little research has been done on this field. Therefore, we must include our own analysis in the foregoing part, which support a holding time of a maximum of 30 minutes. However, 95 % of the potential return is achieved within the first ten minutes. Choice of holding time will also depend on transaction cost, especially the transaction cost of going short. Due to the lending fee and interest rate, the cost of holding a short position overnight is more expensive than intraday trading, and will consequently have an impact on possible profit from short selling.

Based on our own analysis and the transaction cost of trading, we have chosen a holding time of 10 minutes for the scope of this paper. This will limit the transaction cost compared to overnight trading, and according to historic intraday effects of Trump's tweets, provide a possibility of a viable return.

3.2.2 Historic performance

Time frame

By using the developed rules and collected data, we will simulate the strategy's performance from 30th of October 2016 to 30th of October 2017. Most of our observations, 53 trigger events, occur within this time period, and should be sufficient to give an idea of the performance. The reason for the short time frame, is that Trump was not elected president until November 2016.

At this point his influence increased, and comparing earlier tweets would give uneven grounds for comparison.

Simulation prices

Since the majority of Trump's tweets are published outside the opening hours, it is critical that we use prices that are possible to trade upon in the real market. We will thus take positions at the first available price after the tweet and close our positions ten minutes after. For the scope of this paper, we will assume that our trading activity does not impact the market price. According to Schanke (2016), a trader will impact the market price by trading 3-4 % of the stock's daily volume. Since most of the stocks at the Fortune 500 list are highly liquid, it is a justified assumption that we do not have any expenses related to our own market impact.

Transaction costs

Since our trading approach consists of a holding time of ten minutes, the commission fee will only be the related transaction costs. Our estimated transaction cost is based on Nordnet's commission fee which is 0,059 % for each transaction within the American market (Nordnet.no). This gives a transaction cost of 0,118 % for each tweet traded upon. In the sensitivity analysis we will discuss the impact of transaction costs on our trading performance.

Overall findings

This part seeks to analyse the performance of our trading strategy. As seen in Figure 15 the strategy delivered a total return of 9,28 % excluding transaction and opportunity costs, which also equals the annualized return. By accounting for a transaction cost of 11,8 basis points (bps), the total return decreases to 4,44 %. In comparison, the S&P 500 yielded a total return of 21,0 % in the same period. By adjusting for risk, the strategy underperformed compared to the index.

	Trading strategy	S&P 500
Annualized return	9,28 %	21,00 %
Including TC	4,44 %	
Annualized volatility	3,92 %	7,27 %
Sharp-ratio	2,18	2,79

Figure 15 **Overall results** Total return, volatility and Sharp-ratio of our trading strategy compared to the S&P-index. The S&P-index achieves a higher return and volatility, and also a better Sharp-ratio than our trading strategy.

Figure 15 illustrates our trades and the performance of our trading strategy compared with the S&P 500-index. To make comparisons easy, the graph is indexed to 100. By examining the figure, the performance varies by time and the number of tweets. From October 2016, the

strategy delivers a steady return until start of January. When Trump was inaugurated as president in January, the return suddenly escalated as a result of many succumbing tweets with positive returns. This period lasted around one month, followed by a period of stagnation from February to October 2017. The skewness in the return makes it interesting to take a closer look on the performance by dividing the period in three.

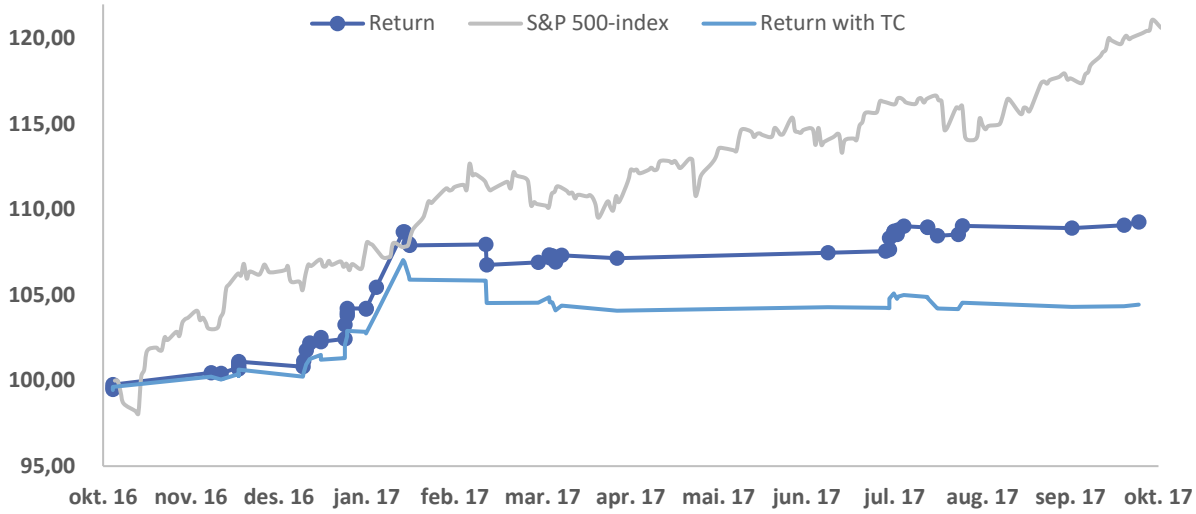


Figure 16 **Total return** The graph compares the return of the trading strategy with the S&P-index.

Total return

Dividing the simulation period into the last quarter of 2016, first of 2017 and from April 1st to October 30th, we achieved a positive total return in each period. However, there is a high degree of variation between the returns in the different periods. Our success rate is somewhat stable, and lies in the interval between 67 % and 74 %. Thus, the variation in return arises mainly due to the differences in number of triggering events (tradable tweets) and return per trade.

	Realized total return		Excuding transaction costs				
Period	Period	Annualized	Period	Annualized	**Trigger events**	**Success rate**	**TR per trade**
10.30.16 - 12.31.16	0,65 %	2,62 %	1,12 %	4,56 %	9	67 %	0,30 %
01.01.16 - 03.31.17	3,46 %	14,55 %	5,82 %	25,37 %	25	68 %	0,38 %
04.01.17 - 10.30.17	0,34 %	0,67 %	2,34 %	4,74 %	19	74 %	0,14 %
Total	**4,44 %**		**9,28 %**		**53,00**	**70 %**	**0,267 %**

Figure 17 **Total return over time** The figure shows the realized return and the return adjusted for transaction cost in the three different time periods.

Most of the triggering events are concentrated around the first quarter of 2017. Given the low rate of return on each trade, the strategy is dependent upon a high number of tweets to be successful. This partially explains why the first quarter of 2017 became the period with highest return.

The average return, excluding transaction costs, of each trade was 0,267 %. This number diverged by an absolute value of around 0,24 % between the three periods. The numbers indicate a potential trend in which the return decreases over time. A closer examination on each trade's return, further reveals a decreasing trend in the returns. As seen in the graph below, the returns are highest in the period around the inauguration, before the return of each trade declines in the following months. This observation is supported by the moving average of the last five trades, as illustrated by the red line, which clearly decreases after the inauguration.

