The impact of social media on movement of the VIX Index: The case of Donald Trump

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Abstract

In my thesis, I investigate the impact of Donald Trump's tweets on the CBOE's Volatility Index (VIX). I analyze a sample of Trump's tweets from January 20, 2017 to April 12, 2020 with the use of AFINN, a sentiment analysis tool. On the one hand, the results reveal that Trump's tweets are not significant predictors of the VIX index. The interaction of Coronavirus and Trump's tweets sentiment scores are also not a significant predictors for the VIX. However, investors are more sensitive to Trump's tweets volume in the Coronavirus than in the non-Coronavirus period. On the other hand, percentage change of VIX on Friday are lower than the change of VIX on other working days.

Keywords: Donald Trump, Twitter, VIX Index, AFINN, Coronavirus.

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List of Abbreviations

Covid-19: Coronavirus pandemic started from 2019.

Dow Jones: Dow Jones Industrial Average (DJIA).

FRED: Federal Reserve Economic Data (Federal Reserve Bank of St. Louis)

FTSE 100: Financial Times Stock Exchange 100 Index.

MCQ: Multi-Classifier for Equities.

MSCI: Morgan Stanley Capital International.

NAFTA: North American Free Trade Agreement.

NLP: Natural Language Processing.

S&P 500: Standard and Poor 500.

VAR: Vector Autoregression.

VIX: Chicago Board Options Exchange's Volatility Index.

Section 1. Introduction

1.1. Motivation

"*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!*"[1]

This was a tweet from newly elected President Donald Trump in 2016. After this simple tweet from Trump, about $1.2 billion USD of Lockheed Martin-corresponds to about 2% of its market value, was lost while Boeing's market value increased by 0.5%[2]. Certainly, the implied volatility of S&P 500 – VIX, fluctuated corresponding to this event. It is not the first time Trump's tweets hit the market. Unlike his predecessor, Trump is seemed to be addicted on Twitter. He usually tweets and in many cases, his tweets reflect his policies before it would be announced officially. He is also well-known because of his unpredicted movement, e.g. executing unprecedented policies on international forums. Up until now, Trump has withdrawn US from the Paris Agreement on climate change mitigation. He also enacted tariffs on steel and aluminum imports and rolled back several trade agreements such as NAFTA. The two most significant affairs during his Presidency are trade war with China and the global Coronavirus pandemic. In 2018, Trump proposed trade barriers on China due to the trade deficits between two countries. This movement leads to many consequences, including turbulence in the stock

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[1] It was made on Dec 23, 2016 from Trump's Twitter account @realDonaldTrump.
[2] https://www.cnbc.com/2016/12/22/lockheed-martin-shares-take-another-tumble-after-trump-tweet.html

market. For example, the Dow Jones Industrial Index dropped nearly 600 points as part of the trade war.

Besides the Dow Jones, VIX values-sometimes referred as "fear gauge", were higher in between 2018 and 2019 than in 2017. This feature is consistent with the trade war between US and China. It should also be noted that in during the Presidency, the global pandemic – Covid-19, makes the first crisis since the Great Recession 2007-2009. In March 16 2020, VIX hit 82.7%, even higher than its value during the peak of global financial crisis in 2007-2009. Trump's uncertain temper, following by unpredicted tweets and decisions, makes the markets more uncertain.

It seems that not only Trump's tweets but also tweets from other well-known people affect to the financial market. Elon Musk, founder of SpaceX and CEO of Tesla Motors, is a typical example. He also tweets several times and in some cases, his tweets affect greatly to both himself and his companies. For example, after the tweet "Tesla stock price too high imo"[3], $14 billion market value of Tesla was wiped out. Musk also himself suffered the loss of $3 billion. However, the case of Trump is special because he is the leader of the most influence country in the world. He has right to execute policies so what he says can greatly affect to not only the US but also to the rest of the world.

With this purpose, I conduct this research to answer the question: "*Do Trump's tweets impact on the movement of the VIX index?*"

In my paper, I propose the two hypotheses as following:

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[3] It was made on May 1, 2020 from Elon Musk's Twitter.account @elonmusk. "*imo*" is the abbreviation of "In my opinion".

Hypothesis 1: Group of Trump's non-positive tweets has greater impact on difference of VIX than group of positive tweets.

