Financial Anomalies in Social Media – Analyzing Potential Effects of Donald Trump's Tweets on the Stock Market

Author: Ludwig Wolff

Supervisor: Thomas Fischer

Department of Economics
NEKH02

October 2019

Abstract

This paper examines the potential effects of Donald Trump's Twitter activity on the stock market. This is investigated with different methods starting out with limiting Trump's tweets into tweets including four potentially impactful keywords as well as classifying the tweets into different sentiments. To further test the theory of the tweets possible effect on the market an event study was constructed for each keyword and respective sentiment. Although an impact has been suggested on company specific tweets no statistically significant effects of Trump's tweets can be determined on the overall market, concluding that no beneficial trading possibilities or anomalies are found using the classifications and methods demonstrated in this paper. However, a few patterns can be discovered as well as a strong positive correlation between Trump's weekly number of tweets about tariffs and Russian collusion and the weekly Google search activity for those two keywords. Further studies into smaller markets or other approaches may present more significant findings.

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1. Introduction

"I love Twitter.... it's like owning your own newspaper--- without the losses."[1]

- Donald Trump 2012

On the 23rd of April 2013, one of the largest news agencies in the world the *Associated Press* tweeted the following, "Breaking: Two explosions in the White House and Barack Obama is injured" the report of an injured president sent an instantaneous blow to the market and the S&P 500 index fell over 100 points in the following 3 minutes resulting in a removal of $136 billion. The agencies news service quickly responded that their Twitter account had been hacked and that the tweet was false. The index recovered during the following few minutes (Bloomberg 2013).

Even tweets not suggesting the injury of a world leader have caught the eyes of researchers and connections between tweets and stock market have been made throughout the years. Several tweets pointing out flaws, strengths or just speaking negatively/positively of a company have seen its stock price greatly decrease/increase after the tweet. Some examples include Kylie Jenner's rant questioning if anyone even uses the social media platform *Snapchat* anymore, resulting in a downward spiral of 6% for the stock (BBC, 2018). Elon Musk casually writing he had secured funding to take his company *Tesla* private at a stock price of 420, surging the stock to an intraday peak of 14% (Rapier, 2019). Several of Donald Trump's tweets have also followed these trends. A full list of 10 company specific tweets can be found in appendix A.

Multiple reports and studies suggest that a tweet has been impactful for a single company, this paper will dig deeper in analyzing its effect on the overall market. The second biggest index in the U.S. the S&P 500 was chosen for its accessibility but also connection as it includes a lot of the companies Trump has targeted in his tweets. Some of the most noticeable companies that the president has targeted are Amazon, Boeing, Nordstrom and Lockheed Martin.

The examples above and in appendix A, display the effect a short message on Twitter can have on the stock market. If the market is affected by new informative tweets (Elon Musk), but rapidly recovers it could imply that the market quickly responds to new information reaffirming that the theory holds. However, if the market moves by a reflection of a new tweet that does not bring any new information (Kylie Jenner) that would suggest that the market is not efficient at all.

[1] Refer to the following tweet https://twitter.com/realdonaldtrump/status/267286284182118400

1.2 Background

In 2006 the social media network Twitter was founded and has since grown to a user base of 330 million active users[2], the social media works in a form of microblogging where an user can write a message with a maximum of 280-characters[3], these posts or (tweets) as they are called on the platform will show up for that users followers or if you search for the user. 10 years after the creation of Twitter, Donald Trump was elected the 45th president of the United States of America and has of the moment over 65 million followers[4].

Donald Trump's presidential victory was an unexpected event for many[5]. Most people will agree that Trump is unique or at least controversial when compared to former presidents. Unlike former presidents, Trump is a lot more active on social media and foremost on Twitter and, have since the day of election averaged more than 9 tweets a day. He differentiates himself from other presidents and other leaders in a way that he uses Twitter to speak his own mind freely and using it in a way to influence business, sometimes tweeting about decisions he is about to or want to make. This makes Trump's Twitter page the quickest way to consume this news.

1.3 Purpose

This thesis main focus will be analyzing Trump's tweets by sentiment and specific keywords, thereafter, using event studies to test the market efficiency. Checking if any beneficial trading opportunities can be found using this analysis. Behavioral economics suggests irrationality in investors and that people are suggestive to others behavior and consequently to others sentiment including the sentiment from the president himself. The purpose is to build on previous related work as well as contain different approaches to examine the potential effects Trump may have on the overall market using 280-characters or less.

[2] 2019 Q1 statistic, https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/ (last accessed 2019-09-30).
[3] Prior to November 2017 this limit was 140-characters.
[4] Refer to https://twitter.com/RealDonaldTrump (last accessed 2019-09-30).
[5] Popular forecasting website fivethirtyeight gave Trump an estimated 11,9% chance of winning 3 weeks prior to election day, https://projects.fivethirtyeight.com/2016-election-forecast/ (last accessed 2019-10-08).

2. Literature

2.1 Efficient market hypothesis

Previous studies revolving around trying to make sense of fluctuations in the stock market mostly refer to the approach of the efficient market hypothesis or (EMH) for short. EMH is a popular financial economic theory pioneered by Fama (1970), suggesting that the price of assets on the market, efficiently reflects all available information about stocks and the market as a whole, implicating that it is impossible for any investor to consistently achieve greater returns than the market itself. Technical analysis is in this case as good as useless. There has never been a fully consensus on accepting the EMH, but the model has on later years been addressed with more skepticism and criticism (Malkiel, 2003, Subramanian, 2010).

The EMH is sometimes divided into three different forms, each form implying that different information is included in stock market prices.

Weak form:

Future stock prices cannot be predicted by technical analysis. Historical price information and patterns are already reflected in stock prices. Any arbitrage possibility would be exploited by investor until they would become useless.

Semi-strong form:

Includes everything from the weak form and extends to all publicly available information regarding a firm's operation to be reflected in the stock price. Patents, earning forecast, management quality and fundamental data on the firm's products. However, an advantage possibility remains with the use of insider information.

Strong form:

Contains the previous forms as well as all relevant public and private information about the firm is included in the stock price, including insider information.

The theory assumes that the players on the market are rational, risk adverse and no present information asymmetry occurs.

Another subject regarding the previous statement that has grown increasingly popular in later years is behavioral economics, first introduced by Kahneman and Tversky (1979). Here they suggest investors suffer from limitations to their cognitive abilities during decision-making, these tendencies lead to irrational investment decisions and hinders investors in front of arbitrage possibilities causing inefficiency in markets. Likewise, Thaler (2015) argues correspondingly. That the central actors in the economy are not these rational robot-like beings, but instead humans who are prone to errors and predictable in their behavior or rather misbehavior according to the EMH. The concept of behavioral economics opens up new possibilities to study the market and its actors making way for new findings in the ever-long question regarding market efficiency.

2.2. Anomalies

"Discovery starts with anomalies" – *Richard H Thaler (2015 p. 351)*

Market movements that are opposing the EMH are referred to as anomalies. In a paper by Kahneman & Tversky (1986) market anomalies are explained as deviations from markets too general to be overlooked or too systematic to be rejected as random error. More known examples of financial anomalies are the January effect and Halloween effect[6], the former suggest that stock prices tend to have higher abnormal returns in January compared to the rest of the months (Rozeff & Kinney, 1976). Meanwhile the second one proposes performance differences between periods, and that November to April have higher returns than May through October and consequently advocates investors to sell in May and not reinvest until November (Bouman & Jacobsen, 2002).

This study is aimed to research possible anomalies or effects social media could have on the stock market. In 2018, 2.82 billion people where estimated to use social media, an increase from 0.98 billion just 8 years prior[7]. This rapid growth has also led to a surge in academic studies on the matter.

When focusing on Twitter specific studies, Ranco et al. (2015) analyses the impact of Twitter sentiment and their effect on abnormal return during earning announcement and non-earning announcement periods, showing statistically significant dependence between negative and positive sentiment during Twitter volume peaks on both periods. Malaver-Vojvodic (2017) examines the effect Donald Trump's Twitter activity could have on the daily exchange rate of Mexican peso/U.S. Dollar. Gathering a sample of 64 tweets containing words like Mexico, border and immigrants and having a negative tone, suggesting that these tweets had an impact on the foreign exchange rate. Ge et al. (2018) investigated the impact of a limited number of company-specific tweets from Donald Trump, showing results of tweets moving stock prices and increasing trading volume. Also suggesting that more significant results could be available in the future with more tweet data published. This was something Rayeral (2018) continued examining by reviewing the same topic, and adding on more company-specific tweets by the president as well as adding sentiment analysis and attention-based analysis, concluding that statistically significant results are found in both abnormal returns and abnormal volume trading after Trump targets companies in tweets.

Relevant to behavioral economics and the aim for this study are investors called noise traders. Black (1986) defines these noise traders as irrational investors trading on noise in belief that this information will assist them in beating the market. Fama (1970) argues that while acknowledging noise traders, their irrational trading and potential market effects quickly will be corrected by rational investors and that they have no significant effect on market prices. Born et al. (2017) applies the idea that noise traders may act on Trump's tweets by examining

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[6] Also commonly known as: *Sell in May and go away.*

[7] Refer to https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users/ (last accessed 2019-09-30).

Google search activity when the president targets companies on Twitter. Revealing a rise in the Google search activity at the time of the tweet, contributing eventual price differences to be the result of noise traders.

This thesis aims to build on previous work and limitations as well as trying to find different approaches to the area. Instead of testing firm-specific tweets that are limited to a smaller sample size, a study on four keywords are selected. The keywords were chosen based on their associations with President Donald Trump and the increasing activity they had on social media at the start of Trump's president period. A larger focus on sentiment analysis is also implemented with the use of two different methods of sentiment classification. The purpose is to examine both the possible return and Google search activity effects Donald Trump's Twitter usage may have on the market.

Related to these studies, a company called T3, programmed a bot[8] called Trump and Dump, that turned these suggested market inefficiencies into real profit. The bot is set up to quickly react to tweets by Trump that targets publicly listed companies. It then analysis the sentiment of that tweet and if classified as negative the bot shortens the stock of the company targeted. Showcasing results of higher returns than the S&P 500 index (Burns, 2017).

3. Data

3.1 Index

Historical intraday data on stocks and indexes are not the easiest to retrieve. This essay will therefore cover daily updates on the index in the form of closing prices of the S&P500[9]. Using daily instead of hourly/minutely data has its ups and downs. One reason to choose daily is that Trump tweets even if the market is closed, these tweets cannot have an instant impact but will rather reflect on the next market open after the tweet, however it can complicate things since it is also a fact that Trump tweets multiple times a day therefore an instant effect of a tweet will not be shown. Trump's tweets will be reduced to tweets concerning the market and three other specific keywords in the form of fake news, tariffs, and Russian collusion.

The daily data of closing prices for the index S&P500 where analyzed from the 8th of November 2016 until the 7th of June 2019 a total of 647 market days.

[8] A bot, short for robot, is an application programmed to do certain tasks automatically.
[9] Collected through Yahoo finance: https://finance.yahoo.com/quote/%5EGSPC/history?p=%5EGSPC (last accessed 2019-10-14).

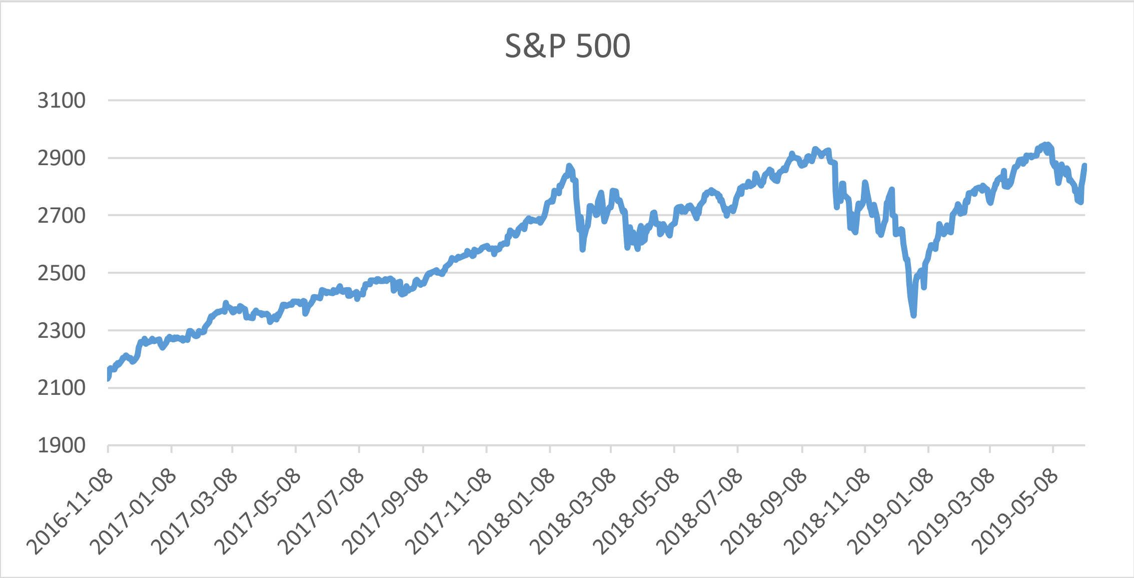

Figure 1 showing the development of the S&P 500 index during the selected period (2016-11-07 to 2019-06-07). Average daily return: 0,048%. Standard deviation: 0,008. Total return: 38,18%.

