Trump's twitter effect on Financial Indexes

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Abstract

This study investigates the impact of Trump's tweets on abnormal returns and trading volumes of the S&P 500, using VADER to determine the sentiment of the daily tweets to identify relevant events. Based on the daily tweets from U.S President Donald Trump's twitter account from 1st January 2018 to 16th December 2019, about 20 event samples had been identified. Statistical analysis using event study techniques demonstrated that only negative tweets could lead to statistically significant abnormal return and trading volumes over 1 or 2 trading days after the tweets. The study did not find any statistically significant relationship among positive tweets, abnormal returns, and trading volumes. According to the analysis, the conclusion of these results demonstrates that Trump's tweet is still another source of information used to predict the U.S stock market return.

***Keywords*:** Donald Trump's tweets, S&P500, Sentimental Analysis, Abnormal return, Trading Volume, VADER (Times New Roman, 11pt)

Introduction

Over the past decades, textual analysis has become one of the prominent areas of researches, thanks to digital media evolution and continual advancement in natural language processing tools (Edmans, García, & Norli, 2007; Clayton, 2014; Chen, Cho, & Jang, 2015; Azar & Lo, 2016). Researchers from various disciplines such as computer science (Sohangir, Petty, & Wang, 2018), marketing (Hennig, Wiertz, & Feldhaus, 2015) and finance (Fang & Peress, 2009), have been extracting sentiments from the massive text available in the internet and social media sources to understand users' opinions, satisfaction or reaction to such information.

In a finance context, textual analysis has been applied to financial news sentiments (Barber & Odean, 2008), microblogging (Sprenger & Welpe, 2014) and twitter account of influential leaders (Rayarel, 2018) to determine the level of their influences on investors' trading or subsequent movements in the markets.

In this light, empirical evidence has been accumulating in the developed markets on the possible impacts between sentiments from the news (Fendel, Burggraf, & Huynh, 2019), google searching (Born, Myers, & Clark, 2017) and social media communication on market movements (Rao & Srivastava 2012), trading activities (Antweiler & Frank, 2004) and policy communication (Fenn, 2019).

Among these studies, investment analysts and finance researchers have been paying attention to the twitter account of President Donald Trump, @realDonaldTrump. Since his accession to the U.S. Presidency in 2017, messages posted on @realDonaldTrump twitter account seemed to cause movements in stock prices of the companies mentioned in his tweets, as well as in the broader indices. In 2017, for instance, Trump's tweets about Nordstrom for unfairly dropping his daughter Ivanka's brands. As a result of his Tweet, share prices of Nordstrom immediately dropped by 1% for a short period before rebounding to 4% from the Nordstrom announcement (Tu, 2017). A similar observation was made on 2nd April 2018. Amazon stock sank by 5% after Trump accused Amazon of taking advantage of the US Postal Service, and he suggested that Amazon does not pay its fair share of tax. (Meyersohn, 2018).

Apart from the preceding incidents on individual companies, the media had turned attention to Trump's Tweets about Trade Wars. Starting in late 2018, Trump had been making headlines on Trade War with China, fueling concerns among major financial markets around the world. Balji & Burgess (2019), for instance, observed that approximately US$ 1.36 trillion market value of global stocks had been wiped out when Trump announced the additional tariff US$200 billion on imported Chinese goods on 5th May 2019.

Further, on 2nd August 2019, there was a drop in the S&P 500, when Donald Trump posted a series of tweets on his plan to impose 10% tariffs on $300 billion worth of imports from China, on top of the previous $250 billion, announced earlier. In reaction, the S&P 500 declined by 0.9% on that day and further dropped by almost 3% over the 3 subsequent days (Liu, 2019). These incidents raised questions on the effect of Trump's Tweets on movement in financial markets.

On the one hand, market reactions to Trump's Tweets are often reported by financial media and observed by practitioners. For instance, J.P.Morgan and Citibank had introduced specific indices to quantify Trump's effect on the volatility of bond yield and foreign exchange markets. More specifically, J.P. Morgan has introduced the Volfefe index to track the effect of Trump's Tweet on the volatility of the two-year and five-year bond yields (Alloway, 2019). Having said that, there had been a limited number of scholarly articles, confirming the impact of Trump's effects on Stock Markets. Relevant published works examined the relationship between the google trend searching on "Donald Trump" and stock market movements, while the other focused on the impact of Trump's Tweets on political news relevant to trade war and its relationship to the return on S&P 500 and VIX (Fendel et al, 2019).