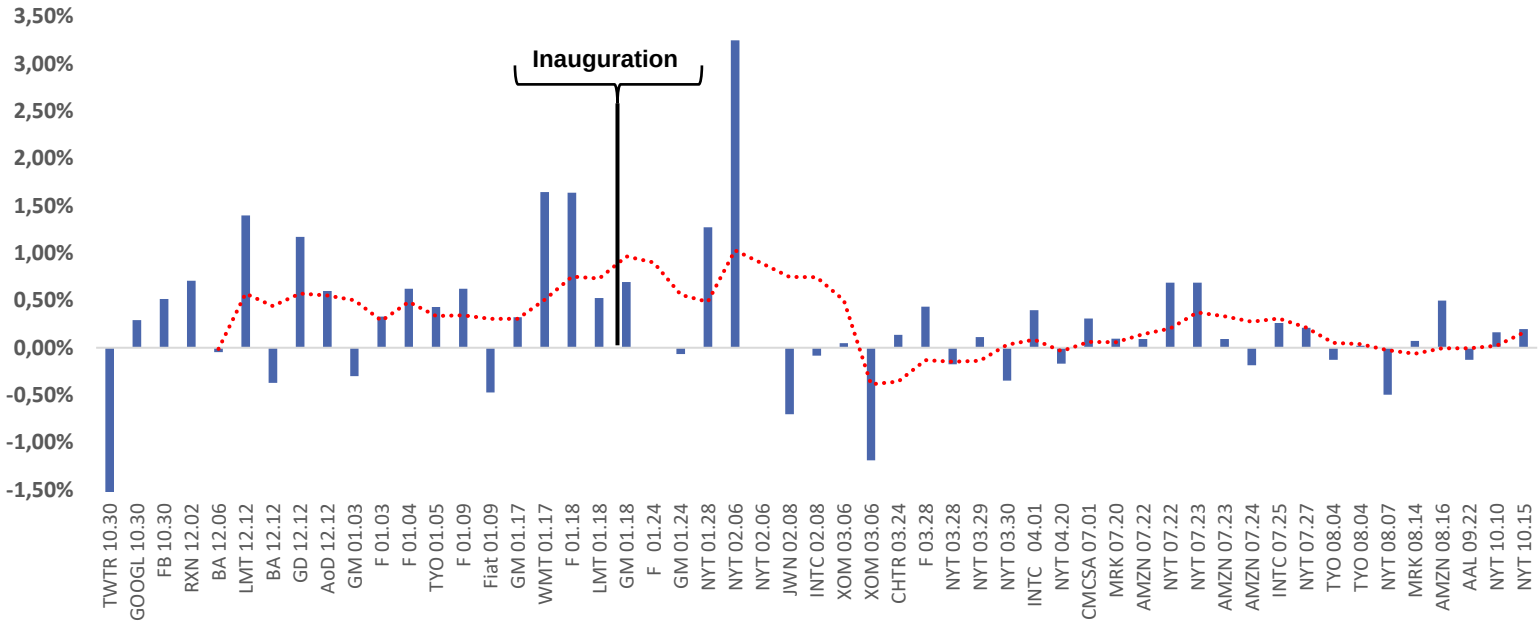


Figure 18 **Return per trade over time** The return on each trade is falling over time, as shown with the moving average of the last five trades (red line).

The combination of a high number of tweets and a higher return on each trade, explains why the total return was highest in the first quarter. In this period, the strategy achieved a realized return of 3,46 %, which corresponds to an annualized return of 14,55 %. Excluding transaction cost the annualized return amounted to 25,47 % and are thus competitive with the annualized index return of 22,86 % in the same period.

Low margin

When trading in a high frequency market, the transaction cost plays an important role determining the strategy's profitability. The gap between the return of the investment and the transaction cost, is the profit made by a trade. In the figure below many of the trades yield small returns, resulting in a loss if the transaction cost exceeds the return. Given a commission fee of 11,8 bps on each trade, our strategy loses in 25 of 53 trades, represented by the red bars. This

illustrates the importance of transaction cost, especially when dealing with high frequency trading and low margins.

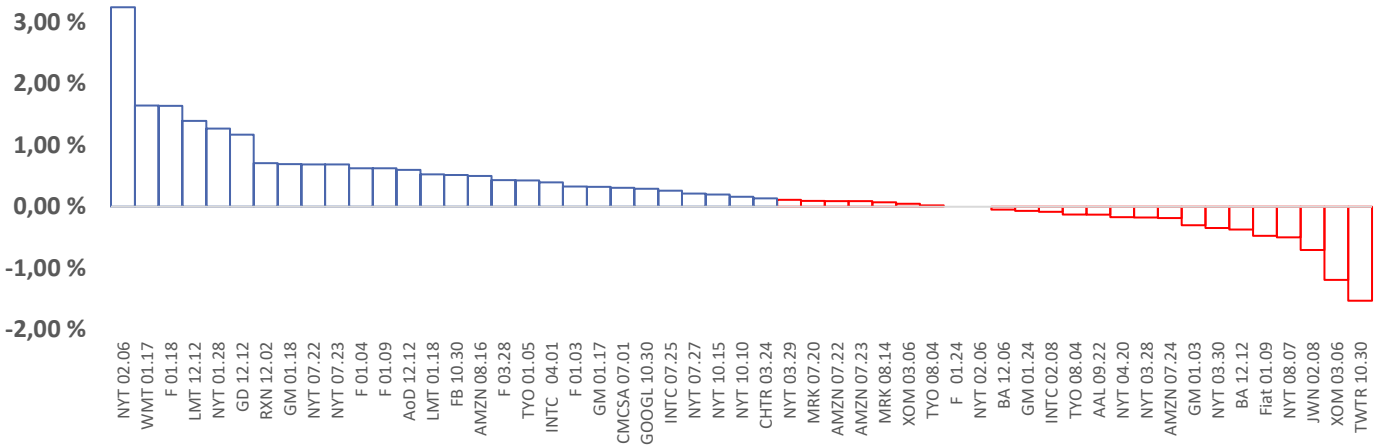


Figure 19 **Low margin** The figure shows the return on each trade, presented from highest to lowest. Notice that there are some outliers that can influence results of the analysis. The red boxes represent trades in which we lose money adjusted for transaction costs.

Sensitivity analysis

Based on this discussion, there are mainly two factors, besides the average return on each trade, that influence the returns of our trading strategy. The first is the transaction cost due to our high frequency trading and low margins. The second is the number of triggering events, meaning the frequency of the tweets. In this part, we will look at how sensitive the returns are to changes in these parameters.