Computing the daily return $r_{i,t}$ for the index was done by using the formula:

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{1}$$

Where $P_{i,t}$ is the closing price of the index and $P_{i,t-1}$ is the closing price the day before.

3.2 Twitter

Tweets where initially gathered through an Application Programming Interface (API)[10] key using Tweepy[11] and the programming language Python, Twitter caps the number of tweets that can be received to 3191. To go back to 8th of November 2016 an archive of Trump's tweets[12] was used to gather all the necessary tweets, a total of 7060. The tweets where collected from Donald Trump's personal account (@RealDonaldTrump) and not the official presidential account (@POTUS) as Trump mostly uses the presidential account to retweet from his personal one.

Since the market is not open daily and Trump tweets multiple times every day, tweets that are published on days when the market is closed must be assigned to the following market day.

[10] API or Application Programming Interface is an interface between a client and a server.
[11] Library that enables python to communicate with twitter and using its API.
[12] Refer to http://www.trumptwitterarchive.com/ (last accessed 2019-09-30).

Tweets where collected at GMT time, and the market closes at 16:00 GMT-4, so tweets collected at a tweet time of 20:00 GMT or later, were also assigned to the following market day.

4. Method

4.1 Sentiment analysis

Throughout the years of usage of the social media platforms it has also been increasingly easier to access a huge chunk of the data shared on these platforms. Behavioral economics is quickly becoming an interesting new perspective for investors and digs deeper down on the rationality of consumers in the market, disregarding the traditional views of efficient markets. (Shiller, 2003). Sentiment plays a part in this and the tone of a tweet from the most followed leader in the world[13] could very well affect the sentiment and behaviors of others as suggested by previous studies. Sentiment analysis is the process of analyzing the emotion in a text, there is a lot of different methods to do this, but the method used here is to analyze if a tweet is either positive, neutral, or negative. Tetlock (2007) shed a light on the effect's media sentiment had on the stock market suggesting that higher levels of pessimistic words in media predicted lower returns on the market the following day

Sentiment analysis in this study will be divided into two groups or rather two methods: Machine learning and lexicon-based analysis. To analyze the tweets, two different programs/codes where used. One using python and one using an add-on (Azure) in excel. The reason for using more than one is to get a more accurate result and being able to compare the two methods to see if there is any credibility in them, complete lack of correlation between the two methods would hint for a low reliability using these methods for sentiment classification

4.1.1 Loughran and McDonald

Loughran and McDonald's (abbreviated to LM) dictionary differs from most sentiment analytical dictionaries as it specifically targets financial text. Loughran & McDonald (2011) suggests that a high percentage of words classified as negative and positive by more well-known dictionaries are words that typically would not be given the same sentiment in the context of finance. I.e. words like gross, lynch, trust, power, and outstanding can have very different meaning in other contexts than finance. Gross and lynch that are usually classified as negative words are reconsidered in LM's dictionary as gross in business statements usually refer to word combinations as (gross margin or gross profit for example). Meanwhile lynch in finance mostly refer to the renowned bank Merrill Lynch. In the positive end, words like trust, power, and outstanding are reconsidered as well (I.e. trust funds, power plant, shares outstanding[14]).

[13] Refer to https://twiplomacy.com/ranking/the-50-most-followed-world-leaders-in-2018/ (last accessed 2019-10-14)
[14] The number of shares currently held by its shareholders

Because of polysemous[15] words like these, Loughran and McDonald argues that it is impossible to perfectly map words to financial sentiment but that their dictionary tries to develop more accurate wordlists that better reflects the tone in financial text.

In the finance sector textual analysis and researches are mostly used to examine the tone of articles, press releases and 10Ks[16]. This paper aims to see its potential in a post capping at 280-characters. While Trump's tweets may not closely reflect the financial jargon used by companies, the interest remains as the focus of the study is to analyze it to the stock market but also because Trump often tweets about the economy, market, taxes, tariffs etc.

It is important to note that the way this study uses LM's dictionaries are purely by its positive and negative wordlists. LM do provide wordlists for more accurate interpretation of sentiment with wordlists containing uncertainty, weak and strong models for example. The LM method was applied by a python script available on their website[17] that was slightly optimized for this paper.

4.1.2 Azure

Azure is a software from Microsoft developed to understand and analyze unstructured text, unlike the LM method, Azure uses something called machine learning, a sort of artificial intelligence. It uses a large amount of example data and past information to program a model for utilizing a certain criterion (Alpaydin, 2004). The criterion in this case involves classifying the sentiment in a tweet. Azure being a Microsoft product has the benefit of accessing a countless source of data and information from their search engine Bing and numerous other products. In contrast to the other method, Azure includes methods dealing with, sarcasm/irony, the impact of upper-lowercase letters and emoticons. Also, word embeddings where words syntactically alike are plotted closer together. Features not possible only using dictionaries. According to multiple benchmarks Azure performs well in identifying sentiment in tweets compared to other similar software (Parimi 2015).

4.1.3 Classification

After analyzing the sentiment on the tweets using both methods, the tweets were given either a positive, neutral or negative sentiment. In the LM method the classification of these tweets where based on the amount of positive and negative words that where included in the tweet. A tweet with more positive words got a rating of positive and a tweet with more negative words got a negative rating. Tweets having the same amount of positive words and negative words were given a neutral rating. This includes tweets where no words included any of the diction-

[15] Words having multiple meanings.
[16] A 10-K is an annual report providing a summary of a Firm's business performance that is required from the SEC (U.S. Securities and Exchange Commission)
[17] See https://sraf.nd.edu/textual-analysis/code/ (last accessed 2019-10-13)

ary classified positive or negative words. Short tweets where consequently often given a neutral rating which clarifies the reason why LM's method, results in noticeably more neutral tweets than Azure which can be seen illustrated in Figure 1.

In the machine learning method Azure, tweets were given a sentiment score between 0 and 1, a higher score indicating a more positive tweet. If the tweet had a sentiment score under 0.45, Azure gave it a negative rating. Between 0.45 and 0.55, it got a neutral rating and over 0.55, the tweet was classified as positive.

An overview of both methods' sentiment rating for all 7060 tweets is found in Figure 1 below.

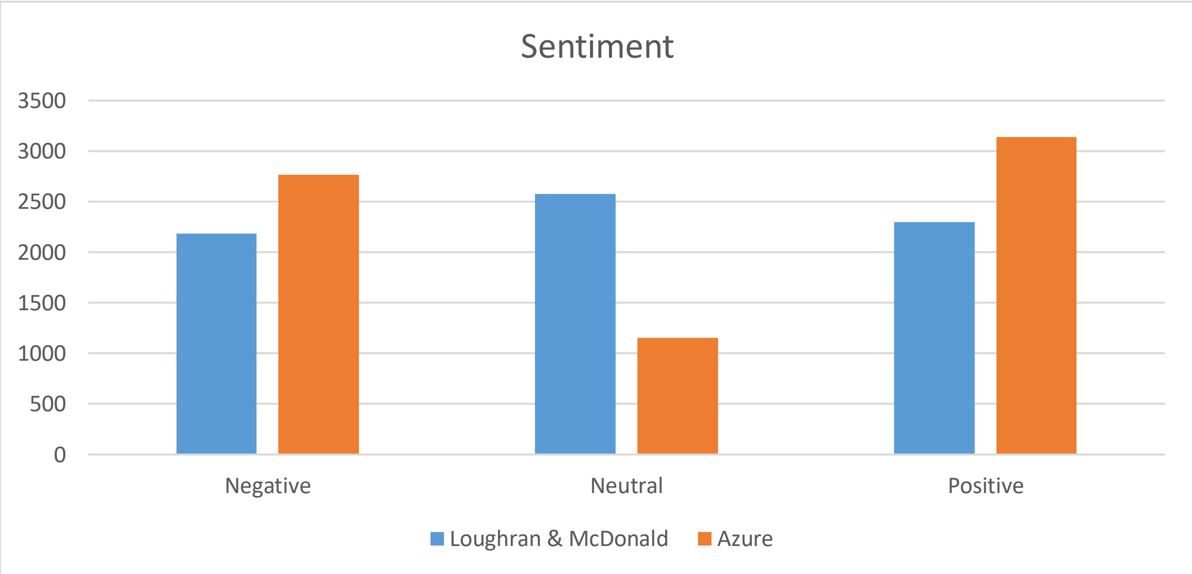

Figure 2 shows the sentiment classification result of all 7060 tweets using both methods

Examples of sentiment rating on a tweet can be seen in Table 1 and Table 2 below, selected based on their given rating.

Examples of sentiments given by Loughran & McDonald	
Very positive tweet	Our Country is doing GREAT. Best financial numbers on the Planet. Great to have USA WINNING AGAIN! - 2018-07-24
Neutral tweet	I will hold a press conference in the near future to discuss the business Cabinet picks and all other topics of interest. Busy times! - 2016-12-13
Very negative tweet	Fines and penalties against Wells Fargo Bank for their bad acts against their customers and others will not be dropped as has incorrectly been reported but will be pursued and if anything substantially increased. I will cut Regs but make penalties severe when caught cheating! – 2017-12-08

Table 1 presents a tweet from all sentiment ratings classified by the LM method. Very positive means that the tweet had an overwhelming amount of positive words in contrast to negative ones. Very negative states the other way around.

Examples of sentiments given by Azure	
Very positive tweet	Very good call yesterday with President Putin of Russia. Tremendous potential for a good/great relationship with Russia despite what you read and see in the Fake News Media. Look how they have misled you on "Russia Collusion." The World can be a better and safer place. Nice! – 2019-05-04
Neutral tweet	Military solutions are now fully in placelocked and loadedshould North Korea act unwisely. Hopefully Kim Jong Un will find another path! – 2017-08-11
Very negative tweet	....When I won the Election in 2016 the @nytimes had to beg their fleeing subscribers for forgiveness in that they covered the Election (and me) so badly. They didn't have a clue it was pathetic. They even apologized to me. But now they are even worse really corrupt reporting! – 2019-04-13

Table 2 Presents a tweet from all sentiment ratings classified by the Azure method. Very positive in this case means that the tweet had a sentiment rating of over 0.99 (1 max), Neutral a rating close to 0.5 and Very negative a rating of below 0.01 (0 min)

To be able to compute and correlate these results, the given sentiment had to be assigned a value. Negative tweets got the value 0, neutral got 0,5 and positive a value of 1. A market day then got the value of the average sentiment for all tweets assigned to that market day. For example, a market day with 5 tweets, 2 positive, 2 neutral, and 1 negative get the sentiment value of 0.6[18]. Following the method of Azure, a market day with a sentiment value of under 0.45 where considered negative, between 0.45 and 0.55 neutral and over 0.55 where considered positive. This gave a similar count of different sentiment for the tweet collection.

The market returns could then be analyzed for the different sentiments based on their average daily return, and sentiment correlation between the two methods could be calculated by using Pearson's correlation coefficient formula:

$$r_{xy} = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}} \tag{2}$$

4.2 Keywords

Four keywords or terms have been selected by its common reoccurrence in Trump's tweets and possible effects on the market. The four terms are: tariffs, stock market, fake news and Russian collusion. A common denominator for these terms is their increasing popularity that took off in the end of October 2016 around the time of the election of Donald Trump, which is illustrated in Figure 2.