With the impending question on Trump's effect, further studies are required to better understand whether there exists the Trump's effect on financial markets. To contribute to the empirical discussion, the purpose of this study is to examine the impact of Trump's Tweets on the S&P 500 from 2018 to 2019. In so doing, this study proposed to determine the sentimental level of Trump's Tweets through Valiance Awareness Dictionary (VADER) and to analyze the statistical relationship with abnormal return and a cumulative return of S&P500. The results of the study could render support to the existing literature as well as provide rooms for future studies.

The objectives of the study

With the frameworks of Born et al. (2017), Rayarel (2018), and Colonescu (2018), this research aims to:

1.)Study the Trump's tweet effect on the S&P500 by analyzing the abnormal return and trading volume of S&P500 to Trump's tweet sentiments.

2.)Examine the impact of Trump's tweet by conducting the sentimental analysis based on VADER and bag-of-word to the series of the S&P500 – whether Trump's tweet with different sentiment does provide any excessive abnormal return and volume to the S&P500 at the same specified interval**.**

Literature Review

Sentimental analysis can be defined as opinion determination's process according to the human's emotion and feeling (Cakra & Trisedya, 2015). This process is performed by the text's classification represented as positive, negative, and neutral sentiments. The social media application such as Facebook, Instagram, and Twitter, are a popular platform in analyzing the polarity of messages through sentimental analysis techniques. Typical approaches to sentiment analysis include machine learning (Rao & Srivastava, 2012) and sentiment analysis, using lexicon approaches (Park & Seo, 2018).

In terms of performance, Sohangir et al. (2018) compare sentimental analysis approaches of social media data by using different machine learning and sentimental lexicons. Logistic Regression, Naïve Bayer, Linear SVW, TextBlob, SentiWordNet, and VADER are used to perform and compare the result of the sentimental analysis. The result demonstrated that VADER is the most accurate lexicon-based and fastest method compared to others. VADER stands for Valence Aware Dictionary Sentiment Reasoning and was created from a generalized, valenced-based, human-curated gold standard sentimental lexicon. VADER also includes the impact of grammatical, syntactical rules, punctuation, capitalization, conjunction, etc. Based on the VADER performance, the text data will be assigned the scoring base on the word in the dictionary and the sentiment score is ranked between 1 and -1 whereby 1 is considered as being extremely positive, -1 is considered as being extremely negative and 0 being neutral. With such techniques, it becomes the popular lexicon-based technique for researchers in analyzing the relationship of sentimental text data from social media to other numerical data (Chauhan, Bansal, & Goel 2018; Park & Soe, 2018; Abraham, Higdon, Nelson, & Ibarra, 2018).

In terms of sentimental analysis on financial markets, Bollen, Mao, & Zeng (2011) in the early author that applied sentimental analysis to their work. With their use of OpinionFinder and Google-Profile of Mood Stage (GPOMS), the daily twitter feeds will be assigned as the various mood stage. Interestingly, these mood time series can be significantly improved the accuracy of DJIA prediction. In the same year, Zhang, Fuehres, & Gloor (2011) use keywords (#Hope, #Happy, #Fear, #Upset, #Nervous, #Positive #Negative) contained in the tweet message to track the sentimental polarity to find the correlation with some aggregated market variables (DJIA, NASDAQ, S&P500, and VIX). The result indicates that the keywords with negative emotional words (#Hope and #Fear) are significantly negative correlated with DJIA, NASDAQ, and S&P500 while the significantly positive relationship was only found in VIX. Also, another aspect of sentimental information is used to find the correlation with the stock market return. For instance, Edmans et al. (2007) discover a strong negative stock reaction on the loss of national soccer teams. Matthias (2011) demonstrates that negative sentiment on Reuter news can be used to predict the stock return, in comparison to the positive sentiment. Augby, Muzwi, & Mezher (2018) study different 25 articles that studied the effect of social media on the stock market prediction. This study as a whole can be concluded that social media can be used as one of the short-term indicative factors to predict the movement of stock for less than 1 year. They also found that Twitter is considered as the first rank of studying social media however, the different sources of social media such as Facebook can provide various impacts on different financial markets in each country.

Twitter is one of the popular social media that the researcher used as a proxy to monitor the predict the financial market movement. Numerous papers discover significant linkage between the financial market and twitter feeds (Azar & Lo, 2016; Zhang et al; Bollen et al. 2011). Also, twitter is still the platform that has been considered as a tool of politicians to expand their speeches such as Narendra Modi (the President of India), Barack Obama (the ex-U.S. President) and most notably Donald John Trump, the 45th president of the United States. As mentioned in the introduction, Donald Trump is considered as the one that actively uses twitter as social media to share his opinion. Many publicly traded firms used to be mentioned in his twitter account during his presidential periods such as Boeing, Toyota, and Lockheed Martin (https://twitter.com/realdonaldtrump).