Average return each trade		Number of tradable tweets										
	0,23 %	Simulation period	10	20	30	40	50	60	70	80	90	100
Commision fee (bps)	0,00 %	9,28 %	2,28 %	4,62 %	7,01 %	9,45 %	11,95 %	14,50 %	17,12 %	19,79 %	22,53 %	25,33 %
	0,05 %	7,23 %	1,77 %	3,58 %	5,42 %	7,29 %	9,19 %	11,13 %	13,10 %	15,11 %	17,15 %	19,23 %
	0,10 %	5,18 %	1,27 %	2,55 %	3,85 %	5,17 %	6,50 %	7,85 %	9,21 %	10,60 %	12,00 %	13,42 %
	0,15 %	3,13 %	0,76 %	1,53 %	2,31 %	3,09 %	3,87 %	4,66 %	5,46 %	6,27 %	7,08 %	7,89 %
	0,20 %	1,08 %	0,26 %	0,52 %	0,78 %	1,05 %	1,31 %	1,57 %	1,84 %	2,10 %	2,37 %	2,63 %
	0,25 %	-0,97 %	-0,24 %	-0,48 %	-0,72 %	-0,96 %	-1,19 %	-1,43 %	-1,67 %	-1,90 %	-2,14 %	-2,37 %
	0,30 %	-3,02 %	-0,74 %	-1,47 %	-2,20 %	-2,92 %	-3,63 %	-4,34 %	-5,05 %	-5,75 %	-6,45 %	-7,14 %

Figure 20 **Sensitivity analysis** The figure shows how the trading profit is sensitive to changes in the number of tweets and the transaction cost. The sensitivity analysis assumes an average return of each 100k invested of 0,226 %, which corresponds to the simulation's findings. The calculation is shown in the appendix.

Figure 20 shows how the realized return varies depending on transaction cost and the number of trades. As seen in the figure, the strategy achieves a negative return when the transaction costs exceed the average return of 0,226 %. Additionally, the figure shows that the performance of the strategy can improve significantly by increasing the number of tweets. This number is limited by how often Trump tweets, but could be increased by improving the trading bot to be able to identify more tradable tweets.

3.2.3 Part conclusion

The annualized total return on our trading strategy is 9,28%, excluding transaction and opportunity cost. Since the S&P index yield an annualized return of 21%, our trading strategy is not profitable taken the alternative cost into account. Including transaction cost and annualized volatility our trading strategy yield a lower Sharpe ratio than the benchmark. However, we have seen that the trading strategy is sensitive to the number of tweets and the transaction cost.

4. Weaknesses

As a result of those demarcations we have made and already existing limitations, there are several weaknesses associated with this paper. First, Twitter has limited the amount of tweets you can export from their application interface, which reduced our sample of tweets. Additionally, the sample is further reduced, since we have defined the related companies to be the biggest 500 in the US. This demarcation makes our analysis inefficient to predict the average return of the companies outside the Fortune 500 list. The implication of only 61 trigger events makes our findings also vulnerable to outliers.

Secondly, the firms' stock prices are restricted to only ten-time points. The Bloomberg Terminal has its restrictions to export intraday data, which do not give our analysis continuous stock prices over time. Especially, this is a weakness in the time interval 0 to 30 minutes, whereas the highest profit exists. Our analysis does not show at what time most of the average return at ten minutes occurs, (which was the chosen holding period in the trading strategy). Therefore, we do not have any basis to claim which holding time within the time interval zero to 30 minutes is most profitable. As in the presented Toyota example the price change happened immediately, and therefore the trading performance and market impact could be higher if our analysis would be able to take this in consideration.

Thirdly, it is, as previously pointed out, difficult to isolate the market impact of Trump's tweets. Especially due to few published tweets within the stock market's opening hours. There are several differences among the tweets, as differences in time of publication and if Trump is tweeting about already established news or provides new information to the market. This makes it difficult on a general basis to state if Trump's tweets have a high correlation relationship or even a causality with the stock prices.

5. Conclusion

This paper has attempted to answer the following research question: *«Do the tweets of Donald Trump influence the stock price of targeted companies, and is it possible to design a trading strategy to profit from this information?"* Based on our analysis we can conclude that Trump does have an influence on the stock price of the companies he targets. We have also established that it is possible to design a strategy that can turn a profit. However, its return is lower than our benchmark which makes our trading strategy unprofitable.

To analyse Trump's market impact, we have gathered data and analysed different financial objectives. Our calculations of both the average return and the success-rate indicates that the tweets have a significant impact on the stock market. We also found that the effect is greater right after publication of the tweets - on average a price change of 0,52 % in the ten-minute period following the tweet. Due to our t-test, we can claim this to be significant better than the S&P 500 index. However, despite that there is a clear pattern between the tweets and the market's reaction, further analysis have to be made to isolate the pure Trump-effect.

Having established Trump's market impact, we sought to create our strategy. By creating a bot with rules for which criteria to provoke a trigger, analysation of the tweets sentiment, the type of trade and holding time, we analysed the strategy's performance over the last year. The trading strategy yielded a lower risk-adjusted return than the S&P-index in the same time period. However, increasing the number of tweets or reducing the transaction cost, would increase the competitiveness of the strategy.

In further analyses, it would be interesting to collect more data to examine the price change for the tweets within market hours, to better estimate the pure-effect. Due to low number of observations within opening hours, this analysis is not able to investigate this. It could also be interesting to analyse which effect the tweets has on the volatility of the targeted stocks.