The VIX measures the volatility of S&P 500 options[4]. Normally, the negative news will be focused more than the positive news. Psychologists and economists have spent time to justify this asymmetry relationship. Kernell (1977) shows the evidence that negative information has bigger impact in voting than positive news. Kahneman and Tversky (1979) provide the *Prospect Theory* to show that because of aversion, people care more on loss than gain in the same level. Using UK time-series analyses, Soroka (2006) finds that negative economic information attracts more responses from public than positive economic information. The author also finds the same trend in case of mass media content. Smales (2016) tests the impact of aggregate news sentiment on implied volatility. He found that news sentiment negatively impacts the change in implied volatility. Also in that article, the author assessed the asymmetrical impact of positive and negative news on the change of VIX. Unsurprisingly, the sentiment of news negatively affects the change of VIX, that is, the positive news negatively affects the change of VIX and vice versa. Sharing the same idea, Groß-Klußmann and Hautsch (2011) find the release of relevant news increases the implied volatility, with the impact of positive news is less than the negative news.

Overall, I expect Trump's non-positive tweets have greater impact on difference of VIX than his positive tweets.

Hypothesis 2: The number of tweets increases VIX.

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[4] Black and Scholes (1973) provide the theoretical framework of European call option. CBOE's VIX Index is the implied volatility on that paper. Please refer to it for further details.

Byström (2009), by using Google News, finds strong positive correlation between volatility of MSCI World Index and VIX Index, and the volume of news on the market that available to the investors. This finding means the volatility of the market increases with the increase in volume of relevant news to the investors. On another work with same author, Byström (2016), by examining over nine million stock market-related news stories in both English and Chinese, finds the directional link between news and volatility. The author also finds that regardless of languages, news volume improves forecasts.

In general, I expect the number of tweets Trump makes every day positively affects the change in return of VIX.

In my thesis, I investigate the effect of the number of Trump's daily tweets and their sentiment on the movement of the VIX Index. The main contribution of this thesis to the literature is the connection between Trump's tweets and the fluctuation of the VIX Index. The result shows that after controlling by macroeconomic and financial indices, including the S&P 500 and Dow Jones, Trump's tweets sentiment scores and number of tweets are not significant predictors of the VIX return. The interaction of coronavirus and Trump's tweets is also not a significant predictor for the return of VIX. Meanwhile, the result shows the significant lower value in return of VIX on Friday than the returns of VIX on other days, except on weekends. Another remarkable result is that investors are more sensitive to volume of Trump's tweets during the Coronavirus.

The rest of the paper is organized as follows. In chapter 2, I present details of the models, including formulas about specific variables, and statistics descriptions. Details about the sentiment analysis and how sentiment scores assigned are also discussed. Chapter 3 presents the main results of the paper. In chapter 4, I conclude the paper with implications, limitations and potential extensions of the paper.

1.2. Literature review

The relationship between volatility and announcement has been investigated for a while. Onan, Salih, and Yasar (2014) investigate the impact of macroeconomics announcement on implied volatility and the VIX Index. One of the findings in the paper is that the good and bad news affect asymmetrically. There is also a trend to find the way to predict the stock market by investigating social media.

Many studies already do research in the broader sense. Strycharz, Strauss and Trilling (2018) find the reciprocal relationship between the closing prices of three companies listed on the Amsterdam Exchange Index and online media coverage related to these three firms in the period between 2014 and 2015. Burgraff, Fendel, and Huynh (2019) focus mainly on tweets related to trade war. They find that this category of Trump's tweets predicts the S&P 500 and VIX. In the paper, the authors also find a significant difference between average VIX "with tweets" and "without tweets". Nisar and Yeung (2018) consider Twitter as a tool to forecast the movement of the stock market by considering politics-related sentiment and the movement of British FTSE 100. However, they do not find a significant effect of this relationship. Mao et al (2016) take research on the daily number of tweets that mentioned S&P 500 stocks. The authors find that stock market indicators are correlated with the number of tweets per day.

Bollen, Mao and Zeng (2011) collect a large scale of Twitter data between February 28, 2008 and December 19, 2008 and find that the predictions of the Dow Jones index improve if sentiment score is included in the model. Papaioannou et al (2013) provides the model to forecast the EUR/USD exchange rate in a high-frequency intraday trading with the use of Twitter data. The authors find that Twitter information in some cases provides the efficient forecast regarding the very short forex.

Nguyen, Shirai and Velcin (2015) shows the effectiveness of the sentiment analysis in predicting stock prices. The model in this article, including the sentiment score, performs better than the model with only historical prices. Smales (2016) examines the relationship between aggregate news sentiment based on stock indices and the fluctuation of VIX Index. The author finds the negative relationship between them. Using VAR analysis, Smales (2016) also finds strong positive relationship between previous and current period differences in volatility and returns of stocks.

