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Do President Trump's Tweets Increase Uncertainty in the US Economy?

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Abstract

When President Trump tweets, does it change uncertainty in the economy? This study gathers President Trump's tweets off his twitter accounts from October 2016 to October 2017 and classifies each of them as either negative (expected to increase uncertainty), positive (expected to decrease uncertainty) or neutral (no effect expected on uncertainty). I find that tweets with a negative sentiment were followed by an increase in uncertainty in the VIX and S&P 500 1 and 2 minutes after the tweet. Similar results were found for positive tweets. Non-neutral tweets increase trading volume in the VIX and S&P 500 by up to 200% in the hour following the tweet. Overall, this study finds that up to 2 minutes after the non-neutral tweet, investors appear to be trading based on the sentiment value of that tweet. However, after 2 minutes, investors trading strategies appear to veer away from tweet sentiment value, but trading volumes in these indices are still much higher than normal. Policy makers should be aware of this increased volatility stemming from the President's unconventional twitter use and may suggest more conventional ways to spread new information to the financial markets.

Keywords

Finance, Stock Market, President Trump, VIX, S&P 500, Uncertainty

Subject Categories

Business | Finance and Financial Management

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Do President Trump's Tweets Increase Uncertainty in the US Economy?

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Undergraduate Honors Thesis

Advisor: Jay Horvath

Abstract

When President Trump tweets, does it change uncertainty in the economy? This study gathers President Trump's tweets off his twitter accounts from October 2016 to October 2017 and classifies each of them as either negative (expected to increase uncertainty), positive (expected to decrease uncertainty) or neutral (no effect expected on uncertainty). I find that tweets with a negative sentiment were followed by an increase in uncertainty in the VIX and S&P 500 1 and 2 minutes after the tweet. Similar results were found for positive tweets. Non-neutral tweets increase trading volume in the VIX and S&P 500 by up to 200% in the hour following the tweet. Overall, this study finds that up to 2 minutes after the non-neutral tweet, investors appear to be trading based on the sentiment value of that tweet. However, after 2 minutes, investors trading strategies appear to veer away from tweet sentiment value, but trading volumes in these indices are still much higher than normal. Policy makers should be aware of this increased volatility stemming from the President's unconventional twitter use and may suggest more conventional ways to spread new information to the financial markets.

Introduction and Literature Review

Since he was elected, President Trump has been using twitter as a main channel to spread his thoughts. As the efficient market hypothesis states, all new information should be priced into markets almost immediately. Since twitter is just another source of information, these tweets should be processed and priced in just the same as any other White House announcement. However, President Trump tends to use twitter in unique ways compared to President Obama, who was the first President to have a twitter account. President Trump's tweets occur at all hours of the day and often include inflammatory rhetoric. This paper aims to see if this unique type of information, sent directly from one of the world's most influential people to everyone with an internet connection, has any impact on uncertainty in the United States economy.

Even though President Trump has only been in office for a short period of time, there has been previous research on this topic that this study will extend upon. Ge, Kurov and Wolfe (2017) have recently published a paper from which I will use many of the same methods. In their study, they look at company specific tweets and the effects those tweets have on the stock prices over time. They conclude that investors pay attention to presidential company-specific statements even when such statements have no lasting effect on shareholder value. I plan to expand these thoughts into the picture of the overall economy and see what macroeconomic effect these tweets may have.

Born, Myers, and Clark (2017) have added to this analysis of company specific tweets. They find that "the bulk of the market's reaction to Trump's tweets is from the open(ing price) to the market's close on the announcement day. Negative tweets are associated with a (negative) abnormal return the day following the tweet. Since the tweets do not appear to contain any new information, this suggests that irrational/noise traders are responsible for the pricing impacts" (Born, 9). In their paper they also note that trading volume increases by 87% on the day of the tweet and 56% on the day after the tweet. To accompany trading volume increases, google search volume about the mentioned company increases during the time period of the tweet and then falls off in the subsequent weeks. This supports the idea that most of the trades are coming from relatively uninformed "noise" traders. My studies will add on to their findings on increases in trading volume, but I will break this down to minute by minute volume changes to amplify the effects of these tweets on the macroeconomy.