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7. Appendix

7.1 Triggering events

Date	Stock	Sentiment	Price info		10 min	30 min	1 hour	2 hours	3 hours	5 hours	EoD	EoD 2	EoD 4	EoD 7
07.12.15 7:00	Amazon	-1			672,51	668,40	664,11	660,50	665,49	667,66	669,83	678,44	661,09	658,64
			Time of tweet	675,5	0,44 %	1,05 %	1,69 %	2,22 %	1,48 %	1,16 %	0,84 %	-0,44 %	2,13 %	2,50 %
			Price EOD	672,64	0,02 %	0,63 %	1,27 %	1,80 %	1,06 %	0,74 %	0,42 %	-0,86 %	1,72 %	2,08 %
12.05.15 6:01	Verizon	-1			49,19	49,49	49,37	49,43	49,53	49,68	49,60	49,74	49,72	49,55
			Time of tweet	49,4	0,43 %	-0,18 %	0,06 %	-0,06 %	-0,26 %	-0,57 %	-0,40 %	-0,69 %	-0,65 %	-0,30 %
			Price EOD	49,81	1,24 %	0,64 %	0,88 %	0,76 %	0,56 %	0,26 %	0,42 %	0,14 %	0,18 %	0,52 %
19.04.15 1:46	Ford	-1			0,67	0,67	0,71	0,71	0,71	0,71	0,70	0,70	0,70	0,66
			Time of tweet	0,671	0,00 %	-0,22 %	-5,66 %	-5,81 %	-5,81 %	-5,81 %	-4,32 %	-4,92 %	-4,32 %	1,64 %
			Price EOD	0,6701	-0,13 %	-0,36 %	-5,81 %	-5,95 %	-5,95 %	-5,95 %	-4,46 %	-5,06 %	-4,46 %	1,51 %
03.01.17 4:30	General Motors	-1			35,00	35,26	35,45	35,07	35,00	35,01	35,13	37,10	36,00	37,34
			Time of tweet	34,89	-0,30 %	-1,06 %	-1,61 %	-0,52 %	-0,32 %	-0,34 %	-0,69 %	-6,33 %	-3,18 %	-7,02 %
			Price EOD	34,825	-0,49 %	-1,25 %	-1,79 %	-0,70 %	-0,50 %	-0,53 %	-0,88 %	-6,53 %	-3,37 %	-7,22 %
04.12.15 15:52	Macy's	-1			38,58	38,51	38,65	39,00	39,04	39,19	39,33	39,34	38,51	36,76
			Time of tweet	38,995	1,06 %	1,24 %	0,88 %	0,00 %	-0,12 %	-0,50 %	-0,86 %	-0,88 %	1,24 %	5,73 %
			Price EOD	38,995	1,06 %	1,24 %	0,88 %	0,00 %	-0,12 %	-0,50 %	-0,86 %	-0,88 %	1,24 %	5,73 %
25.08.16 19:47	Mylan	-1			43,37	43,09	42,91	42,76	42,85	42,85	42,85	42,95	42,70	39,97
			Time of tweet	43,4564	0,20 %	0,84 %	1,26 %	1,61 %	1,40 %	1,40 %	1,40 %	1,17 %	1,74 %	8,02 %
			Price EOD	43,4564	0,20 %	0,84 %	1,26 %	1,61 %	1,40 %	1,40 %	1,40 %	1,17 %	1,74 %	8,02 %
19.08.16 5:43	New York Times	-1			12,90	12,91	13,00	13,02	13,00	13,00	13,05	13,05	13,17	13,03
			Time of tweet	12,9	0,00 %	-0,08 %	-0,78 %	-0,93 %	-0,74 %	-0,78 %	-1,16 %	-1,16 %	-2,09 %	-1,01 %
			Price EOD	12,94	0,31 %	0,23 %	-0,46 %	-0,62 %	-0,43 %	-0,46 %	-0,85 %	-0,85 %	-1,78 %	-0,70 %
06.12.16 5:52	Boeing	-1			150,91	150,85	151,37	151,29	151,29	152,11	152,23	154,20	156,45	156,67
			Time of tweet	150,75	-0,11 %	-0,07 %	-0,41 %	-0,36 %	-0,36 %	-0,90 %	-0,98 %	-2,29 %	-3,78 %	-3,93 %
			Price EOD	152,2	0,85 %	0,89 %	0,55 %	0,60 %	0,60 %	0,06 %	-0,02 %	-1,31 %	-2,79 %	-2,94 %
12.12.16 5:26	Lockheed Martin	-1			248,80	249,15	247,03	247,22	248,02	252,83	253,23	253,34	250,73	252,12
			Time of tweet	252,33	1,40 %	1,26 %	2,10 %	2,03 %	1,71 %	-0,20 %	-0,35 %	-0,40 %	0,63 %	0,08 %
			Price EOD	259,77	4,22 %	4,09 %	4,90 %	4,83 %	4,52 %	2,67 %	2,52 %	2,48 %	3,48 %	2,94 %
12.12.16 5:26	Boeing	-1			156,91	157,28	155,93	156,19	156,29	156,41	157,21	156,78	153,88	156,23
			Time of tweet	156,33	-0,37 %	-0,60 %	0,26 %	0,09 %	0,03 %	-0,05 %	-0,56 %	-0,29 %	1,57 %	0,06 %
			Price EOD	156,5	-0,26 %	-0,50 %	0,36 %	0,20 %	0,13 %	0,06 %	-0,45 %	-0,18 %	1,67 %	0,17 %
12.12.16 5:26	General Dynamics	-1			170,20	170,29	170,03	171,15	171,07	173,46	173,74	174,31	174,17	174,62
			Time of tweet	172,22	1,17 %	1,12 %	1,27 %	0,62 %	0,67 %	-0,72 %	-0,88 %	-1,21 %	-1,13 %	-1,39 %
			Price EOD	175,21	2,86 %	2,81 %	2,96 %	2,32 %	2,36 %	1,00 %	0,84 %	0,51 %	0,59 %	0,34 %
12.12.16 5:26	Aerospace of defence	-1			142,14	143,20	142,32	142,76	142,40	143,15	142,47	142,85	142,01	142,77
			Time of tweet	143	0,60 %	-0,14 %	0,47 %	0,17 %	0,42 %	-0,10 %	0,37 %	0,10 %	0,69 %	0,16 %
			Price EOD	145,1408	2,07 %	1,34 %	1,94 %	1,64 %	1,89 %	1,37 %	1,84 %	1,58 %	2,16 %	1,63 %
05.01.17 10:14	Toyota	-1			120,67	120,56	120,78	120,61	120,44	120,44	120,44	120,12	119,73	119,64
			Time of tweet	121,19	0,43 %	0,52 %	0,34 %	0,48 %	0,62 %	0,62 %	0,62 %	0,88 %	1,20 %	1,28 %
			Price EOD	121,26	0,49 %	0,58 %	0,40 %	0,54 %	0,68 %	0,68 %	0,68 %	0,94 %	1,26 %	1,34 %
16.08.17 3:12	Amazon	-1			976,85	975,62	976,60	981,42	986,25	976,00	978,02	961,83	953,62	957,56
			Time of tweet	981,75	0,50 %	0,62 %	0,52 %	0,03 %	-0,46 %	0,59 %	0,38 %	2,03 %	2,87 %	2,46 %
			Price EOD	982,95	0,62 %	0,75 %	0,65 %	0,16 %	-0,34 %	0,71 %	0,50 %	2,15 %	2,98 %	2,58 %
08.02.17 7:51	Nordstrom	-0,5			42,91	41,83	42,75	42,88	43,14	43,71	44,54	45,81	44,36	46,14
			Time of tweet	42,61	-0,70 %	1,83 %	-0,33 %	-0,63 %	-1,23 %	-2,58 %	-4,53 %	-7,51 %	-4,11 %	-8,27 %
			Price EOD	42,75	-0,37 %	2,15 %	0,00 %	-0,30 %	-0,90 %	-2,25 %	-4,19 %	-7,16 %	-3,77 %	-7,92 %
02.12.16 19:06	Rexnord	-1			20,37	20,41	20,46	20,57	20,28	20,28	20,28	20,48	20,00	20,83
			Time of tweet	20,515	0,71 %	0,51 %	0,27 %	-0,24 %	1,15 %	1,15 %	1,15 %	0,17 %	2,51 %	-1,54 %
			Price EOD	20,515	0,71 %	0,51 %	0,27 %	-0,24 %	1,15 %	1,15 %	1,15 %	0,17 %	2,51 %	-1,54 %
15.11.15 16:57	T-Mobile	-1			37,86	37,57	38,03	37,57	37,84	37,83	37,87	38,15	37,73	38,44
			Time of tweet	38,25	1,02 %	1,78 %	0,58 %	1,78 %	1,07 %	1,11 %	0,99 %	0,26 %	1,36 %	-0,50 %
			Price EOD	38,68	2,12 %	2,87 %	1,68 %	2,87 %	2,17 %	2,21 %	2,09 %	1,37 %	2,46 %	0,62 %
30.10.16 7:26	Twitter	-0,5			17,92	17,88	17,91	17,79	17,81	17,79	17,94	17,48	17,59	18,37
			Time of tweet	17,65	-1,53 %	-1,30 %	-1,47 %	-0,79 %	-0,91 %	-0,76 %	-1,64 %	0,96 %	0,34 %	-4,08 %
			Price EOD	17,7	-1,24 %	-1,02 %	-1,19 %	-0,51 %	-0,62 %	-0,48 %	-1,36 %	1,24 %	0,62 %	-3,79 %
30.10.16 7:26	Google	-0,5			794,53	791,14	792,47	792,40	791,10	784,71	784,73	783,61	762,13	789,29
			Time of tweet	796,86	0,29 %	0,72 %	0,55 %	0,56 %	0,72 %	1,52 %	1,52 %	1,66 %	4,36 %	0,95 %
			Price EOD	795,37	0,11 %	0,53 %	0,36 %	0,37 %	0,54 %	1,34 %	1,34 %	1,48 %	4,18 %	0,76 %
30.10.16 7:26	Facebook	-0,5			131,44	131,46	131,48	131,67	131,58	131,13	130,99	129,50	120,00	124,23
			Time of tweet	132,12	0,51 %	0,50 %	0,48 %	0,34 %	0,41 %	0,75 %	0,86 %	1,99 %	9,17 %	5,98 %
			Price EOD	131,33	-0,08 %	-0,10 %	-0,11 %	-0,26 %	-0,19 %	0,16 %	0,26 %	1,40 %	8,63 %	5,41 %
04.08.17 5:02	Mazda	1			7,80	7,74	7,73	7,73	7,73	7,74	7,71	7,72	7,65	7,41
			Time of tweet	7,8099	-0,13 %	-0,90 %	-1,02 %	-1,02 %	-1,02 %	-0,96 %	-1,28 %	-1,15 %	-2,05 %	-5,12 %
			Price EOD	7,9	-1,27 %	-2,03 %	-2,15 %	-2,15 %	-2,15 %	-2,09 %	-2,41 %	-2,28 %	-3,16 %	-6,20 %
04.08.17 5:02	Toyota	1			113,79	113,60	113,44	113,39	113,43	113,47	113,65	113,65	114,22	112,11
			Time of tweet	113,76	0,02 %	-0,14 %	-0,28 %	-0,33 %	-0,29 %	-0,25 %	-0,10 %	-0,10 %	0,40 %	-1,45 %
			Price EOD	112,75	0,92 %	0,75 %	0,61 %	0,57 %	0,60 %	0,64 %	0,80 %	0,80 %	1,30 %	-0,57 %
15.10.17 6:25	New York Times	-0,5			19,15	19,23	19,23	19,20	19,10	19,15	19,18	19,03	19,05	19,65
			Time of tweet	19,188	0,20 %	-0,19 %	-0,19 %	-0,06 %	0,46 %	0,20 %	0,07 %	0,85 %	0,72 %	-2,41 %
			Price EOD	19,125	-0,13 %	-0,52 %	-0,52 %	-0,39 %	0,13 %	-0,13 %	-0,26 %	0,52 %	0,39 %	-2,75 %
10.10.17 5:50	New York Times	-0,5			19,27	19,13	19,13	19,13	19,13	19,13	19,25	19,23	19,13	19,10
			Time of tweet	19,3	0,16 %	0,91 %	0,91 %	0,91 %	0,91 %	0,91 %	0,91 %	0,39 %	0,91 %	1,04 %
			Price EOD	19,175	-0,49 %	0,26 %	0,26 %	0,26 %	0,26 %	0,26 %	0,26 %	-0,26 %	0,26 %	0,39 %
22.09.17 10:54	American Airlines	1			46,51	46,82	47,14	47,04	47,28	47,19	47,06	47,73	46,82	47,73
			Time of tweet	46,57	-0,13 %	0,54 %	1,22 %	1,01 %	1,52 %	1,33 %	1,05 %	2,49 %	0,54 %	2,49 %
			Price EOD	46,29	0,48 %	1,14 %	1,84 %	1,62 %	2,14 %	1,94 %	1,66 %	3,11 %	1,14 %	3,11 %
14.08.17 15:09	Merch Pharma	-1			62,84	62,96	62,93	62,78	62,78	62,66	62,63	62,52	61,83	62,45
			Time of tweet	62,89	0,07 %	-0,11 %	-0,06 %	0,17 %	0,17 %	0,37 %	0,41 %	0,59 %	1,69 %	0,70 %
			Price EOD	62,4	-0,71 %	-0,90 %	-0,85 %	-0,61 %	-0,61 %	-0,42 %	-0,37 %	-0,19 %	0,91 %	-0,08 %
07.08.17 13:39	New York Times	-0,5			19,17	19,03	19,03	19,08	19,20	19,15	19,13	19,00	18,60	18,20
			Time of tweet	19,075	-0,50 %	0,26 %	0,26 %	0,00 %	-0,66 %	-0,39 %	-0,26 %	0,39 %	2,49 %	4,59 %
			Price EOD	19,15	-0,10 %	0,65 %	0,65 %	0,39 %	-0,26 %	0,00 %	0,13 %	0,78 %	2,87 %	4,96 %