Recently, the global pandemic Covid-19 has recently played an important role on the fluctuation of the global economy. A recent paper by Albulescu (2020) shows news on COVID-19 marginal negatively affect the oil prices, while controlling for the role of VIX Index. Mamaysky (2020) examines the interaction between financial market and news related to Coronavirus pandemic. Mzoughi et al. (2020) examine the effect of Covid-19 outbreak on oil and stock market volatility between January and March 2020 by VAR model. The result shows that the global pandemic has greater impact on equity volatility than crude oil prices. Bakas and Triantafyllou (2020) empirically assess the effect of economic uncertainty related to Covid-19 outbreak on the volatility of some indices such as gold and crude oil prices. The outcomes of the article show that uncertainty related to coronavirus outbreak impact negatively on the volatility of commodity markets while it affects gold market less significant but positively.

Overall, there is a gap in literatures. Previously, the effect of Trump's tweets from working days has not been studied. Meanwhile, most of previous works focus solely on effect of the volume of Trump's tweets on stock indices while several articles implement simple methods to measure sentiment. Meanwhile, my paper implements a new method – NLP, to measure sentiment of texts. Basically, implementing machine learning into economic paper seems to be uncommon. Therefore, I hope my paper can contribute to the literatures.

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Section 2. Research Design

2.1. Data and Methodology

I employ two types of data. The first type is text data – Trump's tweets and the second type is economical and financial indices.

Regarding economical and financial indices, I gathered data for 4 variables. They are CBOE's VIX Index, the S&P 500 adjusted closing price, the Dow Jones Index adjusted closing price, and the Economic Policy Uncertainty Index for the US. I gathered VIX, S&P 500, and Dow Jones data from Yahoo! Finance[5]. I employed the website[6] of FRED to retrieve data of Economic Policy Uncertainty Index for US. It should be noted that Economic Policy Uncertainty Index measures the uncertainty of economic policy[7]. All four variables above were collected from the same period with Trump's tweets. Figure 1 includes the graphs of all 4 variables. I also include a dummy variable for coronavirus period. It is 1 for day after January 1, 2020 and 0 for otherwise.

Trump's tweets are public on the Internet so it is not difficult to collect them. The website named: "Trump Twitter Archive"[8] is the website created by Brendan Brown in 2018. This site has collected about 33000 tweets, mainly from Trump's account @realDonaldTrump since 2009. This site also has collected tweets from other people, such as his daughter Ivanka

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[5] https://finance.yahoo.com/
[6] https://fred.stlouisfed.org/series/USEPUINDXD
[7] For more information, please visit https://www.policyuncertainty.com/
[8] http://www.trumptwitterarchive.com/

Trump and Vice President Mike Pence. I retrieved data from January 21, 2017, one day after Trump took office, to April 12, 2020. After deleting retweets and cleaning data, there are 11372 tweets in the list (including tweets on weekends).

Trump's tweets are texts so they need to be quantified into numbers. The idea is to measure and assign sentiment score to each tweet. This value can be either positive or non-positive. Based on the score of each tweet, people can construct a daily sentiment time series for further research. The mechanism of this tool based on bag-of-words model (Colonescu, 2018). Each tweet is decomposed in words based on bag-of-words model, then it is compared to a package's dictionary. Finally, it gives out the score to the word (Colonescu, 2018).

Generally, there are several packages to measure the sentiment of news. Kearney and Lombra (2004) simply use the indices on days they are announced as the proxies of news. To measure sentiment of texts, Smales (2016) provide MCQ to find sentiment score of news. It assigns 0 to negative sentiment, 50 to neutral and 100 to positive. In my paper, I employ AFINN to measure sentiment of the tweets from Trump. AFINN was developed by Finn Arup Nielsen in 2011 to build a sentiment lexicon. The latest version of this tool has about 2477 unique words. Each word is assigned by a score between -5 and 5, with 5 is the highest score and -5 is the lowest score that each word can attain. Most of the positive words are assigned with +2 and most of the negative words are assigned with -2 (Nielsen, 2011). After assign score for each word, the package gives the score for each sentence. For example, AFINN gives Trump's personal superlative tweet *"I will be the greatest job-producing president in American history"*[9] 3.0 in terms of sentiment score.

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[9] It was made on Jan 23, 2016 from Trump's Twitter account @realDonaldTrump.