Many researchers studied the relationship of Trump's tweets to the financial market. Born et al. (2017) use standard event study techniques to find the relationship of a positive and negative sentiment of Trump's tweets to opening and the close stock price of 10 publicly traded firms. Demonstrating by average abnormal return (AAR), cumulative average abnormal return (CAAR), average abnormal trading volume (AAV), and google searching activities, the result indicates that the price and trading volume, combined with the Google Search activity of 10 publicly traded firms are correlated with sentimental content of Trump's tweet messages. Similarly, Rayarel (2018) also apply the same technique as Born et al. (2017) to find the effect of Donald Trump's company-specific tweets on the stock market. The result reveals that Trump's tweet leads to a statistically abnormal return on the company stock price. Interestingly, few authors study the relationship of Trump's tweet feeds to the stock market indices. Colonescu (2018) looks at the effect of the daily flow of Donald Trump's tweet on the DJIA and some currency exchange rates. By using AFINN lexicon, the tweets are assigned the score to quantify the sentimental analysis. Indicated by the regression model, there is some short-time effect of Trump's announcement on twitter to

DJIA and the US-Canadian currency exchange rate.

In recent years, many research papers have linked the relationship of Trump's tweet on company-specific firms but to the best of my knowledge, there still have no research on the effect of Donald Trump's tweets on an aggregated market variable such as S&P500. This paper would apply the concept of Born et al (2017), Rayarel (2018), and Colonscu (2018) to S&P 500 by using VADER to conduct the sentimental analysis. The event study technique (AAR, CAAR, and AAV) would be applied to find the relationship of Trump's tweet to the financial index (S&P 500). However, this paper would use the more recent period from the year 2018 to 2019 of Trump's tweet data to test analysis. During these periods, there are many world circumstances like the U.S – China Trade war that ignite me to study more on the impact of it.

Hypothesis

In accordance with Born et al. (2017) and Rayarel (2018), this study examines the following hypotheses.

Table1: Hypotheses

Hypotheses No.	Formulas
Hypotheses 1	$H_0: AAR = 0$ $H_1: ARR \neq 0$
Hypotheses 2	$H_0: CAAR = 0$ $H_1: CARR \neq 0$
Hypotheses 3	$H_0: AAV = 0$ $H_1: AAV \neq 0$

Explanation

<u>Hypotheses 1</u>

H_0: claim that Trump's tweet has no impact on S&P500

H_1: rejects H_0 that Trump's tweet has an impact on S&P500

<u>Hypotheses 2</u>

H_0: claim that Trump's effect exists only 1 day on the event date

H_1: rejects H_0 that Trump's effect exists more than 1 days of the next trading day

<u>Hypotheses 3</u>

H_0: claim that Trump's tweet has no impact on the trading volume of S&P500

H_1: rejects H_0 that Trump's tweet has an impact on the trading volume of S&P500

Data Collection

<u>List of Trump's tweets</u>

Tweets from Donald Trump's tweets are collected starting from 1st January 2018 to 16th December 2019 totaling 10,000 messages via http://www.trumptwitterarchive.com in which this website directly gathers the information from @realDonaldTrump, Trump's twitter account. Subsequently, retweet and other data unrelated to tweets written by Donald Trump are eliminated. Usually, Donald Trump spread out his opinion on twitter via 2 accounts which are @POTUS, his US president account and @realDonaldTrump, his private account. This study applies @realDonaldTrump as a sample to test the hypothesis because he often uses this account to share his opinion while @POTUS will be used as retweeting of his personal account. Also, the number of followers for @realDonaldTrump is twice times compared to @POTUS, his US president account. This is the reason why in US president account will not provide any new information. To be more realistic, this paper assigns the tweet posting after the market close at

4:00 pm to the next trading day since tweet posted after market close should be affected on the stock market in the next trading day.

<u>Stock market data</u>

The financial data of S&P500 in both historical closing prices and trading volumes are gathered from 2 sources, from 1st January 2018 to 16th December 2019, which are https://eikon.thomsonreuters.com/index.html and https://finance.yahoo.com/. The reason for using 2 sources of information is to cross-check the right information and filling some of the missing data belonging to some periods. According to Antweiler & Frank (2004), this research would apply the closing price of the market index to perform the logarithmic daily stock return whereby the return is calculated by the following formula

$$R_{i,t} = \frac{In(P_{i,t})}{In(P_{i,t-1})} \qquad (1)$$

Where $(R_{i,t})$ is the daily return of index i at day t. $P_{i,t}$ is the closing price of stock i at day t and $Pi, t-1$ is the previous day's closing price for stock i.