27.07.17 3:48 New York Times	-0,5			18,81	18,85	19,05	19,38	19,53	19,70	20,05	19,28	19,10	19,15
		Time of tweet	18,85	0,21 %	0,00 %	-1,06 %	-2,79 %	-3,58 %	-4,51 %	-6,37 %	-2,25 %	-1,33 %	-1,59 %
		Price EOD	18,35	-2,51 %	-2,72 %	-3,81 %	-5,59 %	-6,40 %	-7,36 %	-9,26 %	-5,04 %	-4,09 %	-4,36 %
25.07.17 3:12 Intel	-0,5			34,47	34,58	34,62	34,71	34,70	34,61	34,67	34,75	35,31	36,64
		Time of tweet	34,56	0,26 %	-0,04 %	-0,17 %	-0,42 %	-0,41 %	-0,14 %	-0,32 %	-0,55 %	-2,17 %	-6,02 %
		Price EOD	34,5	0,09 %	-0,22 %	-0,35 %	-0,59 %	-0,58 %	-0,32 %	-0,49 %	-0,72 %	-2,35 %	-6,20 %
24.07.17 19:23 Amazon	-1			1039,24	1039,79	1039,93	1039,93	1039,93	1039,93	1039,93	1039,87	1046,00	996,19
		Time of tweet	1037,33	-0,18 %	-0,24 %	-0,25 %	-0,25 %	-0,25 %	-0,25 %	-0,25 %	-0,24 %	-0,84 %	3,97 %
		Price EOD	1025,67	-1,32 %	-1,38 %	-1,39 %	-1,39 %	-1,39 %	-1,39 %	-1,39 %	-1,38 %	-1,98 %	2,87 %
23.07.17 16:57 New York Times	-0,5			18,03	18,13	18,05	18,23	18,25	18,25	18,28	18,45	20,05	19,10
		Time of tweet	18,15	0,69 %	0,14 %	0,55 %	-0,41 %	-0,55 %	-0,55 %	-0,69 %	-1,65 %	-10,47 %	-5,23 %
		Price EOD	18,05	0,14 %	-0,42 %	0,00 %	-0,97 %	-1,11 %	-1,11 %	-1,25 %	-2,22 %	-11,08 %	-5,82 %
23.07.17 16:57 Amazon	-0,5			1032,09	1033,62	1032,60	1034,37	1038,57	1039,93	1038,95	1039,87	1046,00	996,19
		Time of tweet	1033,035	0,09 %	-0,06 %	0,04 %	-0,13 %	-0,54 %	-0,67 %	-0,57 %	-0,66 %	-1,26 %	3,57 %
		Price EOD	1025,67	-0,63 %	-0,78 %	-0,68 %	-0,85 %	-1,26 %	-1,39 %	-1,29 %	-1,38 %	-1,98 %	2,87 %
22.07.17 3:45 New York Times	-0,5			18,03	18,13	18,05	18,23	18,25	18,25	18,28	18,45	20,05	19,10
		Time of tweet	18,15	0,69 %	0,14 %	0,55 %	-0,41 %	-0,55 %	-0,55 %	-0,69 %	-1,65 %	-10,47 %	-5,23 %
		Price EOD	18,05	0,14 %	-0,42 %	0,00 %	-0,97 %	-1,11 %	-1,11 %	-1,25 %	-2,22 %	-11,08 %	-5,82 %
22.07.17 3:33 Amazon	-1			1032,09	1033,62	1032,60	1034,37	1038,57	1039,93	1038,95	1039,87	1046,00	996,19
		Time of tweet	1033,035	0,09 %	-0,06 %	0,04 %	-0,13 %	-0,54 %	-0,67 %	-0,57 %	-0,66 %	-1,26 %	3,57 %
		Price EOD	1025,67	-0,63 %	-0,78 %	-0,68 %	-0,85 %	-1,26 %	-1,39 %	-1,29 %	-1,38 %	-1,98 %	2,87 %
20.07.17 20:31 Merch Pharma	1			63,16	63,19	63,09	63,09	63,09	63,09	63,09	62,09	62,38	64,11
		Time of tweet	63,095	0,10 %	0,15 %	-0,02 %	-0,02 %	-0,02 %	-0,02 %	-0,02 %	-1,59 %	-1,13 %	1,61 %
		Price EOD	63,095	0,10 %	0,15 %	-0,02 %	-0,02 %	-0,02 %	-0,02 %	-0,02 %	-1,59 %	-1,13 %	1,61 %
01.07.17 5:59 Comcast	0,5			39,15	38,91	38,73	38,62	38,36	38,36	38,36	38,36	38,25	38,76
		Time of tweet	39,03	0,31 %	-0,31 %	-0,77 %	-1,06 %	-1,72 %	-1,72 %	-1,72 %	-1,72 %	-2,00 %	-0,69 %
		Price EOD	38,93	0,57 %	-0,05 %	-0,51 %	-0,81 %	-1,46 %	-1,46 %	-1,46 %	-1,46 %	-1,75 %	-0,44 %
20.04.17 6:48 New York Times	-0,5			14,75	14,73	14,60	14,65	14,68	14,73	14,65	14,85	14,80	14,40
		Time of tweet	14,725	-0,17 %	0,00 %	0,85 %	0,51 %	0,34 %	-0,01 %	0,51 %	-0,85 %	-0,51 %	2,21 %
		Price EOD	14,75	0,00 %	0,17 %	1,02 %	0,68 %	0,51 %	0,16 %	0,68 %	-0,68 %	-0,34 %	2,37 %
01.04.17 9:50 Intel	-1			36,28	36,65	36,47	36,27	36,29	36,22	36,16	36,28	36,03	35,80
		Time of tweet	36,425	0,40 %	-0,62 %	-0,11 %	0,43 %	0,37 %	0,56 %	0,73 %	0,40 %	1,08 %	1,72 %
		Price EOD	36,07	-0,58 %	-1,61 %	-1,10 %	-0,55 %	-0,61 %	-0,42 %	-0,25 %	-0,58 %	0,11 %	0,75 %
30.03.17 7:27 New York Times	-0,5			14,50	14,55	14,65	14,55	14,60	14,70	14,55	14,38	14,60	14,45
		Time of tweet	14,45	-0,35 %	-0,69 %	-1,38 %	-0,69 %	-1,04 %	-1,73 %	-0,69 %	0,52 %	-1,04 %	0,00 %
		Price EOD	14,45	-0,35 %	-0,69 %	-1,38 %	-0,69 %	-1,04 %	-1,73 %	-0,69 %	0,52 %	-1,04 %	0,00 %
29.03.17 5:01 New York Times	-0,5			14,45	14,45	14,50	14,40	14,45	14,45	14,45	14,55	14,20	14,48
		Time of tweet	14,4663	0,11 %	0,11 %	-0,23 %	0,46 %	0,11 %	0,11 %	0,11 %	-0,58 %	1,84 %	-0,06 %
		Price EOD	14,45	0,00 %	0,00 %	-0,35 %	0,35 %	0,00 %	0,00 %	0,00 %	-0,69 %	1,73 %	-0,17 %
28.03.17 8:26 New York Times	-0,5			14,30	14,35	14,25	14,38	14,39	14,43	14,45	14,45	14,38	14,38
		Time of tweet	14,275	-0,18 %	-0,53 %	0,18 %	-0,70 %	-0,79 %	-1,05 %	-1,23 %	-1,23 %	-0,70 %	-0,70 %
		Price EOD	14,25	-0,35 %	-0,70 %	0,00 %	-0,88 %	-0,96 %	-1,23 %	-1,40 %	-1,40 %	-0,88 %	-0,88 %
28.03.17 3:36 Ford	1			11,56	11,55	11,62	11,72	11,70	11,77	11,65	11,68	11,63	11,25
		Time of tweet	11,51	0,43 %	0,30 %	0,96 %	1,82 %	1,65 %	2,26 %	1,22 %	1,48 %	1,04 %	-2,26 %