Colonescu (2018) proposes two ways to construct the daily sentiment time series, average sentiment score method and extreme-value method (extreme sentiment score, positive or non-positive of the day). In the first method, the author computes the aggregate sentiment score, then divides by the aggregate number of tweets on that day. In the second method, the author retains only tweets with extreme sentiment score on that day, assuming the message with great impact of the day is the message attracts most responses from the public (Colonescu, 2018). In my opinion, each method has its own limitations. The limitation of average sentiment score is that it neutralizes the important tweets by the non-important ones. The limitation of extreme-value method is that it focuses only on tweets with extreme sentiment scores while some of the other important news are not considered even they can still affect the market and decisions of investors.

In my paper, I use the different method. First, I use AFINN to assign sentiment score to each tweet. I separate all of tweets into two groups: positive and non-positive group of tweets based on their AFINN scores. Tweets with positive AFINN scores are assigned to the positive group and vice versa. After assigning groups to the tweets; the daily AFINN score, with two components for two groups, is computed by taking the aggregate AFINN score of each group of tweets on the day. Following that step, I take the absolute value of the non-positive tweets score. In the case there is only one kind of tweets (only positive or non-positive type) on a particular day, I assign 1 unit to the empty box to make the reasonable logarithm calculation later. The number of tweets each day is also counted. For example, suppose the aggregate score of positive and absolute value of aggregate score of non-positive groups of the day are 15 and 14, respectively and there are 10 tweets in this day; then the daily AFINN score is (15, 14) and number of tweets is 10. This process is taken entirely by Python language.

The dependent variable in the model is the logarithm change in CBOE's VIX. There are three independent variables, absolute value of sentiment scores for positive and non-

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positive groups and total number of tweets each day. All of them are in logarithm of their value. Control variables are logarithm change in the Economics Policy Uncertainty Index of the US, the Dow Jones Index and the S&P 500. The reason I take logarithm all these variables is to standardize the interpretation, percentage change versus percentage change. Normally, financial data is interpreted in percentage change of return. Therefore, using logarithm can make it easier to interpret results at specific time. There is also a dummy variable *corona* in the model to illustrate whether period is before or after the global pandemic. I assign the day January 1, 2020 as the transitional point. After that day, the value is 1. Otherwise, it will be 0.

Meanwhile, on weekends and holidays, the financial market is closed so for those days, data is unavailable. In total, there are 796 observations in the model. Figure 2 includes the graphs of Trump's tweets elements, including sentiment score for each group (positive and non-positive) and aggregate number of tweets per day.

Table 1 describes the variables and formulas in the model.

Table 1. Description of variables

	Variable	Description	Formulas
	Dependent variable		
1	$diff\_vix$	Log change in VIX index	$log\left(\dfrac{closing\_vix_t}{closing\_vix_{t-1}}\right)$
	Independent variables		
2	ln_count	Log of total number of tweets each day	$log(count_t)$
3	$ln\_positive$	Log of total AFINN score each day for positive sentiment	$log(positive\_afinn_t)$
4	$ln\_non\_positive$	Log of total AFINN score each day for non-positive sentiment	$log(positive\_non\_afinn_t)$
	Control variables		
5	$diff\_sp500$	Log change in S&P 500 index	$log\left(\dfrac{closing\_sp500_t}{closing\_sp500_{t-1}}\right)$
6	$diff\_dji$	Log change in Dow Jones index	$log\left(\dfrac{closing\_dji_t}{closing\_dji_{t-1}}\right)$
7	$diff\_usepuindxd$	Log change in Economic Policy Uncertainty US	$log\left(\dfrac{closing\_usepuindxd_t}{closing\_usepuindxd_{t-1}}\right)$
8	$corona$	Dummy variable for coronavirus period	$= \begin{cases} 1\ if\ date\ is\ after\ Jan\ 1, 2020 \\ 0\ otherwise \end{cases}$

2.2. Descriptive statistics

Table 2 describes the correlation of variables in the model. Table 3 illustrates the summary statistics of variables. Both raw variables and variables in the final models are counted.

From table 2, there is a negative relationship between difference of VIX returns and the two indices, S&P 500 and Dow Jones. From the summary statistics table, it can be observed that the mean and standard deviations of log returns of S&P 500 and Dow Jones are nearly identical. Figure 1 shows the graphs of both variables. It can be seen that the two variables suffer a huge loss during the pandemic while they share the same trend in the pre-Corona period. The opposite trend is found in the case of VIX Index and Economic Policy Uncertainty in US. During the Corona period, VIX and Economic Policy Uncertainty in US rocket their value about 1.5-2 times greater than their highest values in the pre Corona period, respectively.