[18] (2*1 + 2*0.5 + 1*0) = 3, (3/5) = 0.6

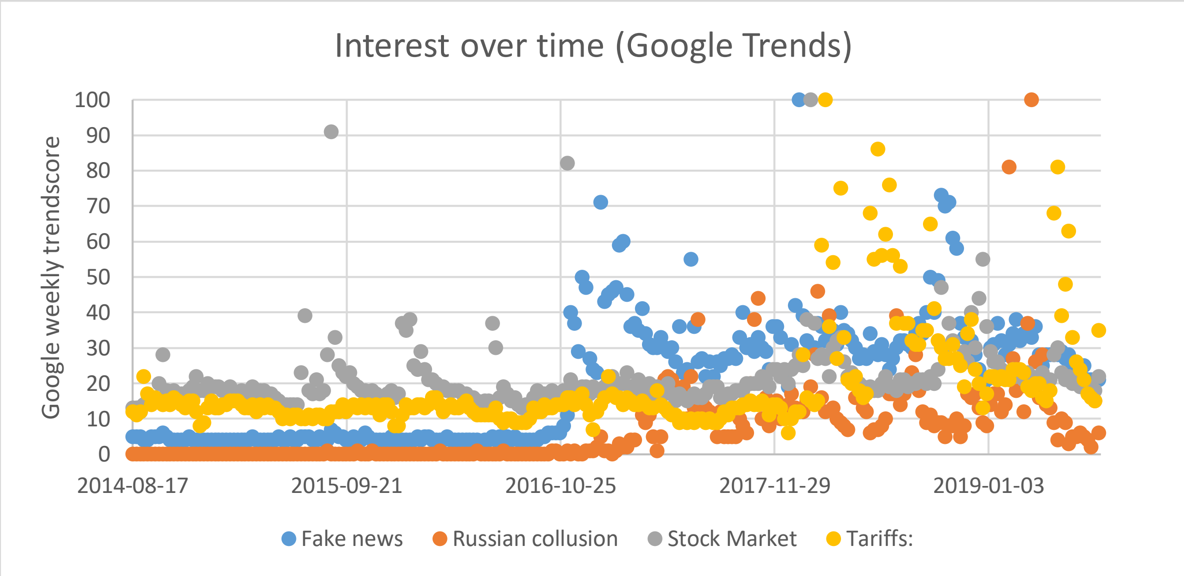

Figure 3 Shows the interest over time for each keyword during the period 2014-08-17 to 2019-08-11, (https://trends.google.com/trends, last accessed on 2019-08-12)

Tariffs

This act of setting up a tax on imports or exports between states has recently gained increasingly attention from media because of Trump's numerous exclamations on Twitter to raise tariffs for China when importing from the US, this has started multiple headlines about potential trade wars. Possible effects tariffs may have on the market have studies dating back to the great depression where The Smoot-Hawley Tariff, legislated in 1930, raised foreign import tariffs. This tariff legislation later got blamed for aggravating the ongoing recession in the U.S (Irwin 1998).

Stock market

This keyword is pretty much straight forward. Trump frequently uses the platform to express the achievements of the stock market since the start of the election. In Figure 1 the S&P 500 index is shown to have increased around 38% since the election in November 2016.

Fake news

The term fake news rapidly grew famous around the time of the 2016 election. Meaning intentional fabricated news stories, the president himself has welcomed the term almost as a slogan and has repeatedly used it towards various mainstream medias in the US. Out of the four keywords and terms, fake news is by far the most common one seen on the president's Twitter account.

Russian collusion

After Trump's election there were accusations of a collusion between Russia and Donald Trump, suggesting that Russia interfered with the presidential election in 2016. This started an ongoing investigation from the FBI and earlier this year a limited report on the matter was released to the public[19]. The allegations and results of this investigation has had Trump tweeting on the matter a few hundred times.

4.3 Event study

The common method in related studies, comparing tweets with market efficiency is to perform an event study where the tweet represents the event. Event studies are then utilized to measure the impact of an event on the value of a firm or stock, most cases the event in question is an earnings announcement, a stock split or a merger between firms. The origin of the method comes from a study by James Dolley (1933), where he examined the price change at the time of a stock split. Showing results pointing in the direction of it being much more likely for the price to increase instead of decline after a stock split.

In this study, a tweet will be counted as an event and instead of a single stock the events effect will be measured on the S&P 500 index alone.

Of course, the study is also subject to some limitations since Trump tweets multiple times a day. A study on all his tweets would therefore not be insightful and any results would be to clustered and insignificant on a daily basis. The event study will be carried out on three of the four selected keywords in this study and might show slightly skewed results as overlapping events occur here as well but not in the same scale. The reasoning for only three of the keywords is due to the huge number of tweets regarding fake news. More than one-third of the days include a tweet about fake news which makes it way to frequent to perform an event study on that keyword.

Models:
While the market model:

$$R_i = \alpha_i + \beta_i R_{mt} + \varepsilon_i \tag{3}$$

is the preferred and most commonly used model for event studies (MacKinlay, 1997), this paper will be using another model. The reasoning for this is the use of an index instead of a stock. Since only using an index (market) $\alpha_i = 1$ and $\beta_i = 0$. The market model would require both a stock and a market index.

The model used here will be the constant mean return model. Which basically means that the

[19] Robert S. Mueller, III, 2019. Report On The Investigation Into Russian Interference In The 2016 Presidential Election

expected return can be calculated as the mean return for the S&P 500 over the estimation window. When calculating the abnormal return, the expected return is subtracted from the actual return. Even though this model is a bit simpler than the market model, Brown and Warner (1980) suggests that the results from this model does not differ much from the more advanced models.

Adding up the abnormal returns over an event window, one can measure the total impact of the event over that particular window. This study will feature an event window of 11 days, beginning 5 days prior to the event and ending 5 days after the event. This measure is called cumulative abnormal return (CAR):

$$CAR_{T1,T2} = \sum_{t=T_1}^{T_2} AR_{i,t} \tag{4}$$

T1 represents the start of the event window, while T2 declares the end of the event window.

To show the effect of all events for the keywords equations 5 and 6 are used to compound the average of the abnormal and cumulative abnormal returns for all events.

Average abnormal return (AAR):

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{5}$$

Cumulative average abnormal return (CAAR):

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_{T1,T2} \tag{6}$$

N represents the number of events (tweets)

To test if there is any statistically significant result from the event study a t-test is implemented on the AAR and CAAR.

$$t_{AAR} = \sqrt{N}\frac{AAR_t}{S_{AAR}} \tag{7}$$

$$t_{CAAR} = \frac{CAAR}{S_{AAR}\sqrt{T2 - T1 + 1}} \tag{8}$$

Here S_{AAR} is the standard deviation for the average abnormal returns and $T2 - T1$ is the length of the event window.

5. Results

5.1 Overview, sentiment, keywords and returns

The tables below present the different daily average returns for each sentiment and for each keyword, starting with a table overview of all the market days sentiment, in the last row of the tables the correlation between the two sentiment methods are demonstrated.

Overview	LM Amount	LM Return	Azure Amount	Azure Return
Positive	263	0,085%	294	0,075%
Neutral	183	-0,022%	158	0,034%
Negative	201	0,062%	195	0,018%
Total	647	0,048%	647	0,048%
Sentiment correlation				0,409

Table 3 shows an overview of the daily return for all the tweets and for the three sentiment classifications. Also presents the correlation between the sentiments given by both methods

Azure shows a positive trend in the daily sentiment result and the daily return. Suggesting that a more positive sentiment, result in a higher market return. LM's method presents highest average returns on days with positive sentiment but have a worse return for neutral days than negative ones.

The correlation between the two methods have an overall positive correlation (0,409) indicating that both methods often rate a tweet similar.

Tariffs	LM Amount	LM Return	Azure Amount	Azure Retun
Positive	18	-0,226%	19	0,044%
Neutral	17	0,010%	15	0,018%
Negative	23	0,052%	24	-0,159%
Total	58	-0,047%	58	-0,047%
Sentiment correlation				0,173

Table 4 shows an overview of the average daily return for the tweets including the keyword tariffs. Also presents the correlation between the sentiments given by both methods

The days mentioning tariffs have overall a negative daily return which may be a result of the negative implications that come with the proposition of new tariffs as well as a potential trade war between China and the US as a result is a frequent warning from mass media.
The correlation between both methods on tweets about tariffs still have a positive correlation although relatively lower than the others. This may explain the differences between sentiment and daily returns between the two methods presented in Table 4.

Stock Market	LM Amount	LM return	Azure amount	Azure return
Positive	29	0,229%	27	0,161%
Neutral	13	0,222%	7	-0,133%
Negative	11	-0,207%	19	0,203%
Total	53	0,137%	53	0,137%
Sentiment correlation				0,362

Table 5 shows an overview of the average daily return for the tweets including the keyword stock market. Also presents the correlation between the sentiments given by both methods

In the days Trump tweet about the market, it shows a higher daily return than the average over the total days. An explanation for this is that Trump often tweets about the market in a positive way, he comments when the index reaches an all-time high or when the market has gone through an upswing. The correlation between the higher returns and this keyword is probably more likely a reason of Trump tweeting about the market when it is performing well, rather than the market performing well because of Trump’s tweets.

Fake News	LM Amount	LM Return	Azure Amount	Azure Return
Positive	40	0,070%	46	0,155%
Neutral	70	-0,012%	38	-0,086%
Negative	124	0,110%	150	0,078%
Total	234	0,067%	234	0,067%
Sentiment correlation				0,256

Table 6 shows an overview of the average daily return for the tweets including the keyword fake news. Also presents the correlation between the sentiments given by both methods

Tweeted in a total of 234 out of the sampled 647 market days by Donald Trump, it makes sense that the average daily return for fake news closely mimics that of the overall daily return.

Russian collusion	LM Amount	LM return	Azure amount	Azure return
Positive	0	0	17	0,593%
Neutral	10	0,370%	10	-0,354%
Negative	77	-0,054%	60	-0,116%
Total	87	-0,005%	87	-0,005%
Sentiment correlation				0,288

Table 7 shows an overview of the average daily return for the tweets including the keywords Russian collusion. Also presents the correlation between the sentiments given by both methods

Something noteworthy is the total lack of positive tweets from the LM sentiment analysis which states that Donald trump's tweets about this subject never includes more positive than negative words. Another thing to look at is that the return Azure positive tweets presents is relatively high in comparison to all other presented average returns.

Overall a few patterns can be perceived, Tweets classified as positive by Azure gives a higher average daily return than the total average return on all 5 tables. In most cases it also is the sentiment giving the highest returns. The sentiment correlation between the two methods are positive for all keywords.

5.2 Event study results

5.2.1 Average abnormal returns

The average abnormal returns were compounded for an event window of 11 days starting with 5 days prior to the event. Below the results for the AAR will be displayed in tables showing mean return for each day in the event windows along with the t-statistic in brackets below. Graphs of the numbers presented in the tables below are found in appendix B.

AAR: Tariffs		**Loughran & McDonald**			**Azure**		
Event day	Overall (58)	Positive (19)	Neutral (15)	Negative (24)	Positive (18)	Neutral (17)	Negative (23)
-5	0,127% (0,159)	0,168% (0,211)	0,249% (0,312)	0,005% (0,006)	-0,042% (-0,053)	-0,297% (-0,372)	0,527% (0,660)
-4	0,002% (0,003)	0,038% (0,048)	0,090% (0,113)	-0,091% (-0,114)	-0,146% (-0,183)	0,157% (0,197)	0,023% (0,029)
-3	-0,092% (-0,115)	-0,153% (-0,192)	-0,113% (-0,141)	-0,028% (-0,035)	-0,253% (-0,316)	-0,221% (-0,277)	0,117% (0,146)
-2	0,128% (0,161)	-0,056% (-0,070)	0,159% (0,199)	0,250% (0,314)	-0,123% (-0,154)	0,087% (0,109)	0,353% (0,442)
-1	0,105% (0,132)	0,076% (0,095)	0,544% (0,682)	-0,197% (-0,246)	0,036% (0,046)	0,497% (0,623)	-0,085% (-0,107)
0	-0,094% (-0,118)	-0,273% (-0,342)	-0,038% (-0,048)	0,004% (0,005)	-0,004% (-0,005)	-0,030% (-0,037)	-0,206% (-0,259)
1	-0,099% (-0,123)	-0,138% (-0,173)	0,004% (0,006)	-0,144% (-0,180)	-0,169% (-0,211)	-0,181% (-0,226)	0,008% (0,010)
2	0,163% (0,204)	0,255% (0,319)	0,220% (0,276)	0,048% (0,060)	0,124% (0,156)	0,115% (0,144)	0,223% (0,279)
3	-0,042% (-0,053)	-0,061% (-0,077)	-0,186% (-0,233)	0,079% (0,099)	-0,142% (-0,178)	0,162% (0,203)	-0,090% (-0,112)
4	-0,031% (-0,039)	-0,358% (-0,448)	0,102% (0,128)	0,126% (0,158)	-0,028% (-0,036)	-0,240% (-0,301)	0,098% (0,122)
5	-0,100% (-0,125)	0,135% (0,170)	-0,414% (-0,519)	-0,051% (-0,064)	-0,093% (-0,117)	0,085% (0,106)	-0,220% (-0,275)

Table 8 Shows the average abnormal returns for the keyword tariffs during an event window of 11 days,
(T-values in brackets) An absolute value of over 1.96 would indicate statistically significant on 95% level
**** p<0,01 ** p<0,05 * p<0,1*

No significant results are presented in Table 8 concerning the 11-day AAR event study for the keyword tariffs. In general, regardless of their sentiment, market days including a tweet by Trump about tariffs presents a negative daily return on the index.