		Price EOD	11,46	0,87 %	0,74 %	1,40 %	2,27 %	2,09 %	2,71 %	1,66 %	1,92 %	1,48 %	-1,83 %
24.03.17 10:59 Charter Communications	1			326,67	326,92	326,96	326,79	326,69	324,74	325,35	323,15	325,94	328,27
		Time of tweet	326,22	0,14 %	0,21 %	0,23 %	0,17 %	0,14 %	-0,45 %	-0,27 %	-0,94 %	-0,09 %	0,63 %
		Price EOD	323,22	1,07 %	1,14 %	1,16 %	1,10 %	1,07 %	0,47 %	0,66 %	-0,02 %	0,84 %	1,56 %
06.03.17 19:49 Exxon Mobile	1			81,75	82,75	82,73	82,73	82,73	82,73	82,82	82,51	81,68	81,00
		Time of tweet	82,735	-1,19 %	0,02 %	-0,01 %	-0,01 %	-0,01 %	-0,01 %	0,10 %	-0,27 %	-1,28 %	-2,10 %
		Price EOD	82,43	-0,82 %	0,39 %	0,36 %	0,36 %	0,36 %	0,36 %	0,47 %	0,10 %	-0,91 %	-1,73 %
06.03.17 13:19 Exxon Mobile	1			82,51	81,57	82,79	82,66	82,77	82,75	82,82	82,51	81,68	81,00
		Time of tweet	82,47	0,05 %	-1,09 %	0,39 %	0,23 %	0,36 %	0,34 %	0,42 %	0,05 %	-0,96 %	-1,78 %
		Price EOD	82,43	0,10 %	-1,04 %	0,44 %	0,28 %	0,41 %	0,39 %	0,47 %	0,10 %	-0,91 %	-1,73 %
08.02.17 11:22 Intel	1			36,24	36,20	36,30	36,63	36,39	36,41	36,38	36,35	35,32	36,05
		Time of tweet	36,27	-0,08 %	-0,18 %	0,08 %	0,98 %	0,33 %	0,39 %	0,30 %	0,22 %	-2,62 %	-0,61 %
		Price EOD	36,35	-0,30 %	-0,40 %	-0,14 %	0,76 %	0,11 %	0,17 %	0,08 %	0,00 %	-2,83 %	-0,83 %
06.02.17 8:32 New York Times	-0,5			14,15	14,25	14,25	14,40	14,40	14,55	14,53	14,50	14,80	15,85
		Time of tweet	14,625	3,25 %	2,56 %	2,56 %	1,54 %	1,54 %	0,51 %	0,68 %	0,85 %	-1,20 %	-8,38 %
		Price EOD	14,75	4,07 %	3,39 %	3,39 %	2,37 %	2,37 %	1,36 %	1,53 %	1,69 %	-0,34 %	-7,46 %
06.02.17 18:33 New York Times	-0,5			14,40	14,40	14,45	14,55	14,55	14,70	14,70	14,80	15,50	15,92
		Time of tweet	14,4	0,00 %	0,00 %	-0,35 %	-1,04 %	-1,04 %	-2,08 %	-2,08 %	-2,78 %	-7,64 %	-10,56 %
		Price EOD	14,75	2,37 %	2,37 %	2,03 %	1,36 %	1,36 %	0,34 %	0,34 %	-0,34 %	-5,08 %	-7,93 %
28.01.17 5:08 New York Times	-0,5			13,18	13,10	13,20	13,18	13,30	13,50	13,35	13,55	13,55	14,70
		Time of tweet	13,35	1,27 %	1,87 %	1,12 %	1,29 %	0,37 %	-1,12 %	0,00 %	-1,50 %	-1,50 %	-10,11 %
		Price EOD	13,35	1,27 %	1,87 %	1,12 %	1,29 %	0,37 %	-1,12 %	0,00 %	-1,50 %	-1,50 %	-10,11 %
24.01.17 16:46 Ford	1			12,50	12,50	12,52	12,55	12,58	12,61	12,61	12,78	12,50	12,32
		Time of tweet	12,5	0,00 %	0,00 %	0,16 %	0,36 %	0,60 %	0,88 %	0,88 %	2,24 %	-0,04 %	-1,48 %
		Price EOD	12,31	1,54 %	1,54 %	1,71 %	1,91 %	2,15 %	2,44 %	2,44 %	3,82 %	1,50 %	0,04 %
24.01.17 16:46 General Motors	1			37,07	37,06	37,22	37,18	37,17	37,00	37,01	38,29	37,02	36,12
		Time of tweet	37,095	-0,07 %	-0,09 %	0,32 %	0,22 %	0,20 %	-0,26 %	-0,23 %	3,21 %	-0,20 %	-2,63 %
		Price EOD	36,63	1,20 %	1,17 %	1,60 %	1,49 %	1,47 %	1,01 %	1,04 %	4,52 %	1,06 %	-1,39 %
17.01.17 9:55 General Motors	1			37,40	37,69	37,55	37,34	37,50	37,26	37,35	37,47	37,00	38,26
		Time of tweet	37,28	0,32 %	1,09 %	0,72 %	0,16 %	0,59 %	-0,05 %	0,19 %	0,50 %	-0,75 %	2,63 %
		Price EOD	37,34	0,16 %	0,92 %	0,56 %	0,00 %	0,43 %	-0,21 %	0,03 %	0,33 %	-0,91 %	2,46 %
17.01.17 9:55 Walmart	1			69,18	68,93	69,12	68,88	68,73	68,41	68,43	68,07	67,12	66,79
		Time of tweet	68,06	1,65 %	1,28 %	1,56 %	1,20 %	0,98 %	0,51 %	0,54 %	0,01 %	-1,38 %	-1,87 %
		Price EOD	67,1	3,10 %	2,73 %	3,01 %	2,65 %	2,43 %	1,94 %	1,98 %	1,45 %	0,03 %	-0,46 %
09.01.17 6:16 Ford	1			12,88	12,99	13,08	13,16	13,22	13,16	13,17	12,78	12,63	12,59
		Time of tweet	12,8	0,63 %	1,48 %	2,19 %	2,81 %	3,28 %	2,81 %	2,89 %	-0,16 %	-1,33 %	-1,64 %
		Price EOD	12,58	2,38 %	3,26 %	3,97 %	4,61 %	5,09 %	4,61 %	4,69 %	1,59 %	0,40 %	0,08 %
09.01.17 6:16 Fiat	1			10,51	10,50	10,58	10,66	10,60	10,54	10,57	10,82	9,99	9,49
		Time of tweet	10,56	-0,47 %	-0,57 %	0,14 %	0,95 %	0,33 %	-0,19 %	0,09 %	2,46 %	-5,40 %	-10,13 %
		Price EOD	10,425	0,82 %	0,72 %	1,44 %	2,25 %	1,63 %	1,10 %	1,39 %	3,79 %	-4,17 %	-8,97 %
04.01.17 5:19 Ford	1			12,88	12,99	13,08	13,16	13,22	13,16	13,17	12,78	12,63	12,59
		Time of tweet	12,8	0,63 %	1,48 %	2,19 %	2,84 %	3,25 %	2,81 %	2,89 %	-0,16 %	-1,33 %	-1,64 %
		Price EOD	12,58	2,38 %	3,26 %	3,97 %	4,63 %	5,06 %	4,61 %	4,69 %	1,59 %	0,40 %	0,08 %
03.01.17 8:44 Ford	1			12,22	12,36	12,49	12,43	12,51	12,53	12,58	13,15	12,77	12,67
		Time of tweet	12,18	0,33 %	1,48 %	2,55 %	2,05 %	2,71 %	2,87 %	3,28 %	7,96 %	4,80 %	4,02 %
		Price EOD	12,14	0,66 %	1,81 %	2,88 %	2,39 %	3,05 %	3,21 %	3,62 %	8,32 %	5,15 %	4,37 %