Methodology

Briefly, the first step consists in **defining the event and estimation window** of chosen events. This step is to identify the time interval over the event's occurrence. Then, Trump's tweet data would be flowed by the process of **sentimental analysis** by using Valence Aware Dictionary and Sentiment Reasoner (VADER). The purpose of this text mining is to assign a sentimental measure (Positive or Negative) to each tweet and to construct a series of sentiment. After assigning the sentimental polarity for each tweet message, chosen events are defined base on the **Degree of Bullishness** and **Latent Dirichlet Allocation (LDA) model** also are simultaneously applied to those sentimental tweets to identify the bag-of-words related to the sentimental analysis resulting from VADER. Base on chosen the event samples, **abnormal return (AR)**, **cumulative abnormal return (CAR)** and **abnormal trading volume (AV)** of the S&P500 are calculated to demonstrate the impact of Trump's tweet sentiment. Finally, the **T-test (Brown & Warner,1995)** is used to test the significant degree of the result for each element.

Define event and estimation window

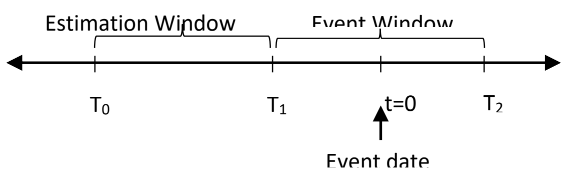

Figure 1 Timeline of an event

This is defined as the key period of an event study. On the event study timeline, $t = 0$ is the day in which the occurrence of tweet event. The event window is ranged between T_1 *and* T_2 where T_1 is the first day of the event window. T_2 is the last day of the event window. Usually, there is no consensus on the length of the event window as there are different window periods used in different academic papers. In existing paper, the event window varies from 1 to 20 days. Sprenger et al. (2010) used 20 days event window to test the abnormal return of stock and volume while Born et al. (2017) applied 10 days as an event window. According to the paper of Born et al. (2017) and Rayarel (2018), they stated that Trump's tweet effect would no longer significant after five trading days. Therefore, this research will apply 10 days as the event window (5 days before and after event dates). The next step is to identify the estimation window where T_0 to T_1 is the interval period of the estimation window. T_1 is the first day of estimation window and T_0 is the last day of the estimation window. The estimation window is the period before the event window in which it is used to define the scope of expected return. The estimation window varies from 30 to 250 days. Sprenger et al. (2014) and Rayarel (2018), for instance, use estimation window 120 days and 250 days respectively while Fenn (2019) uses 100 days. However, there is no standard method to define the estimation window. Therefore, this paper will try 50 days as an estimation window starting from -56 day to -6 day. Intentionally, the gap of 5 days is to prevent the overlapping between the event window and the estimation window.

Sentiment analysis

Valence aware dictionary and sentimental reasoner (VADER), one of the sentimental lexicon methods, is used to perform the polarity of each Trump's tweet. VADER would match Trump's tweet content with a social media dictionary and assign the score to each tweet and categorize the tweets as positive, negative, or neutral. The general purpose of this process is used to quantify sentiment. VADER assigns a sentimental value in the range of -1 and +1 whereby +1 is considered as being extremely positive, -1 is considered as being extremely negative and 0 is treated as neutral.

Sample Selection

After the sentimental score is defined, the next step is to select the event samples. The process of defining event samples for this study is based on 2 methods which are the degree of bullishness and beg-of-word method.

1.Degree of Bullishness

By applying some of Antweiler & Frank (2004), Rao & Srivastava (2012), and Sprenger et al. (2014) techniques, the degree of bullishness is defined as:

$$Bullishness = In\left(\frac{1 + M_t^{Positive}}{1 + M_t^{Negative}}\right) \qquad (2)$$

Where $M_t^{Positive}$ and $M_t^{Negative}$ are the number of positive and negative tweets on day t. This Logarithm of bullishness measures the explanation of surplus degree on that specific day. The higher bullishness implies the larger number of positive messages in a specific sentiment and vice versa.

2.Beg-of-Word method

After the 20 event dates are defined, each tweet will be decomposed by words (the "bag-of-word" method) to identify the word related to groups of sentiment in each event date. Latent Dirichlet Allocation (LDA) model, a generative probability model for collections of discrete data, is used to conduct the bag-of-word method (Colonescu, 2018). LDA would take a corpus of the unannotated document as input and produces two outputs, a set of "Topics" and assignment of the document to the topics where both are represented as a probability distribution.

Return Calculation

To analyze the impact of Trump's tweet on the S&P500, the event study technique is performed on 20 event dates. The use of abnormal return (AR) on each event date is calculated to find the effect of Trump's tweet on that day (t=0). Following the calculating of cumulative abnormal return (CAR), this method is to find how long Trump's tweet effect does exist after the event date. Finally, abnormal trading volume (AV), the same calculation as the abnormal return, is computed for testing an attention-based investment.