AAR: Stock market		Loughran & McDonald			Azure		
Event day	Overall (53)	Positive (29)	Neutral (13)	Negative (11)	Positive (27)	Neutral (7)	Negative (19)
-5	-0,069% (-0,087)	-0,146% (-0,183)	-0,022% (-0,028)	0,078% (0,098)	-0,201% (-0,252)	-0,087% (-0,109)	0,125% (0,156)
-4	0,042% (0,053)	0,001% (0,001)	-0,140% (-0,176)	0,367% (0,459)	0,041% (0,052)	-0,192% (-0,241)	0,130% (0,163)
-3	0,012% (0,016)	-0,082% (-0,102)	0,169% (0,212)	0,076% (0,096)	-0,093% (-0,116)	0,467% (0,585)	-0,006% (-0,007)
-2	0,007% (0,009)	0,014% (0,018)	-0,116% (-0,146)	0,135% (0,169)	0,013% (0,016)	-0,259% (-0,324)	0,097% (0,121)
-1	0,292% (0,366)	0,367% (0,460)	0,062% (0,077)	0,367% (0,459)	0,332% (0,415)	-0,052% (-0,065)	0,363% (0,455)
0	0,085% (0,107)	0,177% (0,222)	0,170% (0,213)	-0,258% (-0,324)	0,109% (0,136)	-0,185% (-0,232)	0,151% (0,189)
1	-0,024% (-0,030)	-0,077% (-0,096)	0,008% (0,010)	0,076% (0,095)	-0,170% (-0,213)	0,158% (0,198)	0,116% (0,145)
2	-0,022% (-0,027)	0,001% (0,001)	-0,040% (-0,050)	-0,060% (-0,075)	0,078% (0,098)	-0,099% (-0,124)	-0,135% (-0,169)
3	0,070% (0,088)	0,059% (0,074)	-0,084% (-0,106)	0,282% (0,353)	-0,003% (-0,004)	0,146% (0,183)	0,147% (0,184)
4	0,163% (0,204)	0,100% (0,126)	0,421% (0,527)	0,022% (0,028)	0,077% (0,097)	0,188% (0,236)	0,274% (0,344)
5	-0,114% (-0,143)	-0,042% (-0,052)	-0,165% (-0,206)	-0,246% (-0,308)	-0,154% (-0,193)	-0,358% (-0,448)	0,033% (0,041)

Table 9 Shows the Average Abnormal Returns for the keywords Stock Market during an event window of 11 days (T-values in brackets) An absolute value of over 1.96 would indicate statistically significant on 95% level
**** p<0,01 ** p<0,05 * p<0,1*

No significant results are presented in Table 9 regarding the 11-day AAR event study for the keyword stock market. However, Following up on what was said in Table 3 that the correlation between higher returns on days Trump tweets about the market is more likely a byproduct of Trump tweeting about it when It performs well rather than the other way around which Table 7 suggest to some extent by examining event day -1. A day before Trump's tweets about the stock market, the return is higher than on any other event day studied.

AAR: Russian collusion		Loughran & McDonald			Azure		
Event day	Overall (87)	Positive (0)	Neutral (10)	Negative (77)	Positive (17)	Neutral (10)	Negative (60)
-5	0,021% (0,026)	x	-0,118% (-0,148)	0,039% (0,049)	-0,132% (-0,165)	0,058% (0,072)	0,058% (0,073)
-4	-0,045% (-0,056)	x	0,099% (0,124)	-0,064% (-0,080)	-0,119% (-0,149)	0,073% (0,091)	-0,044% (-0,055)
-3	0,019% (0,023)	x	0,225% (0,282)	-0,008% (-0,010)	0,460% (0,576)	-0,256% (-0,321)	-0,061% (-0,076)
-2	0,007% (0,008)	x	-0,235% (-0,295)	0,038% (0,048)	-0,069% (-0,086)	-0,081% (-0,102)	0,043% (0,053)
-1	-0,097% (-0,121)	x	-0,711% (-0,891)	-0,017% (-0,021)	-0,252% (-0,316)	0,064% (0,080)	-0,080% (-0,100)
0	-0,054% (-0,068)	x	0,321% (0,402)	-0,103% (-0,129)	0,543% (0,680)	-0,403% (-0,505)	-0,165% (-0,207)
1	0,068% (0,085)	x	-0,201% (-0,252)	0,103% (0,129)	-0,280% (-0,350)	0,364% (0,457)	0,117% (0,146)
2	-0,061% (-0,076)	x	-0,483% (-0,605)	-0,006% (-0,007)	-0,050% (-0,063)	0,026% (0,032)	-0,078% (-0,098)
3	-0,137% (-0,172)	x	-0,340% (-0,340)	-0,111% (-0,139)	0,249% (0,312)	0,062% (0,077)	-0,280% (-0,350)
4	0,019% (0,024)	x	-0,695% (-0,870)	0,112% (0,140)	-0,064% (-0,081)	0,230% (0,288)	0,007% (0,009)
5	0,014% (0,017)	x	0,317% (0,397)	-0,026% (-0,032)	0,092% (0,115)	-0,495% (-0,619)	0,076% (0,096)

Table 10 Shows the Average Abnormal Returns for the keywords Russian collusion during an event window of 11 days (T-values in brackets) An absolute value of over 1.96 would indicate statistically significant on 95% level
**** p<0,01 ** p<0,05 * p<0,1*

No significant results are presented in Table 10 concerning the 11-day AAR event study for the keyword Russian collusion. Patterns noticed are that the most positive sentiment for each method have the highest daily returns for the event day (0). This completely turns around the day after the event and the days with positive sentiment regarding Russian collusion decrease their returns while negative sentiments increase returns on event day (1).

5.2.2 Cumulative average abnormal returns

The cumulative average abnormal returns were compounded for an event window of 11 days starting with 5 days prior to the event. Below the results for the CAAR will be displayed in tables showing mean return for each day in the event windows along with the t-statistic in brackets below. Graphs of the numbers presented in the tables below are found in appendix C

CAAR: Tariffs		**Loughran & McDonald**			**Azure**		
Event day	Overview	Positive	Neutral	Negative	Positive	Neutral	Negative
-5	0,127% (0,159)	-0,042% (-0,053)	-0,297% (-0,373)	0,527% (0,660)	0,168% (0,211)	0,249% (0,312)	-0,043% (-0,054)
-4	0,129% (0,115)	-0,189% (-0,167)	-0,140% (-0,124)	0,550% (0,487)	0,206% (0,183)	0,339% (0,301)	-0,148% (-0,131)
-3	0,038% (0,027)	-0,441% (-0,319)	-0,361% (-0,261)	0,667% (0,482)	0,053% (0,039)	0,227% (0,164)	-0,173% (-0,125)
-2	0,166% (0,104)	-0,564% (-0,354)	-0,274% (-0,172)	1,020% (0,639)	-0,003% (-0,002)	0,385% (0,241)	0,071% (0,045)
-1	0,271% (0,152)	-0,528% (-0,296)	0,223% (0,125)	0,934% (0,524)	0,073% (0,041)	0,929% (0,521)	-0,211% (-0,118)
0	0,177% (0,091)	-0,532% (-0,272)	0,193% (0,099)	0,728% (0,372)	-0,200% (-0,102)	0,891% (0,456)	-0,199% (-0,102)
1	0,078% (0,037)	-0,700% (-0,332)	0,012% (0,006)	0,736% (0,349)	-0,338% (-0,160)	0,896% (0,424)	-0,318% (-0,151)
2	0,241% (0,107)	-0,576% (-0,255)	0,127% (0,056)	0,959% (0,524)	-0,083% (-0,037)	1,116% (0,495)	-0,240% (-0,106)
3	0,199% (0,083)	-0,718% (-0,300)	0,289% (0,121)	0,869% (0,363)	-0,144% (-0,060)	0,930% (0,389)	-0,152% (-0,063)
4	0,168% (0,067)	-0,747% (-0,296)	0,049% (0,019)	0,967% (0,383)	-0,502% (-0,199)	1,033% (0,409)	-0,026% (-0,010)
5	0,068% (0,026)	-0,840% (-0,317)	0,133% (0,050)	0,747% (0,282)	-0,367% (-0,139)	0,619% (0,234)	-0,012% (-0,005)

Table 11 Shows a 11-day Cumulative Average Abnormal Return between 5 days prior till 5 days after the tweets.
(T-values in brackets) An absolute value of over 1.96 would indicate statistically significant on 95% level
**** p<0,01 ** p<0,05 * p<0,1*

No statistically significant day in the event window is presented in Table 11 reflecting the CAAR event study of the keyword tariffs. Positive tweets classified by both methods showcase a slight negative return for the following days of event day (0).

CAAR: Stock market		Loughran & McDonald			Azure		
Event day	Overall	Positive	Neutral	Negative	Positive	Neutral	Negative
-5	-0,069% (-0,087)	-0,146% (-0,184)	-0,022% (-0,028)	0,078% (0,098)	-0,201% (-0,252)	-0,087% (-0,109)	0,125% (0,156)
-4	-0,027% (-0,024)	-0,146% (-0,129)	-0,163% (-0,144)	0,445% (0,395)	-0,160% (-0,142)	-0,279% (-0,248)	0,255% (0,226)
-3	-0,015% (-0,011)	-0,227% (-0,165)	0,006% (0,005)	0,522% (0,377)	-0,253% (-0,183)	0,188% (0,136)	0,249% (0,180)
-2	-0,007% (-0,005)	-0,213% (-0,134)	-0,110% (-0,069)	0,656% (0,411)	-0,239% (-0,150)	-0,071% (-0,044)	0,346% (0,217)
-1	0,285% (0,160)	0,154% (0,086)	-0,048% (-0,027)	1,023% (0,574)	0,092% (0,052)	-0,123% (-0,069)	0,709% (0,397)
0	0,370% (0,189)	0,331% (0,169)	0,122% (0,062)	0,765% (0,391)	0,201% (0,103)	-0,308% (-0,157)	0,860% (0,440)
1	0,346% (0,164)	0,254% (0,121)	0,130% (0,062)	0,841% (0,398)	0,031% (0,015)	-0,150% (-0,071)	0,976% (0,462)
2	0,324% (0,144)	0,255% (0,113)	0,091% (0,040)	0,781% (0,346)	0,109% (0,048)	-0,248% (-0,110)	0,841% (0,373)
3	0,394% (0,165)	0,315% (0,131)	0,007% (0,003)	1,063% (0,444)	0,105% (0,044)	-0,102% (-0,043)	0,988% (0,413)
4	0,557% (0,221)	0,415% (0,164)	0,427% (0,169)	1,085% (0,430)	0,183% (0,072)	0,086% (0,034)	1,262% (0,500)
5	0,443% (0,167)	0,373% (0,141)	0,263% (0,099)	0,839% (0,317)	0,028% (0,011)	-0,272% (-0,103)	1,295% (0,489)

Table 12 Shows a 11-day Cumulative Average Abnormal Return between 5 days prior till 5 days after the tweets.
(T-values in brackets) An absolute value of over 1.96 would indicate statistically significant on 95% level
**** p<0,01 ** p<0,05 * p<0,1*

No significant results are presented in Table 12 regarding the 11-day CAAR event study for the keyword stock market. As discussed in the AAR table for stock market, a pattern of higher returns for event day -1 is shown. This is illustrated more clearly in Figure 16 and 17 that are found in appendix C.