President Trump's twitter account is full of statements that are difficult to analyze, which makes picking significant tweets more problematic. Watt (2017) looks into all of Trump's tweets and "apply the three classical modes of rhetoric—forensic/judicial, deliberative, and epideictic/ceremonial rhetoric—to see how the modes manifest in Donald Trump's tweets as a presidential candidate, as President-Elect, and as President" (Watt, 1). Typically, politicians stick to the deliberative mode, as it gets their talking point across the best and brings up issues for debate while making a case for or against a certain issue. Trump does have some tweets that use deliberative mode, for example: "I will issue a lifetime ban against senior executive branch officials lobbying on behalf of a FOREIGN GOVERNMENT! #DrainTheSwamp" (Watt, 3). However, this is the least frequent mode that Trump tweets in, so we are forced to look at other areas of rhetoric where the President may have economically impactful tweets. Trump tends to use the forensic mode the most in his tweets, which consists "placing blame or praise for something that happened in the past" (Watt, 2). Here is an example of Trump's use of forensic tweeting: "Everyone is laughing at the @nytimes for the lame hit piece they did on me and women. I gave them many names of women I helped-refused to use" (Watt, 3). I will use their ideas about President Trump's non-standard modes of political rhetoric when trying to analyze if a tweet will increase, decrease, or have no effect on uncertainty.

When trying to decide how to capture the reaction to these tweets, I referenced Zheludev, Smith, and Aste (2014). In this paper they use sentiment analysis to predict future changes in financial markets. They find that "social media sentiment in a broad-based system like Twitter is indicative of future market movements only in a narrow range of assets, and that such social media sentiments are more indicative than just message volumes" (Zheludev, 11). I will expand on their research in two ways. First, I will find the narrow range of assets that represent the macroeconomy and would be significantly impacted by President Trump's twitter accounts, which I find evidence for the VIX and S&P 500. Secondly, I will look at more overall sentiment value rather than message volume as an indication for an increase or decrease in uncertainty caused by President Trump's tweets.

Zhang, Fuehres, and Gloor's (2011) paper looks to see the effect on the VIX, Dow, NASDAQ and S&P500 using a similar type of sentiment analysis as Zheludev, Smith and Aste. They notice that no matter what the sentiment, “when emotions on twitter fly high, that is when people express a lot of hope, fear, and worry, the Dow goes down the next day” (Zhang, 61). They also find that emotional tweets have a very strong positive correlation with the VIX, something that I will be expanding on in my paper. This study notes the importance of lag time on these indices, using an average of the current day and the two previous days to predict the stock market indicators for the next day. This index displays significant negative correlations to Dow, NASDAQ and S&P500, and significant positive correlation to VIX. My paper will contribute to their findings by using the VIX when looking at non-neutral tweets from the President and looking at how lag time may reverse the original effects of the tweet.

Data

I collect tweets from President Trump’s two twitter accounts, @POTUS and @realDonaldTrump, directly from Twitter from October 2016 (right after Trump won the Republican Primary Election) to October 2017 (the date I started my analysis). Then I gather data at daily time intervals for the VIX. This data came from Wharton Research Data Services and looks at open and close values of the VIX during the same interval that I collected tweets. For intraday data, I use minute by minute data from February 2017 to November 2017 for the VXX and SPY, which is used as proxies for the VIX and S&P 500. I got this data from Dukascopy, a Swiss forex bank and marketplace. This was all the data required to carry out my research.

Method

First, I go through every tweet that I collected and assign a sentiment value based on the content of that tweet. These sentiment values are -1 for a negative tweet, 0 for a neutral tweet, and 1 for a positive tweet. The thinking behind this is that negative tweets would likely increase uncertainty, neutral tweets should have no effect, and positive tweets should decrease uncertainty. Tweet sentiment is fairly obvious to the reader as President Trump often conveys a strong message in his tweets. Some examples of my classifications are below:

Negative/Increasing Uncertainty (value of -1)

"The era of strategic patience with the North Korea regime has failed. That patience is over. We are working closely…"

Positive/Decreasing Uncertainty (value of 1)

"Starting to develop a much better relationship with Pakistan and its leaders. I want to thank them for their cooperation on many fronts."

Neutral/No Change on Uncertainty (value of 0)

"Wishing everyone a safe and Happy Halloween! #Halloween2017"

After assigning these sentiment values I then narrow these tweets down to only tweets that occurred on trading days (Monday – Friday, excluding holidays) that had a non-neural sentiment value, call this dataset **A** (size = 140). I made subsets of set A depending on the time of the tweet:

1. If the tweet occurs before market hours (12am – 9:29am EST) is it called **Ab** (size = 67)
2. If the tweet occurs during market hours (9:30am – 4:00pm EST) is it called **Ad** (size = 34)
3. If the tweet occurs after market hours, (4:01pm – 11:59pm EST) is it called **Aa** (size = 39)

I split the tweets up into these subsets because depending on when the tweet occurs, the response by financial markets will vary. A tweet that occurs at midnight will likely see less trading volume and therefore less of a reaction than a tweet that occurs at 1pm on a trading day. By separating these tweets into categories, it is easier to measure meaningful reactions through the filter of different indices.