On table 3, the variables *positive_afinn* and *non_positive_afinn* are the raw sentiment scores of two tweets groups. *positive_afinn* is raw sentiment score of positive group while *non_positive_afinn* is absolute value of raw sentiment score of non-positive group, all computed by AFINN. The mean AFINN score of the positive group is 26.3187 unit, greater than the absolute value of mean AFINN score of non-positive group, 14.4278 unit. It should also be noted that the maximum value of the positive group is significantly greater than the counterpart from the rest group by 50 percent. Consequently, the log versions of these two variables in the official models, *ln_positive* and *ln_non_positive*, share the similar properties listed before. On average, Trump tweets approximately 10 times per day while the maximum tweets he makes every day is 36.

The statistics of tweets on working days is summarized on table 4. Wednesday is the day with highest number of tweets while Monday is the day with lowest number of tweets. This

feature is also true when we talk about the average sentiment score for positive group. Wednesday still dominates the rest with average AFINN score is 31.770 while Monday's average AFINN score is only 21.413. Meanwhile, the average sentiment score of non-positive group is largest on Thursday and smallest on Friday. These values are 15.543 and 13.253, respectively. Except Monday and Thursday, the remaining working days share the same feature: the average sentiment score of positive group is at least two times greater than the average sentiment score of the non-positive group.

Table 2. Correlation table

	$diff\_dji$	$diff\_sp500$	$diff\_vix$	$diff\_usepu$	ln_count	ln_non_posi	$ln\_positiv$
$diff\_dji$	1.0000						
$diff\_sp500$	0.9795	1.0000					
$diff\_vix$	-0.6203	-0.6698	1.0000				
$diff\_usepui$	0.0312	0.0299	-0.0378	1.0000			
ln_count	0.0528	0.0565	-0.0778	0.0207	1.0000		
ln_non_posit	0.0894	0.0919	-0.0620	-0.0221	0.6611	1.0000	
$ln\_positive$	0.0239	0.0266	-0.0556	-0.0187	0.7089	0.2348	1.0000

Source: Own calculation by STATA

Table 3. Summary statistics

This table provides number of observations, mean, standard errors, minimum and maximum values for all variables. The total number of observations is 796.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	N	mean	sd	min	max
diff_dji	796	.0002252	.0139588	-.1384182	.1076441
diff_sp500	796	.0002583	.0131973	-.1276522	.0896831
diff_vix	796	.001613	.0880991	-.2998312	.7682452
diff_usepuindxd	796	.0013522	.5085819	-1.710337	2.303838
ln_positive	797	2.902226	.9749718	0	5.003946
ln_non_positive	797	2.049103	1.266149	0	4.61512
positive_afinn	797	26.3187	21.09553	1	149
non_positive_afinn	797	14.42785	14.42147	1	101
ln_count	797	2.128226	.6980702	0	3.583519
count	797	10.34128	6.271613	1	36
coronavirus	797	.0865747	.2813873	0	1
weekday	797	3.012547	1.419478	1	5

Source: Own calculation by STATA

Table 4. Trump's tweets distribution on working days.

	Number of tweets	Average number of tweets	Average AFINN (positive)	Average AFINN (non-positive)
Monday	1436	9.573	21.413	15.180
Tuesday	1615	9.969	26.086	13.802
Wednesday	1814	11.267	31.770	14.416
Thursday	1632	10.074	24.043	15.543
Friday	1745	10.771	27.951	13.253

Source: Own calculation by PYTHON

Table 5. Effects of Trump's Tweets on VIX.

Dependent variable is daily log change in VIX. The first model controls for weekdays effect. The last three columns are models with interactions between coronavirus and Trump's tweets specifications. Robust standard errors are in parenthesis.