CAAR: Russian collusion		Loughran & McDonald			Azure		
Event day	Overview	Positive	Neutral	Negative	Positive	Neutral	Negative
-5	0,017% (0,022)	x	-0,118% (-0,148)	0,035% (0,044)	-0,132% (-0,165)	0,058% (0,072)	0,053% (0,066)
-4	-0,025% (-0,022)	x	-0,019% (-0,017)	-0,026% (-0,023)	-0,250% (-0,222)	0,131% (0,116)	0,013% (0,011)
-3	-0,013% (-0,010)	x	0,206% (0,149)	-0,042% (-0,030)	0,210% (0,152)	-0,125% (-0,091)	-0,058% (-0,042)
-2	0,004% (0,003)	x	-0,030% (-0,019)	0,009% (0,005)	0,141% (0,089)	-0,207% (-0,130)	0,001% (0,000)
-1	-0,094% (-0,052)	x	-0,741% (-0,415)	-0,010% (-0,005)	-0,111% (-0,062)	-0,143% (-0,080)	-0,081% (-0,045)
0	-0,131% (-0,067)	x	-0,420% (-0,215)	-0,093% (-0,048)	0,433% (0,221)	-0,546% (-0,279)	-0,221% (-0,113)
1	-0,080% (-0,038)	x	-0,621% (-0,294)	-0,010% (-0,005)	0,153% (0,072)	-0,182% (-0,086)	-0,129% (-0,061)
2	-0,135% (-0,060)	x	-1,104% (-0,489)	-0,010% (-0,004)	0,103% (0,046)	-0,156% (-0,069)	-0,199% (-0,088)
3	-0,298% (-0,125)	x	-1,445% (-0,604)	-0,149% (-0,062)	0,352% (0,147)	-0,094% (-0,039)	-0,516% (-0,216)
4	-0,270% (-0,107)	x	-2,139% (-0,848)	-0,027% (-0,011)	0,288% (0,114)	0,136% (0,054)	-0,495% (-0,196)
5	-0,265% (-0,100)	x	-1,822% (-0,689)	-0,063% (-0,024)	0,380% (0,143)	-0,358% (-0,135)	-0,432% (-0,163)

Table 13 Shows a 11-day Cumulative Average Abnormal Return between 5 days prior till 5 days after the tweets.
(T-values in brackets) An absolute t-value of over 1.96 would indicate statistically significant on 95% level
**** p<0,01 ** p<0,05 * p<0,1*

No significant results are presented in Table 13 concerning the 11-day CAAR event study for the keyword Russian collusion. The CAAR show results that may have been expected if days with negative Twitter sentiment should reflect in a decrease of the market prices and vice versa with positive sentiment. Although LM’s method does not present any positive sentiment for tweets involving Russian collusion, the tweets regarding the keyword given a positive sentiment from Azure seem to increase a fair amount at the market day for the positive tweet. This is more clearly illustrated in Figure 18 in appendix C.

5.3 Online attention

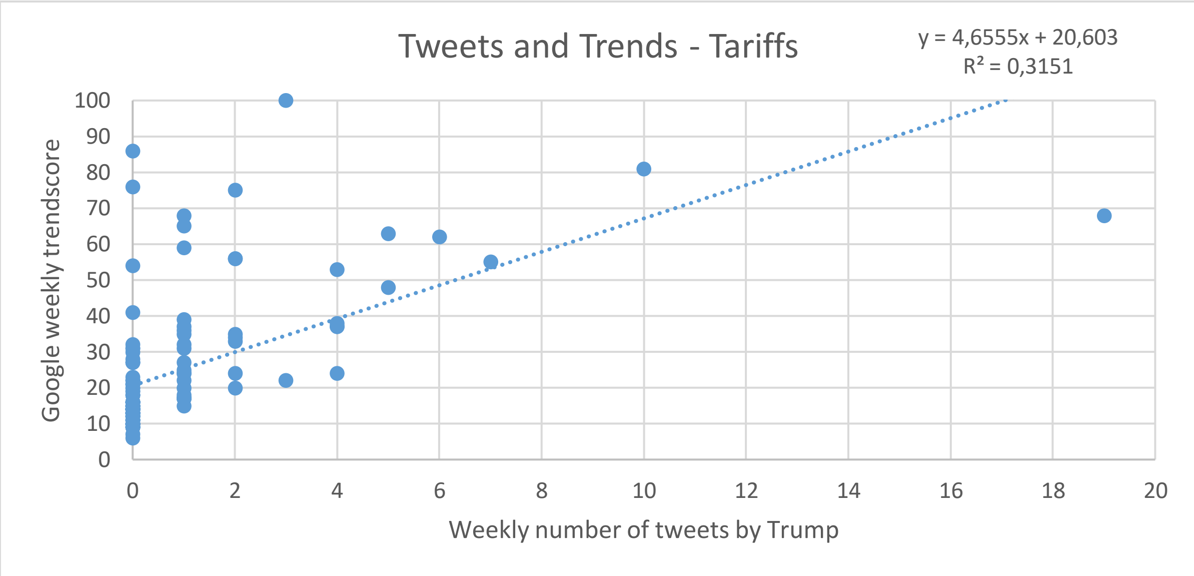

Figure 4 Correlation = 0,561

Figure 4 suggest some interesting results, that the amount of tweets Trump make about tariffs in a week affect the Google search activity of the word tariffs online that same week. A correlation of 0,561 and a R-square value of 0,315 proposes a high positive correlation and a high effect size.

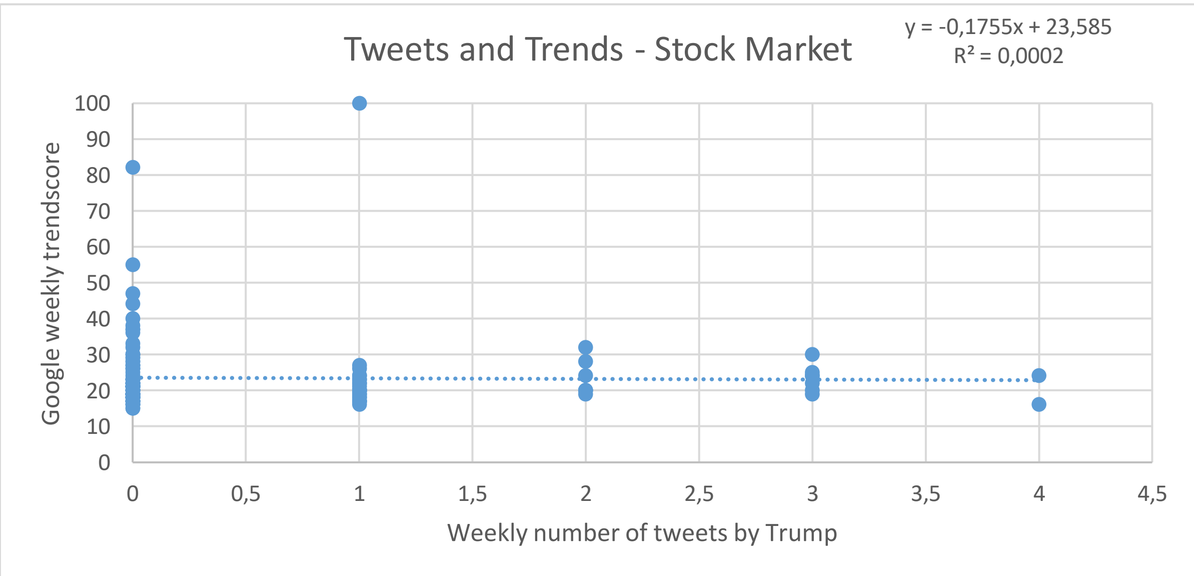

Figure 5 Correlation = -0,015

With a near zero correlation and R-square value, there seems to be no effect between Trump's microblogging about the stock market and the attention it gets online.

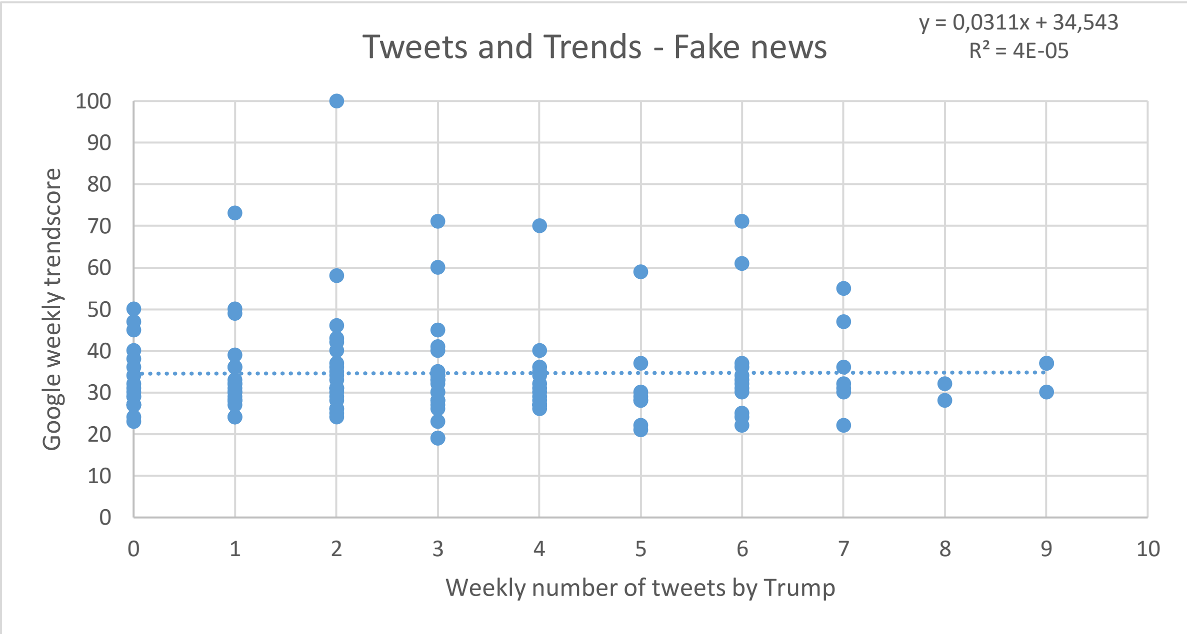

Figure 6 Correlation = 0,006

Similar results here as for stock market tweets, but even more insignificant results which is to be expected from this keyword as it is mentioned by Trump almost every week at least once.

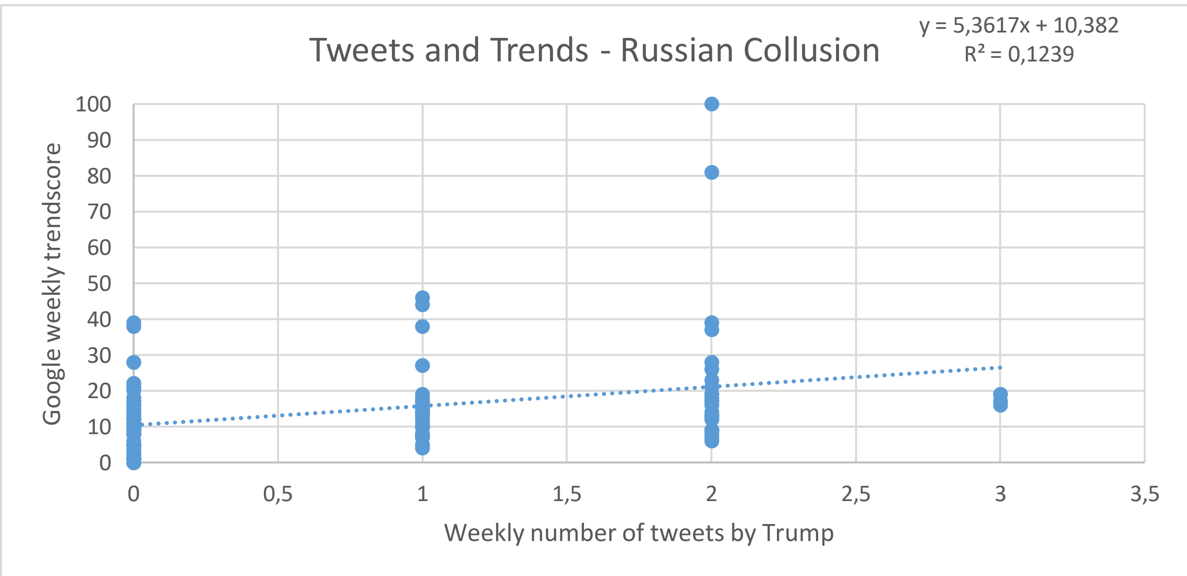

Figure 7 Correlation = 0,352

A return in interest is found in Figure 7, as it just like Figure 4, suggest a moderately high positive correlation and some effect size based on the R-square value.