When the estimation window is defined and the sample sizes are selected, the expected returns of each event date are required to generate abnormal returns. The expected return is used as the benchmark return in a normal situation that is not related to the event of interest. This paper would apply constant mean returns model (CMR) to calculate expected return since this method uses the market price itself that already reflects the market factors to find expected return (Brown & Warner, 1985). The constant mean returns model (CMR) is defined as:

$$Expected\ return = \bar{R}_{m,t} \qquad (3)$$

Where $R_{m,t}$ is the average 50-day estimation period return (estimation window) where this calculation will be started 5 days before the event period. Then, the logarithm daily return on the event dates is subtracted by the expected return to get the abnormal return (AR) whereby the formula defined as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \qquad (4)$$

$AR_{i,t}$ is the abnormal return and $R_{i,t}$ is the daily return for indexes for event I at day T. $E(R_{i,t})$ is the expected return generating from CMR method starting from -56 to -6 days (50 days prior event window).

Due to the large event samples, Born et al. (2017) and Rayarel (2018) suggest that the abnormal return of each event date can be combined into a portfolio and uses average abnormal return to define the impact. The average abnormal return (AAR) is calculated as:

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

Where N is the number of an event study. $AR_{i,t}$ is the average abnormal return for event I at time T.

Next, the cumulative average abnormal return (CAAR) is calculated to find how quickly the market indexes react to Trump's tweets. The CAAR return is expressed as an only single number from different event windows as formula as below.

$$CAAR_{(T_1,T_2)} = \sum_{t=T_1}^{T_2} AAR_t \qquad (6)$$

Where $T1$ is the first day in the event window and $T2$ is the last day of the event window.

Trading Volume calculation

The average abnormal trading volume using the same technique as Rayarel (2018) as the formula as follows:

$$AAV_t = \frac{1}{N}\sum_{i=1}^{N} AV_{i,t} \qquad (7)$$

$$AV_{it} = \left(\frac{V_{i,t} - \bar{V}_i}{\bar{V}_i}\right) \qquad (8)$$

Where AV_{it} is the change in abnormal trading volume for event i on day t, $V_{i,t}$ is the trading abnormal trading volume for event i on day t and $\bar{V}_i$ is the average trading volume of event i on day t. Then, find the average abnormal trading volume as the same technique as an average abnormal return.

Significance test for AAR, CAAR, & AAV (Brown and Warner T-test)

Statistical significance of AAR, CAAR, & AAV is performed using Brown and Warner (1995) T-Tests. According to Brown and Warner

(1985) theory, the T-test method can be used to test the significant relationship between AAR, CAAR, and AAV. This t-statistic is calculated as below. – indicate one main formula & state all this will be applied to AAR, CAAR, and AAV.

$$t = \frac{X_t}{\sigma_X} \qquad (9)$$

Where X_t apply for 3 results which are AAR_t, $CAAR_t,\ and\ AAV_t$. σ_X is the standard deviation of $AAR_t,\ CAAR_t,\ and\ AAV_t$.

Results and discussion

Table2: Abnormal return of positive event dates

N=20					
S&P500	**Period**	**AAR**	**α**	**T-stat**	**P-value**
After Event Date	**5**	-0.22%	0.0026	-0.8455	0.4084
	4	0.24%	0.0016	1.4842	0.1541
	3	0.07%	0.0017	0.4146	0.6831
	2	0.23%	0.0024	0.9658	0.3463
	1	-0.11%	0.0021	-0.5154	0.6122
	0	-0.10%	0.0034	-0.3096	0.7602
Before Event date	**-1**	-0.23%	0.0030	-0.7660	0.4531
	-2	-0.28%	0.0021	-1.3642	0.1884
	-3	0.19%	0.0016	1.1837	0.2511
	-4	0.01%	0.0025	0.0573	0.9549
	-5	0.11%	0.0020	0.5312	0.6015

According to Table2, 20 events with the high bullishness score of Trump's tweets are examined the impact on S&P500. The result shows that the abnormal return on the first trading day of Trump's tweet (t=0) is negative which moves in the opposite direction of the positive sentiment of Trump's tweets. Also, the P-value is statistically insignificantly different from zero. Moreover, after the event date, the abnormal return for the positive tweet is still negative and is not significant. Therefore, this can be implied that positive Trump's tweets have no significant impact on S&P 500 and consistent with the null hypothesis that Trump's tweet has no impact on S&P500 during this period.