18.01.17 4:34 Ford	-1		1,20	1,20	1,20	1,20	1,20	1,21	1,21	1,18	1,20	1,24
	Time of tweet	1,22	1,64 %	1,64 %	1,64 %	1,64 %	1,64 %	0,82 %	1,07 %	3,14 %	1,64 %	-1,97 %
	Price EOD	1,22	1,64 %	1,64 %	1,64 %	1,64 %	1,64 %	0,82 %	1,07 %	3,14 %	1,64 %	-1,97 %
18.01.17 4:34 Lockheed Martin	-1		253,39	253,58	253,27	253,83	254,01	254,11	254,08	257,00	257,67	251,00
	Time of tweet	254,73	0,53 %	0,45 %	0,57 %	0,35 %	0,28 %	0,24 %	0,26 %	-0,89 %	-1,15 %	1,46 %
	Price EOD	254,21	0,32 %	0,25 %	0,37 %	0,15 %	0,08 %	0,04 %	0,05 %	-1,10 %	-1,36 %	1,26 %
18.01.17 4:34 General Motors	-1		37,20	37,23	37,31	37,29	37,25	37,55	37,45	37,29	36,67	37,55
	Time of tweet	37,46	0,69 %	0,61 %	0,40 %	0,47 %	0,56 %	-0,23 %	0,04 %	0,45 %	2,12 %	-0,24 %
	Price EOD	37,35	0,40 %	0,32 %	0,11 %	0,17 %	0,27 %	-0,53 %	-0,25 %	0,16 %	1,83 %	-0,54 %