6. Result discussion

Overview

Analyzing the results of the average daily returns for each keyword and respective sentiment show no significant findings that would indicate that Trump's use of the keywords or the sentiment of those tweets would challenge the theory of market efficiency. Small patterns can be somewhat distinguished as the likes of days Trump tweet about tariffs, those days in general have a negative return while the sort of tweet mentioning the stock market has a higher than average daily return although more likely as a result of good performance in the market before the publishing of the tweet. This hypothesis is supported by the event study and looking back on the average abnormal returns on the day before the stock market tweets. In general market days classified as positive for the different keywords present slightly higher daily returns than days with other sentiments.

Average abnormal and cumulative average abnormal returns

Overall the AAR and CAAR tables show no significant results supporting that Trump's Twitter activity including the four keywords would have any effect on the index market. An important disclosure to make regarding the event studies and the AAR and CAAR results are that because of the many events on the same measured index multiple events are clustered in the same event window. The event study results here include double counting, on some keywords more than others. This might skew the results somewhat, but since no day in the 11-day CAAR window is close to being significant the double counting most likely does not interfere with the result in any substantial way.

Checking on the result of AAR and CAAR for the word tariffs, the returns do not differ much on the event day, it does go down a small amount on the day of tweet. The negative tweet has an initial higher return in the beginning of the event window compared to the positive tweet. When It comes to the word tariffs it is important to note that a tweet classified as positive in this keyword might not reflect the views of people and investors as tariffs induce an uncertainty in the market. Tariffs between China and US which is what is mostly implied in the presidents tweets about the topic, can trigger a trade war between the two countries and

For the results regarding stock market tweets, some uptrend in the returns can be seen days before the tweets suggesting that Trump tweets about the market when it is performing well. Another important bit for this keyword is the sentiment classification might be a little skewed as when trump tweets about the market he often includes the statement that unemployment is down or at a record low. This word combinations seem to result in a negative classification from both methods of sentiment analysis used in this paper.

The diagram showcasing the CAAR for Russian collusion show interesting peaks and lows at the day of the tweets depending on the sentiment of the tweet. However, the return gain or loss on that day is still too low to show any statically significant result.

The result for the keyword fake news is highly insignificant because of the sheer number of tweets on the issue resulting in far too many double counting's to find any useful information. For this reason, an AAR and CAAR study on fake news were abolished.

Online attention

Google trends reveal a strong positive correlation between two of the keywords being used in the president's tweets and Google search activity. It demonstrates that more weekly tweets from Trump regarding tariffs or Russian collusion raises the Google trend score of these key-words on the biggest search engine in the world. This suggest a positive correlation between when Trump tweets about the keywords and the attention it gets online, something that may affect noise traders to act as suggested by the study from Born et al. (2017). A follow up for the two positively correlated keywords can be to analyze potential volume trading effects for the days including tweets by Trump regarding tariffs and Russian collusion.

Problems with overlapping events

As discussed before the results struggles from both the limitations made and the lack of other limitations. The results from the event study is somewhat inconclusive for its continuously overlapping events, this is however a byproduct of too many events for the same measured in-dex. A more specific category of Trump tweets may lead to other results more in line with earlier studies about Trump and his tweets. More interesting would be testing the effects of the keywords on smaller market areas. Tariffs tweets could be analyzed to more targeted stocks or market indexes, a study on their effect on China or companies that specifically would be affected by the introduction of higher tariffs or a so-called trade war. Something along the lines of what Malaver-Vojvodic (2017) examined could be studied as well, but in this instance, examine the foreign exchange rate between U.S. dollars and Chinese yuan in-stead of the Mexican peso. This study also does not factor in the content of the other tweets Trump publishes for the same market day neither does it include other imaginable external ef-fects that might affect the market at the time of the tweets.

Problems with sentiment.

An important thing to note when it comes to the sentiment classification is that it does not per-fectly reflect what the human mind would classify a tweet by. A tweet classified as positive by the methods used in this study might not in reality portrait anything positive. In general, the sentiment of a tweet might not have unanimous classification by humans either, but when dealing with the number of tweets used in this thesis (over 7000), the methods from LM and Azure produce a good estimation of the sentiment for the tweets. Another thing to mention is that a tweet that classifies a tweet about a keyword like tariffs as positive, may not be sus-pected to have a higher abnormal return than a negative one. As the public opinion on tariffs might differ from the president. Loughran and McDonald (2011) discusses the limitations of using dictionaries to define sentiment as there is ambiguous words hard to correctly map to a specific sentiment.

7. Conclusion

An overview of Donald Trump's Twitter activity as president has been analyzed through various methods. Using sentiment analysis and selected keywords to specify potential market effects as well as retrieving a smaller number of events to easier avoid overlapping events when trying to spot any potential effect. The fact that all results of the t-tests are insignificant strongly suggest that this method do not provide evidence that Trump have any direct or lasting effect on the overall market prices. In short: Trying to find and use novel information published on Trump's Twitter account when the president is tweeting about the four selected keywords do not suggest any advantageous trading possibilities regardless of the sentiment rating of the tweets.

In hindsight more limitations to this thesis would have been required for more effective results. However, this paper does provide some indicators to what patterns to further search for. Market days with mostly positive tweets seem to have a slightly higher return than neutral and negative ones. Certain keywords also propose a strong correlation with the online activity they have when the president is tweeting about them suggesting possible attention from noise traders. Future research building on this paper or perhaps including more limitations could innovate other methods to measure the overall market impact. A study on intraday data could show clearer results on both return and volume effects, something that has been reported on multiple company specific tweets shortly after the tweet's publication as well as on the S&P 500 when the fake Obama tweet was published. Further investigation into other keywords or the same keywords but modifications involving other markets like industries, companies of indices more related with the keywords could generate different results.

From previous studies, evidence can be found supporting that Trump do affect the prices for firm-specific stocks through tweets and depending on their sentiment. While no overall market-moving effect was found using the methodology incorporated here, Trump's Twitter activity remains an interesting way to investigate potential market effects and anomalies.

Closing statement

At the end of my time writing this thesis, JPMorgan, one of the largest banks have created an index called Volfefe[20]. The index is solely constructed to measure the market effect of Trump's Twitter activity although at the moment limited to the US bond market. The research states several likely keywords including: Tariffs, China, trade, and billion as more volatility-inducing and market-moving at least immediately after the tweet (Alloway 2019). JPMorgan's research reaffirms the choice of topic to analyze for this paper.

[20] The index is named after a popular, seemingly unfinished tweet that later got deleted from Trump where he ended the tweet with the mysterious word: Covfefe

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Appendices

Appendix A: List of company-specific tweets

Company targeted	"Tweet" – Author, Time.	Stock movement (reference)
Amazon	"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!" – Donald Trump, 2018-04-02.	-3,49% (Bloomberg, 2008)
Biotechnology ETF	"Price gouging like this in the specialty drug market is outrageous. Tomorrow I'll lay out a plan to take it on." – Hillary Clinton, 2015-09-21.	-5% (Rosenfeld & Shah, 2015)
Boeing	"Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!" – Donald Trump, 2016-12-06.	-0,84% (Revesz, 2016)
Chipotle	"I, as you can see, am in the hospital and I have fluids in my arm because the food did not agree with me and I almost died" – Jeremy Jordan, 2017-11-13 (Instagram, not twitter)	-5,90% (Taylor, 2017)
Lockheed-Martin	"The F-35 program and cost is out of control. Billions of dollars can and will be saved on military (and other) purchases after January 20th." – Donald Trump, 2016-12-12.	-4% (Rodinova, 2016)
Lockheed-Martin	"Based on the tremendous cost and cost overruns of the Lockheed Martin F-35, I have asked Boeing to price-out a comparable F-18 Super Hornet!" – Donald Trump, 2016-12-22.	-2% (Rodinova, 2016)
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! @Nordstrom. She is a great person – always pushing me to do the right thing! Terrible!" – Donald Trump, 2017-02-08	-0,70% (Kilgore, 2017)
Snapchat	"sooo does anyone else not open Snapchat anymore? Or is it just me... ugh this is so sad" – Kylie Jenner, 2018-02-21.	-6% (BBC, 2018)
Tesla	Am considering taking Tesla private at $420. Funding secured. – Elon Musk, 2018-08-07.	14% (Rapier, 2019)
Toyota Motor	"Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! Build plant in U.S. or pay big border tax." – Donald Trump, 2017-01-05	-0,50% (Revesz, 2017)

Appendix B: Graphs for the AAR event windows

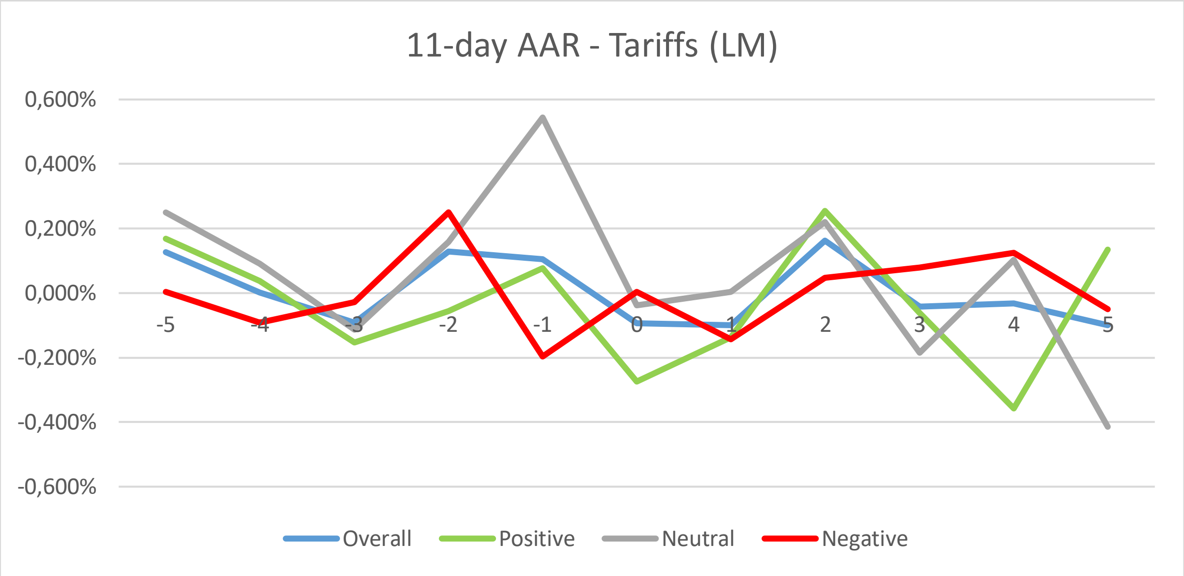

Figure 8 Graphically illustrates the results of the 11-day event study for average abnormal returns for the keyword tariffs using the LM sentiment method