Table3: Abnormal return of negative event dates

N=19					
S&P500	**Period**	**AAR**	**α**	**T-stat**	**P-value**
After Event Date	**5**	-0.17%	0.0016	-1.0852	0.2922
	4	0.05%	0.0015	0.3025	0.7658
	3	-0.01%	0.0021	-0.0471	0.9630
	2	0.16%	0.0016	0.9865	0.3370
	1	-0.04%	0.0016	-0.2680	0.7918
	0	-0.45%	0.0020	-2.2582	**0.0366**
Before Event date	**-1**	0.04%	0.0017	0.2430	0.8108
	-2	0.15%	0.0015	1.0197	0.3214
	-3	-0.08%	0.0013	-0.6253	0.5396

	-4	0.15%	0.0017	0.9159	0.3718
	-5	0.02%	0.0016	0.1157	0.9091

Based on the Table3 above, it displays the abnormal return for a high negative bullishness score with 19 events in samples. It demonstrates that on the date that when Trump starts tweeting some negative messages, abnormal return on S&P500 are seemed to be negative of -0.45% and it is statistically significantly different from zero. However, in the next trading day, even there is small negative abnormal return, the returns are likely to be insignificant on P-value. This can be inferred that Trump's tweets with negative sentiment are likely to provide an impact on S&P500 on the day (t=0). With a 5% level of significance, the null hypothesis is rejected on the claims that negative Trump's tweets do not provide any impact on S&P500 return.

Table4: Cumulative Abnormal return of positive event dates

N=20					
S&P500	**Period**	**AAR**	**α**	**T-stat**	**P-value**
After Event Date	**5**	0.11%	0.0066	0.1649	0.8707
	4	0.33%	0.0062	0.5299	0.6023
	3	0.09%	0.0055	0.1613	0.8736
	2	0.02%	0.0052	0.0316	0.9751
	1	-0.21%	0.0043	-0.4959	0.6257
	0	-0.10%	0.0034	-0.3096	0.7602
Before Event date	**-1**	-0.33%	0.0037	-0.8873	0.3860
	-2	-0.62%	0.0040	-1.5551	0.1364
	-3	-0.43%	0.0045	-0.9373	0.3604
	-4	-0.41%	0.0045	-0.9095	0.3745
	-5	-0.30%	0.0057	-0.5322	0.6008

According to the previous AAR implication, the positive Trump's tweets do not provide any effect to return in S&P500. Therefore, CAAR will be automatically insignificant for this test (Table 10).

Table5: Cumulative Abnormal return of negative event dates

N=19					
S&P500	**Period**	**AAR**	**α**	**T-stat**	**P-value**
After Event Date	**5**	-0.47%	0.0035	-1.3542	0.1924
	4	-0.30%	0.0029	-1.0502	0.3075
	3	-0.35%	0.0030	-1.1594	0.2614
	2	-0.34%	0.0030	-1.1228	0.2763
	1	-0.49%	0.0025	-1.9866	**0.0624**
	0	-0.45%	0.0020	-2.2582	**0.0366**
Before Event date	**-1**	-0.41%	0.0030	-1.3548	0.1922
	-2	-0.26%	0.0038	-0.6834	0.5030

	-3	-0.34%	0.0044	-0.7733	0.4494
	-4	-0.19%	0.0047	-0.4013	0.6929
	-5	-0.17%	0.0051	-0.3260	0.7482

Table5 indicates the cumulative abnormal return for 19 samples of high negative bullishness score belongs to Trump's announcement. According to the result, the effect of Trump's tweet is likely to remain for at least 1 day after the event date indicated by cumulative abnormal return and statistical significance of P-value with on 10% level. Therefore, the test is in line with the alternative hypothesis that Trump's effect will exist more than 1 days in the next trading day.

Table6: Abnormal trading volume for Positive event date.

N=20					
S&P500	**Period**	**AAR**	**α**	**T-stat**	**P-value**
After Event Date	**5**	4.31%	0.0267	1.6132	0.1232
	4	-1.44%	0.0175	-0.8233	0.4206
	3	-0.38%	0.0183	-0.2072	0.8380
	2	1.28%	0.0447	0.2866	0.7775
	1	-4.30%	0.0374	-1.1488	0.2649
	0	3.81%	0.0411	0.9276	0.3653
Before Event date	**-1**	-2.44%	0.0461	-0.5293	0.6027
	-2	3.25%	0.0412	0.7887	0.4400

	-3	1.20%	0.0308	0.3906	0.7005
	-4	-2.03%	0.0222	-0.9180	0.3701
	-5	1.02%	0.0265	0.3838	0.7054

Table7: Abnormal trading volume for Negative event date.