VARIABLES	(1) No_corona	(2) corona_count	(3) corona_scores	(4) corona_all
diff_dji	4.206***	4.246***	4.225***	4.274***
	(1.514)	(1.506)	(1.509)	(1.482)
diff_sp500	-8.851***	-8.897***	-8.898***	-8.929***
	(1.436)	(1.434)	(1.435)	(1.407)
diff_usepuindxd	-0.00180	-0.00194	-0.00188	-0.00181
	(0.00427)	(0.00430)	(0.00429)	(0.00428)
ln_positive	0.00142	0.00119	0.00185	0.00362
	(0.00422)	(0.00408)	(0.00389)	(0.00389)
ln_non_positive	0.00184	0.00188	0.000864	0.00221
	(0.00321)	(0.00307)	(0.00285)	(0.00284)
ln_count	-0.00510	-0.00688	-0.00520	-0.00967
	(0.00850)	(0.00832)	(0.00801)	(0.00798)
corona		-0.0448	0.0136	-0.0311
		(0.0530)	(0.0593)	(0.0571)
ln_positive * corona			-0.0104	-0.0398
			(0.0150)	(0.0250)
ln_non_positive * corona			0.0128	-0.00318
			(0.0114)	(0.0170)
Monday	0.0367***	0.0367***	0.0364***	0.0359***
	(0.00813)	(0.00809)	(0.00814)	(0.00810)
Thursday	0.0218***	0.0223***	0.0216***	0.0220***
	(0.00634)	(0.00636)	(0.00643)	(0.00651)
Tuesday	0.0244***	0.0244***	0.0240***	0.0237***
	(0.00652)	(0.00645)	(0.00651)	(0.00649)
Wednesday	0.0138**	0.0141**	0.0134**	0.0141**
	(0.00617)	(0.00618)	(0.00615)	(0.00624)
ln_count * corona		0.0214		0.0709*
		(0.0200)		(0.0426)
Constant	-0.0132	-0.00970	-0.0126	-0.0112
	(0.00941)	(0.00895)	(0.00887)	(0.00888)
Observations	796	796	796	796
R-squared	0.489	0.491	0.492	0.496

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Section 3. Results

I construct four models with different specifications. The first model, which is different from the rest because of no coronavirus interactions, assesses the relationship between Trump's tweets elements and difference in return of VIX. In all models, I imply the days fixed effect. Table 5 shows the results of the linear regression models. I performed the Breusch-Pagan test and found the strong signal of heteroskedasticity. All the four models are assessed by robust standard errors.

From table 5, it can be seen that in all four models, the results show a statistically significant negative relationship between logarithm change in VIX and logarithm change in S&P 500 Index. The (1) model gives the value of beta coefficient is -8.851 and this coefficient is significant at 1% level of significance. This result is expected as VIX measures the volatility of S&P 500 options. The result can be interpreted as: a 1% increase change in return of S&P 500 leads to a decrease of 8.851% in return of VIX, ceteris paribus. The results also show the statistically significant positive relationship between the logarithm change in VIX and logarithm change in Dow Jones Index. The beta coefficient given by model (1) is 4.206 and statistically significant at 1% level of significance. Meanwhile, the relationship between logarithm change in Economic Policy Uncertainty US and logarithm change in VIX is statistically insignificant.

While the relationships among stock market indices and VIX are statistically significant, Trump's tweets elements, including logarithm in sentiment scores of each group and aggregate number of tweets per day, share statistically insignificant relationships with VIX Index. Although the impact of non-positive group is larger than positive group, there is no significant effect between sentiment scores (both groups) and the log change VIX. Moreover,

the marginal effect between logarithm of aggregate number of tweets and logarithm change in VIX is negatively insignificant even at 10% level of significant; that means there is no significant effect between aggregate number of tweets and the percentage change in VIX. This feature spreads through all four models. These results suggest Trump's tweets elements, including sentiment scores and aggregate number of tweets, do not have a significant effect on change of VIX.

In this paper, I include the fixed effect model with working days in weeks in order to find difference in effect of Trump's tweets on each days. The results in all 4 models show that on working days, the difference in the percentage changing in VIX's return on any working day relative to Friday is greater than zero, controlling for other variables. Most of these results are statistically significant at a 1% level. Only the coefficient of Wednesday is statistically significant at a 5% level. Comparing the results among all working days in all four models, it can be observed the changing in VIX is largest on Monday and smallest on Friday. One interpretation for this result: the difference in percentage changing in VIX's return on Monday relative to Friday is 0.0367 percent, controlling for other variables.

The impact of coronavirus and its interactions with independent variables are assessed in the last three models (2), (3) and (4). Table 5 shows statistically insignificant results on corona's interactions with independent variables, including sentiment scores and aggregate number of tweets each day. Only the interaction between coronavirus and aggregate number of tweets each day is statistically significant at a 10% level. This interesting feature can be interpreted as following: although there is no significant effect of either *ln_count* or *corona* on VIX, in the Coronavirus period, the 1% increase in number of Trump tweets corresponds to the 0.0709% increase in gross return of VIX, ceteris paribus.

Table 6 summarizes the two hypotheses and the decisions.

Table 6. Hypotheses evaluations.

Hypothesis 1	*Group of Trump's non-positive tweets has greater impact on difference of VIX than group of positive tweets.*	**Fail to reject null hypothesis**
Hypothesis 2	*The number of Trump's tweets increases VIX.*	**Fail to reject null hypothesis**

Section 4. Conclusion

This thesis examines the impact of Trump's tweets on the movement of VIX Index. The role of coronavirus as well as effect to the fluctuation of the VIX are also examined.