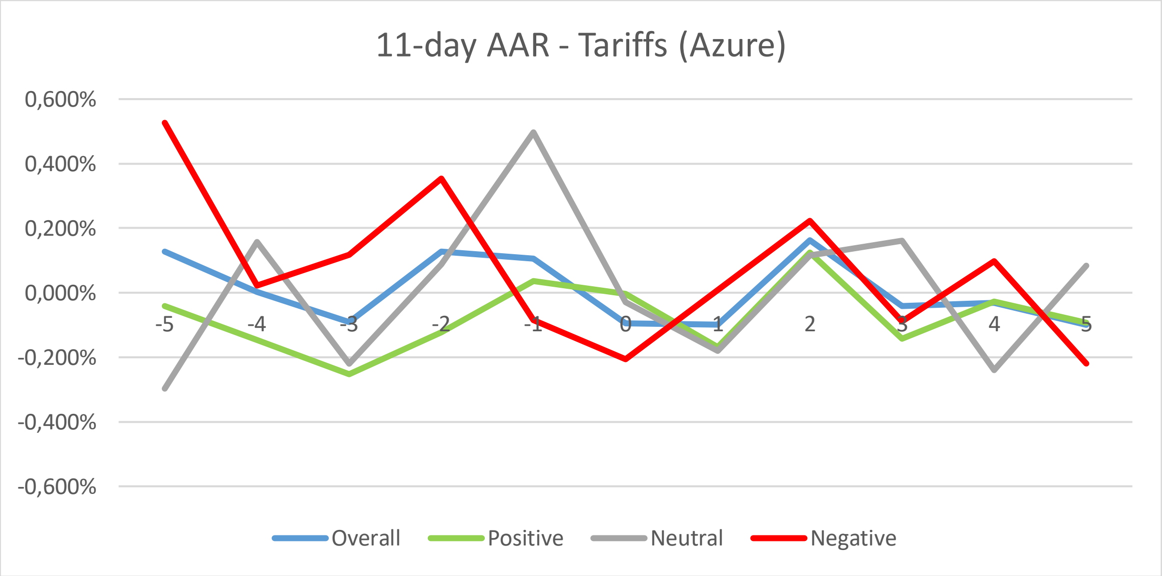

Figure 9 Graphically illustrates the results of the 11-day event study for average abnormal returns for the keyword tariffs using the Azure sentiment method

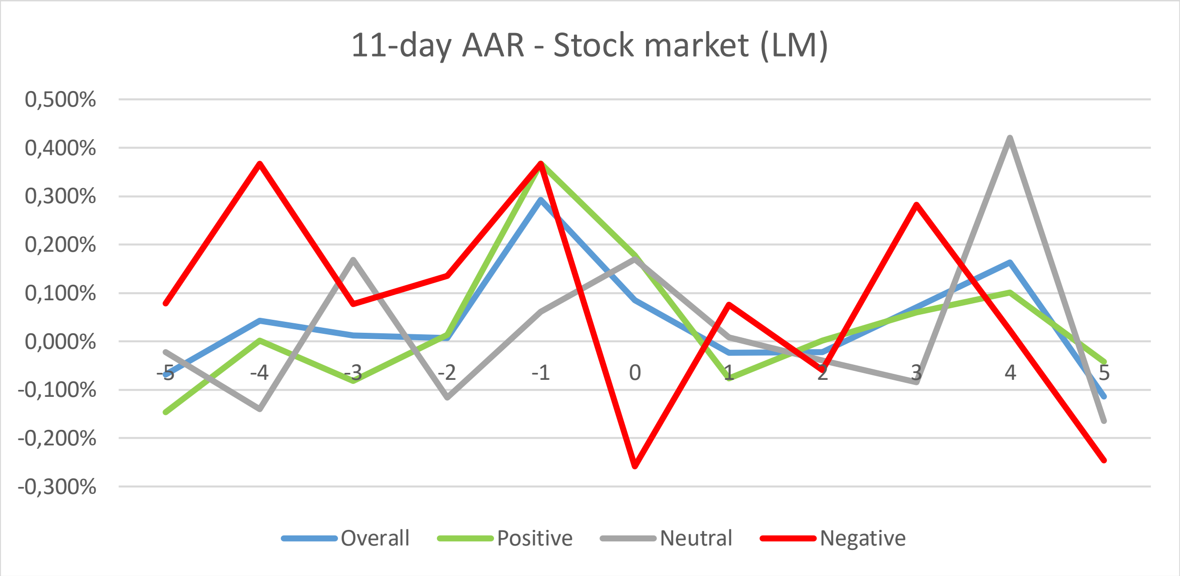

Figure 10 Graphically illustrates the results of the 11-day event study for average abnormal returns for the keyword stock market using the LM sentiment method

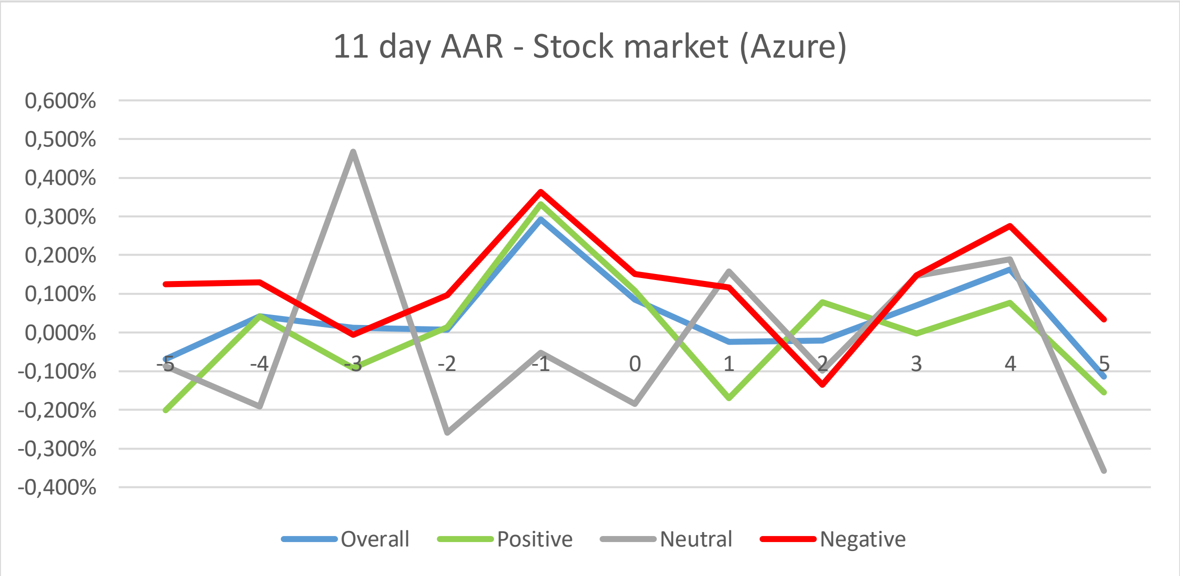

Figure 11 Graphically illustrates the results of the 11-day event study for average abnormal returns for the keyword stock market using the Azure sentiment method

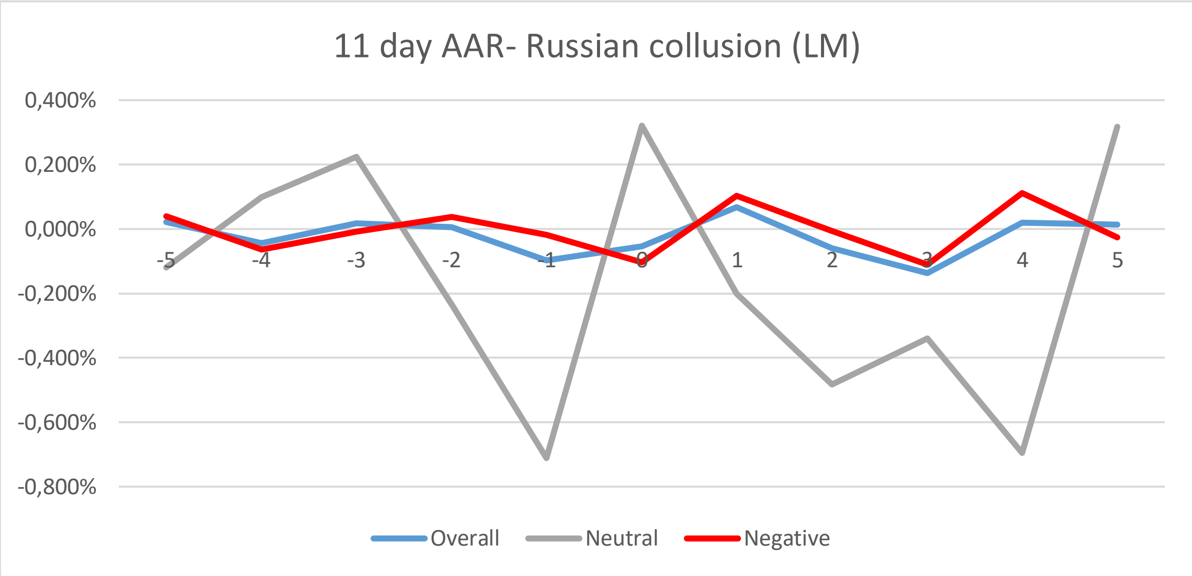

Figure 12 Graphically illustrates the results of the 11-day event study for average abnormal returns for the Russian collusion using the LM sentiment method

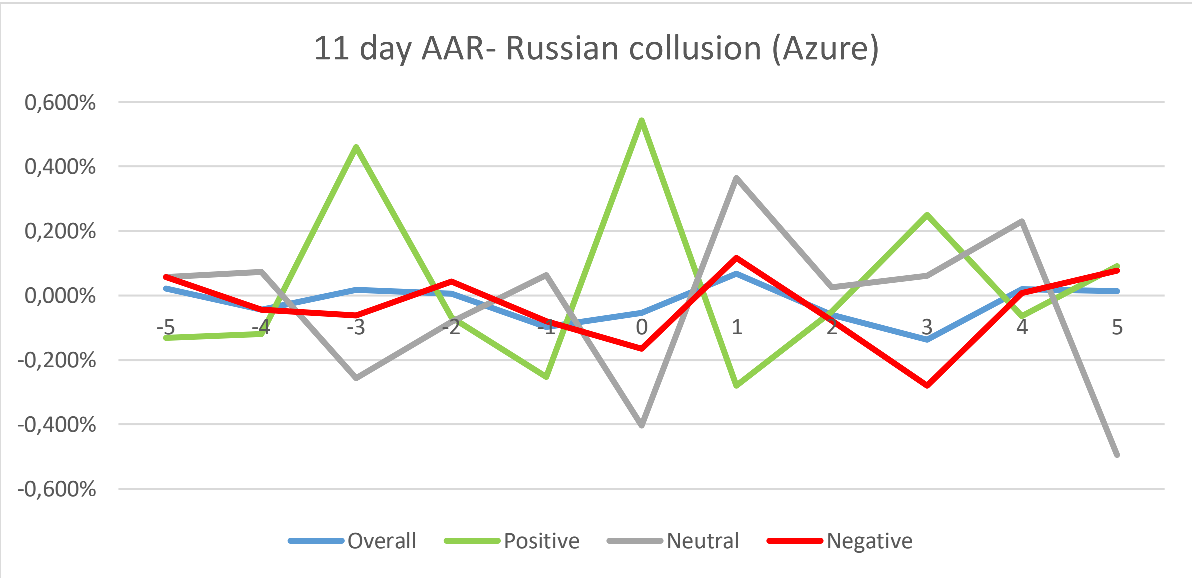

Figure 13 Graphically illustrates the results of the 11-day event study for average abnormal returns for the keyword Russian collusion using the Azure sentiment method

Appendix C: Graphs for the CAAR event windows

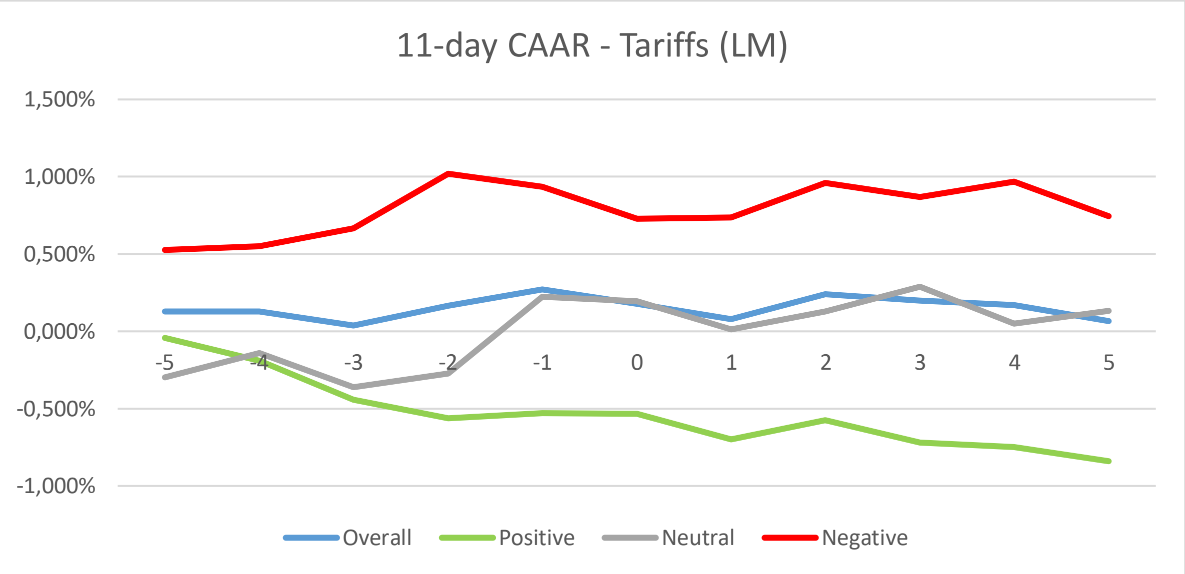

Figure 14 Graphically illustrates the results of the 11-day event study for cumulative average abnormal returns for the keyword tariffs using the LM sentiment method