N=19					
S&P500	**Period**	**AAR**	**α**	**T-stat**	**P-value**
After Event Date	**5**	5.08%	0.0353	1.4386	0.1674
	4	-0.91%	0.0487	-0.1875	0.8534
	3	-2.10%	0.0405	-0.5178	0.6109
	2	0.68%	0.0294	0.2327	0.8186
	1	-3.84%	0.0338	-1.1359	0.2709
	0	4.37%	0.0237	1.8388	**0.0825**
Before Event date	**-1**	-2.75%	0.0360	-0.7642	0.4546
	-2	2.39%	0.0327	0.7315	0.4739
	-3	0.12%	0.0245	0.0479	0.9623
	-4	2.69%	0.0430	0.6260	0.5392
	-5	-0.29%	0.0377	-0.0763	0.9401

Table6&7 show positive and negative bullishness score of abnormal trading volume within the event window related to S&P500. It states that only the negative bullishness score shows slightly of abnormal trading volume with 4.37% and 10% significance of P-value; however, there is no statistically significant on positive event date of the whole event window. Consequently, Trump's tweet with negative sentiment can lead to abnormal trading volume while there is no impact of positive sentiment on the abnormal trading volume of S&P500.

Conclusion

In this research, the hypothesis test is to identify the impact of Trump's tweets related to sentimental analysis upon the short-term movement of S&P500. The sentimental analysis of Trump's tweet is determined by VADER. In response to President Donald Trump's tweet based on sentimental analysis, the result indicates that the negative Trump's tweets appear to have elicited a significant impact on the

movement of S&P500. The negative tweets can generate an abnormal return on S&P500 on the same day as tweeting. However, the impact on Trump's tweets is perfectly eliminated within 2 to 3 trading days according to the result of the cumulative abnormal return. Regarding the positive Trump's tweet, there is no such a significant relationship on S&P500 abnormal return. For the trading volume, only a transitory increase in trading volume for negative Trump's tweets are found in an analysis.

The result of this paper is slightly diffrent from Colonescu (2018) that both positive and negtive sentiment of Trump's tweet can provide an impact on DOW. However, the difference in results could be from the intervals of data, the method to analyze sentiment, the analysis technique, and the difference in indices (Augby et al. 2018).

Finally, the implication of the transitory price effect including the increase in trading volume related to Trump's tweet is that it was the primarily small retail investor called noise trader who focus and response to Trump tweet as one of the market indicators. Interestingly, such traders react to the negative tweet rather than the positive one. Taken as a whole, this study can conclude that sentimental analysis could be considered as an assistance factor to encrypt Trump's tweet impact on the financial index like S&P500.

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References

Abraham, J., Higdon, D., Nelson, J., & Ibarra, J. (2018). Cryptocurrency Price Prediction Using Tweet Volumes and Sentimental Analysis. SMU Data Science Review, 1(3), 1-22.

Alloway, T. (2019, September 9). JPMorgan Creates 'Volfefe' Index to Track Trump Tweet Impact. [Blog post]. Retrieved from https://www.bloomberg.com/news/articles/2019-09-09/jpmorgan-creates-volfefe-index-to-track-trump-tweet-impact.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. Journal of Finance, 36(3), 1259-1294.

Augby, S., Musawi, N., & Mezher, A. (2018). Stock Market Prediction Using Sentimental Analysis Based on Social Network: Analytical Study. Journal of Engineer and Applied Science, 15, 2388-2402.

Azar, P. D., & Lo, A. W. (2016). The Wisdom of Twitter Crowds: Predicting Stock Market Reaction to FOMC Meeting via Twitter Feeds. Journal of Portfolio Management, 22(5), 123-134.

Balji, D., & Burgess, M. (2019, May 8). Each Word of Trump's Tariff Tweets Wiped $13 Billion Off Stocks. Bloomberg. [Blog post]. Retrieved from https://www.bloomberg.com/news/articles/2019-05-08/each-word-of-trump-s-tariff-tweets-wiped-13-billion-off-stocks.

Barber, B. M., & Odean, T. (2008). All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institution Investors. Review of Financial Studies, 21(2), 785-818.

Brown, S.J., & Warner, J.B. (1985). Using Daily Stock Return: The Case of Event Study. Journal of Financial Economics, 14(1), 3-31.

Bollen, J., Mao, H., & Zeng, X. J. (2011) Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1-8.

Born, J. A., Myers D.H., & Clark W. J. (2017) Trump tweets and the efficient Market Hypothesis. Algorithmic Finance 6 (2017), 7, 103-109.

Cakra, Y. E., & Trisedya, B. D. (2016). Stock price prediction using linear regression based on sentiment analysis. 2015 International Conference on Advanced Computer Science and Information Systems (ICACSIS), Depok, 10-11 October 2015 (pp. 147-154). Depok, IEEE: Institute of Electrical and Electronics Engineers.