On the one hand, the results show that on working days, the percentage changing in VIX's return on any working day is relatively greater than its changing on Friday. The greatest changing in VIX's return is on Monday and smallest is on Friday and all these results are statistically significant. The results are not surprising as Monday is normally the day financial market opens.

On the other hand, I find no evidence that Trump's tweets significantly affect the changing in VIX. This result is surprising as many previous researches show the opposite outcome. Although Trump's tweets usually reflect the government's policies, it does not mean that his tweets are the strong signal to the change of the financial market. In other words, investors should not rely solely on his tweets but on all of the news on the markets. The effect of coronavirus to the changing in VIX is also faint, with only the interaction between the number of Trump's tweets and the pandemic is positively significant. As VIX measures the "fear" in the market, this remarkable result implies that in the Coronavirus pandemic, investors are more sensitive to the Trump's tweets volume. When Trump tweets more, it is likely that the gross return of VIX will increase marginally and make the market more uncertain.

I think there are limitations in my model. The first limitation is that I did not count the effect of Trump's tweets on Saturday and Sunday on the next Monday. I only examine the effect of his tweets from the working days on the change of VIX Index. Normally, Trump's tweets on weekend may affect people and as people can still make transaction offers during

weekend, it will be valid in the first opening day of the market. The second problem is that the method I used to measure the sentiment for Trump's tweets has its own limitations. One significant limitation is that in some cases, machine cannot justify sentiment of a sentence correctly because the sentence consists of two polarities. Consequently, the algorithm finds it hard to analyze so it may harm the outcome of the research. Another possible limitation of paper is that there are factors, which have impact on VIX, are not taken in the models but I did not find. One candidate is the daily number of people affected by Coronavirus.

In general, the topic of Trump's tweets is relative new and there are a limited number of papers on it. The paper contributes a humble result about the impact of social media from one particular person to the movement of the VIX Index. This topic can be further studied in the future by evaluating the social network accounts from various well known people whose great influence in the world. One possible extension of the paper is by studying the effect of Trump's tweets categories on the change of VIX. Instead of studying the aggregate number of tweets, we can categorize his tweets into different topics, i.e. trade war between US and China, employment/unemployment, or interest rates, etc. In that scenario, machine learning algorithm is needed to categorize tweets.