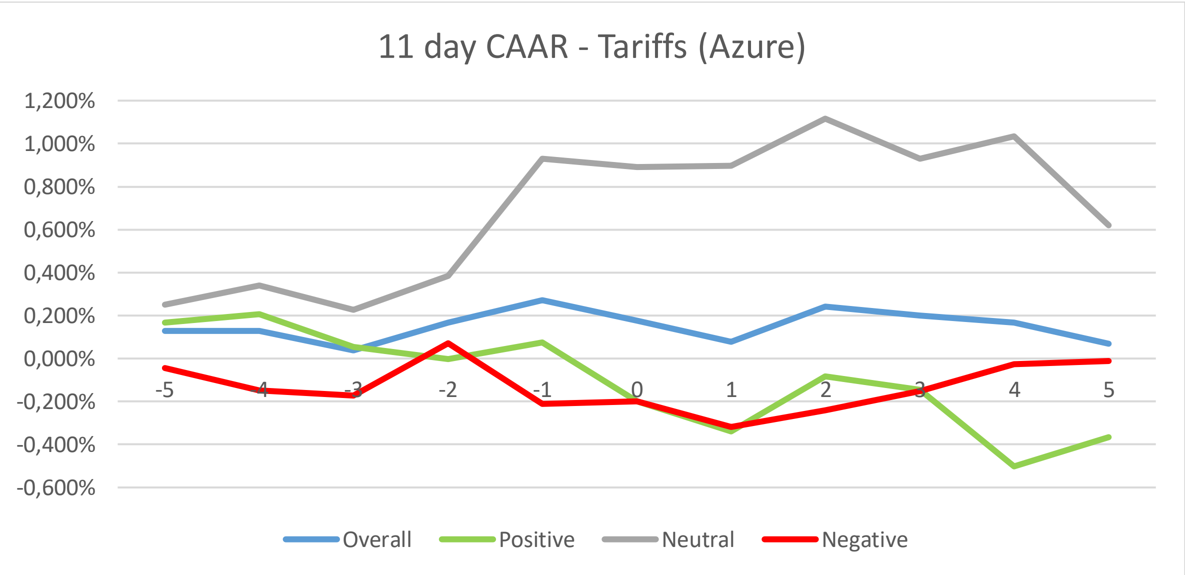

Figure 15 Graphically illustrates the results of the 11-day event study for cumulative average abnormal returns for the keyword tariffs using the Azure sentiment method

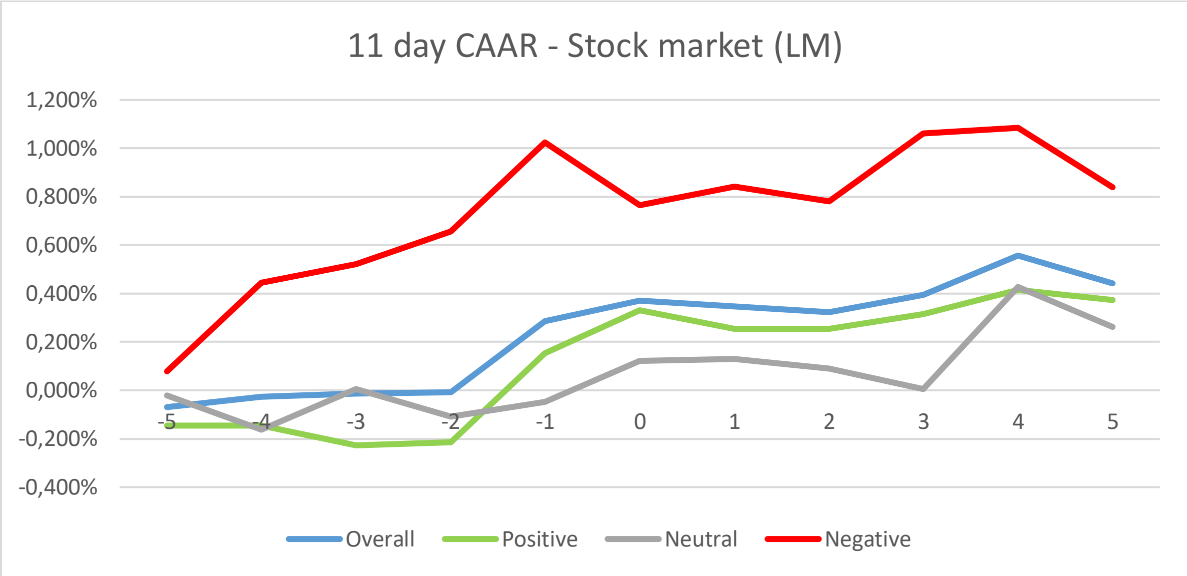

Figure 16 Graphically illustrates the results of the 11-day event study for cumulative average abnormal returns for the keyword stock market using the LM sentiment method

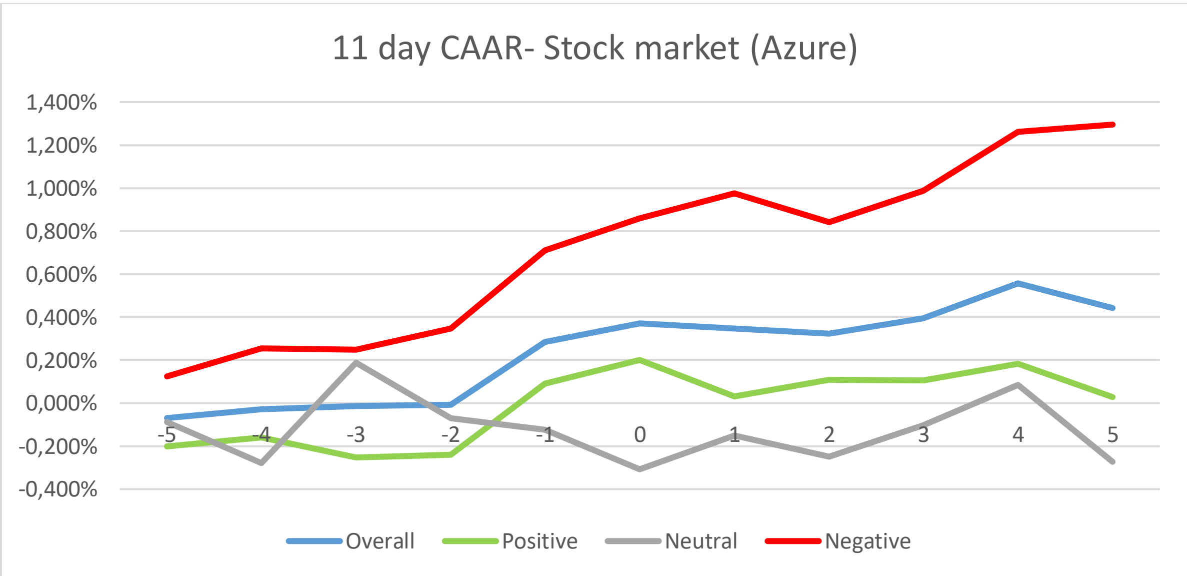

Figure 17 Graphically illustrates the results of the 11-day event study for cumulative average abnormal returns for the keyword stock market using the Azure sentiment method

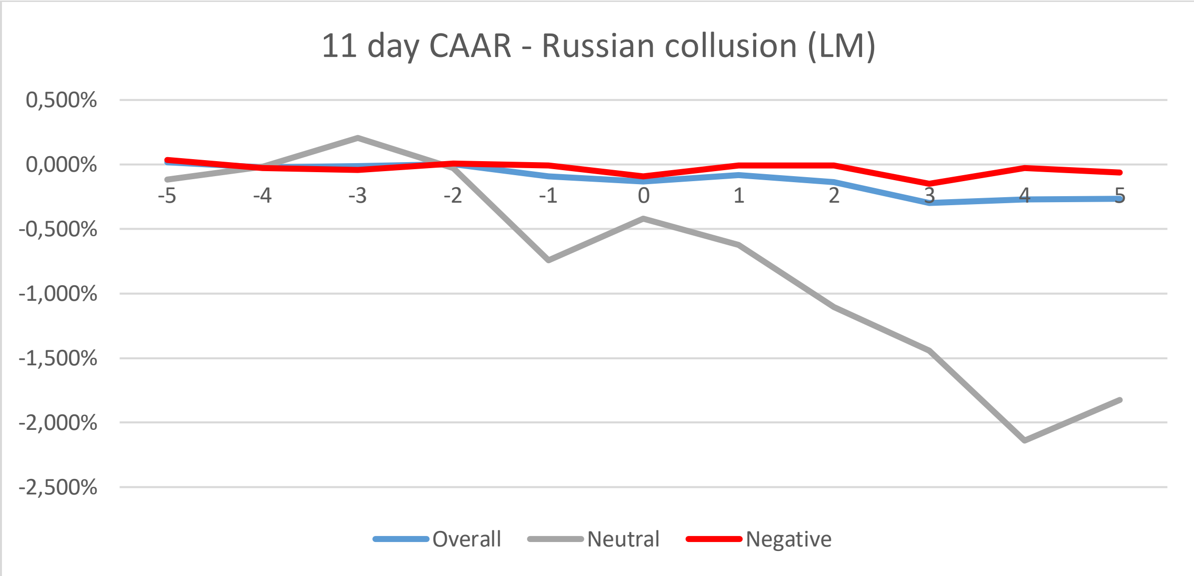

Figure 18 Graphically illustrates the results of the 11-day event study for cumulative average abnormal returns for the keyword Russian collusion using the LM sentiment method

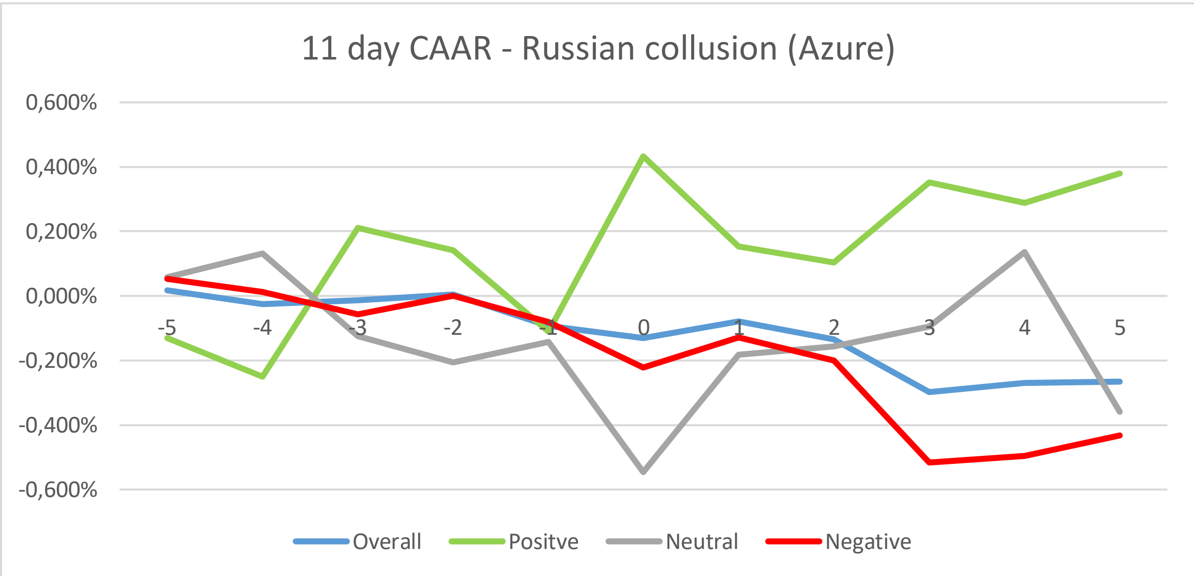

Figure 19 Graphically illustrates the results of the 11-day event study for cumulative average abnormal returns for the keyword Russian collusion using the Azure sentiment method