Chen, X., Cho, Y., & Jang, S.Y. (2015). Crime Prediction Using Twitter Sentiment and Weather. 2015 Systems and Information Engineering Design Symposium, Virginia, 24-24 April 2015 (pp. 63-68). Charlottesville, IEEE: Institute of Electrical and Electronics Engineers.

Clayton, R. B. (2014). The Third Wheel: The Impact of Twitter Use on Relationship Infidelity and Devoice. CYBERPSYCHOLOGY, BEHAVIOR AND SOCIAL NETWORKING 2014, 17(7), 6, 425-430. https://doi.org/10.1089/cyber.2013.0570

Chauhan, V. K., Bansal, A., & Goel, A. (2018) Twitter Sentimental Analysis Using VADER. Journal of Advanced Research, 5, 485-489.

Colonescu, C. (2018). The Effect of Donald Trump’s Tweets on US Financial and Foreign Exchange Markets. Journal of Business and Economy, 1, 1-14.

Edmans, A., García, D., & Norli, Ø. (2007). Sports Sentiment and Stock Returns. The Journal of Finance, 62(4), 1967-1998.

Espenlaub, S., Goergen, M., & Khurshed, A. (2001). IPO lock-in agreements in the UK. Journal of Business Finance & Accounting, 28, 1235-1278.

Fang, L. & Peress, J. (2009). Media Coverage and the Cross-section of Stock Return. Journal of Finance, 30(5), 2023-2052.

Fenn, E. A. (2019). Using Social Media Analytics: The Effect of President Trump's Tweets on Companies' Stock Performance. Accounting 22, 1-27.

Fendel, R., Burggraf, T., & Huynh T. L. (2019). Political News and Stock Price: Evidence from Trump's Trade War. Forthcoming, Applied Economics Letters. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3479822.

Henning-Thurau, T., Wiertz, C., & Feldhaus, F. (2015). Does Twitter matter? The impact of microblogging word of mouth on consumer's adoption of new movies. Journal of the Academy Marketing Science, 43(3), 375-395.

Liu, E. (2019, September 9). Yes, Trump's Tweets Move the Stock Market. But Not for Long. [Blog post]. Retrieved from https://www.barrons.com/articles/donald-trump-twitter-stock-market-51567803655.

Matthias, W. (2011). Reuters sentiment and stock returns (KOF Working Papers No. 288) Retrieved from KOF Swiss Economic Institute, ETH Zurich website: https://econpapers.repec.org/paper/kofwpskof/11-288.htm.

Meyersohn, N. (2018, April 2). Amazon stock sinks following Trump's attacks [Blog post]. Retrieved from https://money.cnn.com/2018/04/02/news/companies/amazon-stock-trump/index.html

Park, C. W., & Seo, D. R. (2018). Sentimental Analysis of Twitter Corpus Related to Artificial Intelligence Assistants. 2018 5th International Conference on Industrial Engineering and Applications (ICIEA), Singapore, 26-28 January 2018 (pp. 495-498). Singapore, IEEE: Institute of Electrical and Electronics Engineers.

Rayarel, K. (2018). The Impact of Donald Trump's Tweets on Financial Markets (Undergraduate Dissertation, The University of Nottingham, Nottingham, United Kingdom). Retrieved from https://www.nottingham.ac.uk/economics/documents/research-first/krishan-rayarel.pdf.

Rao, A. & Srivastava, S. (2012). Analyzing Stock Market Movement Using Twitter Sentimental Analysis. Proceedings of the 2012 International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2012), Northwest Washington, August 2012 (pp. 119-123). Massachusetts, IEEE: Institute of Electrical and Electronics Engineers.

Sohangir, S., Petty, N., & Wang, D. (2018). Financial Sentiment Lexicon Analysis. 2018 IEEE 12th International Conference on Semantic Computing (ICSC), California, 31 January-2 February 2018 (pp. 286-289). Laguna Hills, IEEE: Institute of Electrical and Electronics Engineers.

Sprenger, T., & Welpe, I. M. (2014). Tweets and Trades: The Information Content of Stock Microblogs. European Financial Management, 20(5), 926-957. http://dx.doi.org/10.2139/ssrn.1702854

Tu, J.I. (2017, May 8). Nordstrom stock climbs despite tweet attack from Trump over Ivanka fashions. [Blog post]. Retrieved from https://www.seattletimes.com/business/retail/nordstrom-trump/

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting Stock Market Indicators Through Twitter "I hope it is not as bad as I fear". Procedia – Social and Behavior Science 2011, 26, 55-26. https://doi.org/10.1016/j.sbspro.2011.10.562