Appendices

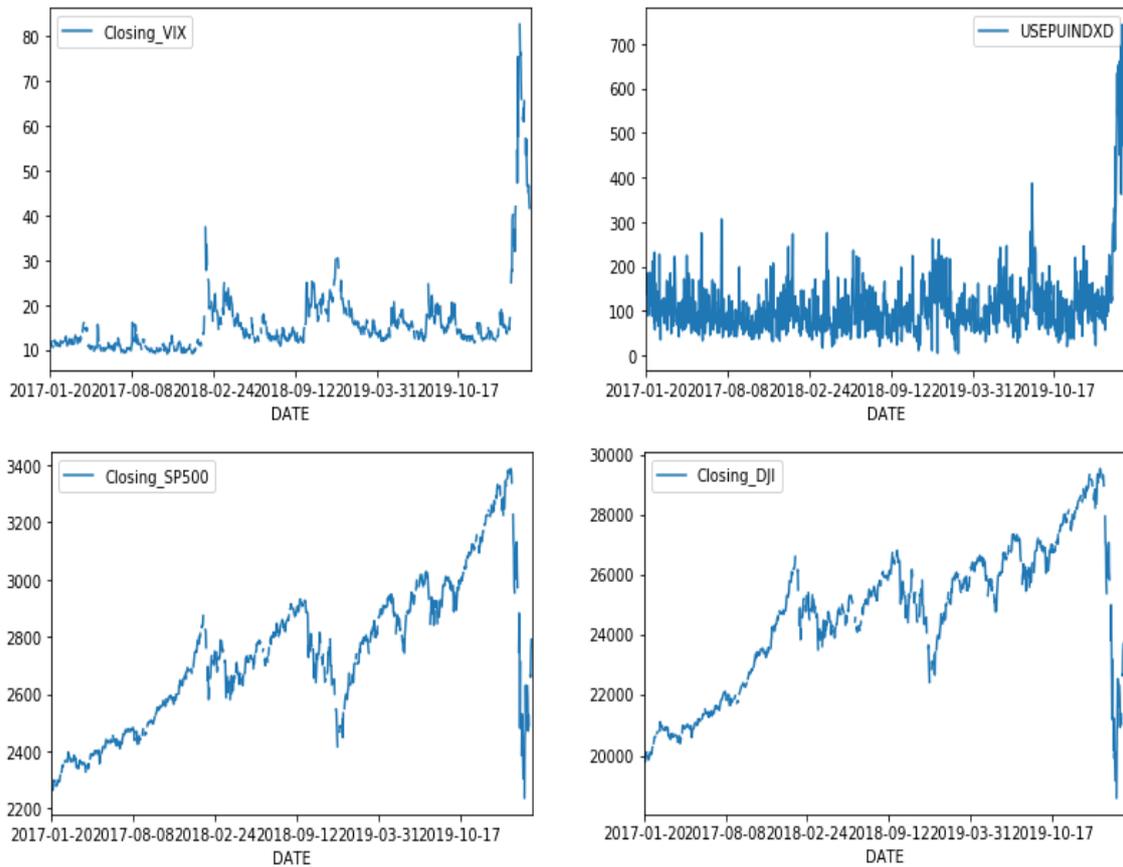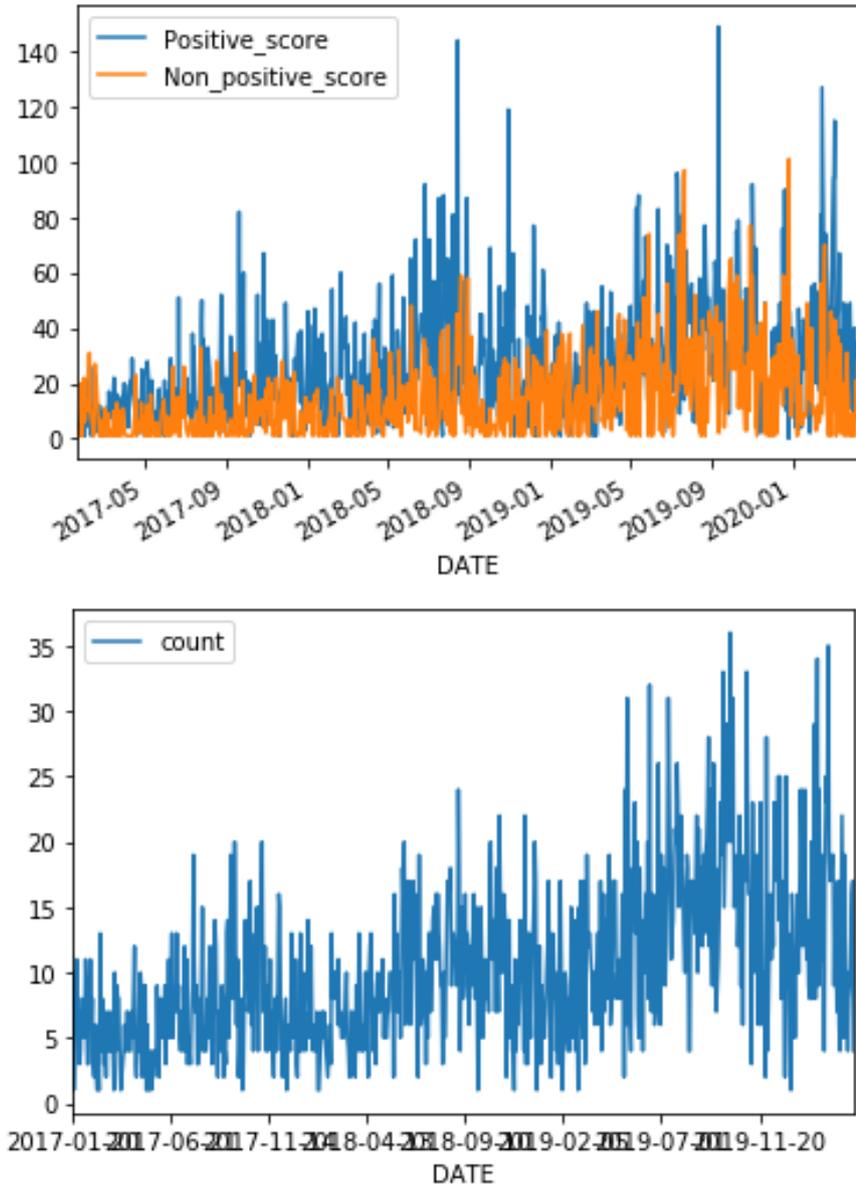Figure 1. Macroeconomics and financial indices graphs

Figure 2. Trump's tweets elements (sentiment score for each group and aggregate number of tweets per day).

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