7.2 Sensitivity analysis

The sensitivity analysis is based on the following formula:

$$(1 + (Average\ return\ each\ trade) - (Transaction\ cost\ per\ trade))^{(Number\ of\ trades)-1}$$

7.3 Identification of tweets

Based on the sample of 3000 tweets, our excel-model identified those tweets that mentioned on of the companies from the Fortune 500, using the following formula.

=SUMPRODUCT(--ISNUMBER(SEARCH($J$4:$L$505;B3)))>0

Where J4:L505 refers to the Fortune 500 list, and cell B3 refers to the tweet.

7.4 Return each trade and indexed return

Return each trade and the indexed development of the trading strategy is shown on the next page.

Date	Stock	Sentiment	10m return	Investment	Trade return	Indexed return	Trade return with TC	Indexed return with TC
30.10.16 7:26	TWTR	-0,5	-1,53 %	33	- 0,51	99,49	- 0,55	99,45
30.10.16 7:26	GOOGL	-0,5	0,29 %	33	0,10	99,59	0,06	99,51
30.10.16 7:26	FB	-0,5	0,51 %	33	0,17	99,76	0,13	99,64
02.12.16 19:06	RXN	-1	0,71 %	100	0,71	100,47	0,59	100,23
06.12.16 5:52	BA	-1	-0,05 %	100	- 0,05	100,42	- 0,16	100,07
12.12.16 5:26	LMT	-1	1,40 %	25	0,35	100,77	0,32	100,39
12.12.16 5:26	BA	-1	-0,37 %	25	- 0,09	100,68	- 0,12	100,26
12.12.16 5:26	GD	-1	1,17 %	25	0,29	100,97	0,26	100,53
12.12.16 5:26	AoD	-1	0,60 %	25	0,15	101,12	0,12	100,65
03.01.17 4:30	GM	-1	-0,30 %	100	- 0,30	100,82	- 0,42	100,23
03.01.17 8:44	F	1	0,33 %	100	0,33	101,15	0,21	100,44
04.01.17 5:19	F	1	0,63 %	100	0,63	101,77	0,51	100,95
05.01.17 10:14	TYO	-1	0,43 %	100	0,43	102,20	0,31	101,26
09.01.17 6:16	F	1	0,63 %	50	0,31	102,51	0,25	101,51
09.01.17 6:16	Fiat	1	-0,47 %	50	- 0,24	102,28	- 0,30	101,22
17.01.17 9:55	GM	1	0,32 %	50	0,16	102,44	0,10	101,32
17.01.17 9:55	WMT	1	1,65 %	50	0,82	103,26	0,76	102,08
18.01.17 4:34	F	-1	1,64 %	33	0,55	103,81	0,51	102,59
18.01.17 4:34	LMT	-1	0,53 %	33	0,18	103,98	0,14	102,72
18.01.17 4:34	GM	-1	0,69 %	33	0,23	104,21	0,19	102,92
24.01.17 16:46	F	1	0,00 %	50	-	104,21	- 0,06	102,86
24.01.17 16:46	GM	1	-0,07 %	50	- 0,03	104,18	- 0,09	102,76
28.01.17 5:08	NYT	-0,5	1,27 %	100	1,27	105,45	1,16	103,92
06.02.17 8:32	NYT	-0,5	3,25 %	100	3,25	108,70	3,13	107,05
06.02.17 18:33	NYT	-0,5	0,00 %	100	-	108,70	- 0,12	106,93
08.02.17 7:51	JWN	-0,5	-0,70 %	100	- 0,70	108,00	- 0,82	106,11
08.02.17 11:22	INTC	1	-0,08 %	100	- 0,08	107,92	- 0,20	105,91
06.03.17 13:19	XOM	1	0,05 %	100	0,05	107,96	- 0,07	105,84
06.03.17 19:49	XOM	1	-1,19 %	100	- 1,19	106,77	- 1,31	104,53
24.03.17 10:59	CHTR	1	0,14 %	100	0,14	106,91	0,02	104,55
28.03.17 3:36	F	1	0,43 %	100	0,43	107,34	0,32	104,87
28.03.17 8:26	NYT	-0,5	-0,18 %	100	- 0,18	107,17	- 0,29	104,57
29.03.17 5:01	NYT	-0,5	0,11 %	100	0,11	107,28	- 0,01	104,57
30.03.17 7:27	NYT	-0,5	-0,35 %	100	- 0,35	106,94	- 0,46	104,10
01.04.17 9:50	INTC	-1	0,40 %	100	0,40	107,33	0,28	104,38
20.04.17 6:48	NYT	-0,5	-0,17 %	100	- 0,17	107,16	- 0,29	104,10
01.07.17 5:59	CMCSA	0,5	0,31 %	100	0,31	107,47	0,19	104,29
20.07.17 20:31	MRK	1	0,10 %	100	0,10	107,57	- 0,02	104,26
22.07.17 3:33	AMZN	-1	0,09 %	100	0,09	107,66	- 0,03	104,24
22.07.17 3:45	NYT	-0,5	0,69 %	100	0,69	108,35	0,57	104,81
23.07.17 16:57	NYT	-0,5	0,69 %	50	0,34	108,69	0,29	105,09
23.07.17 16:57	AMZN	-0,5	0,09 %	50	0,05	108,74	- 0,01	105,08
24.07.17 19:23	AMZN	-1	-0,18 %	100	- 0,18	108,55	- 0,30	104,78
25.07.17 3:12	INTC	-0,5	0,26 %	100	0,26	108,81	0,14	104,92
27.07.17 3:48	NYT	-0,5	0,21 %	100	0,21	109,03	0,09	105,01
04.08.17 5:02	TYO	1	-0,13 %	50	- 0,06	108,96	- 0,12	104,89
04.08.17 5:02	TYO	1	0,02 %	50	0,01	108,97	- 0,05	104,84
07.08.17 13:39	NYT	-0,5	-0,50 %	100	- 0,50	108,47	- 0,62	104,23
14.08.17 15:09	MRK	-1	0,07 %	100	0,07	108,55	- 0,05	104,18
16.08.17 3:12	AMZN	-1	0,50 %	100	0,50	109,05	0,38	104,56
22.09.17 10:54	AAL	1	-0,13 %	100	- 0,13	108,92	- 0,25	104,31
10.10.17 5:50	NYT	-0,5	0,16 %	100	0,16	109,08	0,04	104,36
15.10.17 6:25	NYT	-0,5	0,20 %	100	0,20	109,28	0,08	104,44