After creating the subsets, I apply the financial markets reaction to them. I start with daily open and close data from the VIX. For tweets in **Ab**, I look at the change in the VIX from the previous days close to the current days open. For tweets in **Ad**, I look at the change in the VIX from open to close on the day of the tweet. For tweets in **Aa**, I look at the change in the VIX from that day's close to the next day's open. I collect all these changes in % change and then analyze the results.

For intraday analysis, I gather set **Ad**, and then narrow it down since I was only able to get intraday data from February 2017 to October 2017. This cut down the size of **Ad** from 34 to 20, referred to as set **Ad2**. Using **Ad2** and my intraday financial market datasets I now have one-minute data on the trading volume and open-close values for the VXX and SPY. To analyze the tweets' effect, I record the close value of the index and the volume at the time the tweet occurred. If the tweet occurs at 30 seconds or more past the minute, I rounded up to the next minute to start my analysis. I the tweet occurs between 0 and 29 seconds after the minute I round down. After recording these initial values for price and volume, I look at the % change in these values 1, 2, 5, 15, 30 and 45 minutes after the tweet occurs. Both my daily and intraday analysis use regressions to find the relationship between the tweet sentiment values and the returns on various indices. For these regressions, I use the following model:

$Y_{t+n} = X_t + U_{t+n}$ Y: Returns at time t+n; X: Sentiment value of tweet at time t; U: Error / Unobservable; n is time after tweet (1 minute to 1 day); $U_{t+n} \sim N(0, \sigma^2)$

Results

Daily Timeframes

The process behind this analysis was to start very broad and then work our way down to pinpoint effects from the tweets. To do this, I start my research with the daily time frame, looking at non-neutral tweets and then see if there was any relation to the daily return for the VIX. I start by looking at two different datasets, tweets that occurred during the market hours (set **Ad**) and outside of market hours (sets **Ab**+**Aa**). I compare the median increase of the VIX during market hours with the median increase in the VIX after negative tweets in set **Ad**. I found that there was a smaller increase in the VIX after a negative tweet than normal when measuring on an open to close timeframe. I found similar results for positive tweets during market hours and non-neutral tweets outside of market hours in general. There was however one area that stood out on the daily timeframe. When comparing negative tweets before the market (set **Ab**) with the average increase in the VIX from close to open, these tweets increase the VIX by 5% (P value .38) more than the median VIX increase from close to open. Note that this change is compared to the close to open change for the VIX because tweets from set **Ab** would show an effect on the opening price, not the closing price. After noticing this slight relation between negative tweets that occur before the market, I also compared the change in the VIX after negative tweets in **Ab** and the median change on days of neutral tweets (to act as a control group). Results show that negative tweets in this set increase the VIX by 23% (P value .01) more than the median change from neutral tweets. After running regressions on pre-market tweets and VIX returns, result show that a negative tweet before the market opens corresponds to a 1.1% increase in the VIX on a daily timeframe. There is only a .7% increase in the VIX after a negative tweet in **A**, and a .6% decrease in the VIX after a positive tweet in **A**. In general, the regressions suggest that on daily timeframes, tweets before the market are the most impactful, with a 1.1% change in the VIX depending on the sentiment in the tweet. These regressions can be found in tables A.1-A.4.

Reasons behind the significance of pre-market open tweets aren't necessarily clear in the data but I have two explanations after conducting my research. First, and the most likely explanation, tweets that occur before the market opens generally occur between 6am and 9:30am. When measuring the change from a tweet before the market opens, we are looking at the change from the previous days' close to the current days' open. For example, if a negative tweet occurs at 8:30am, then this information is being priced in and measured at 9:30am. This gives us a much smaller timeframe for analysis since we can see the VIX open just one hour after the tweet compared to the normal daily timeframe. Since these tweets often cause immediate reactions, it is likely that there is a slightly higher increase due to a narrowed down timeframe. The second possible explanation is that investors may be more uncertain how the market will react to the tweet when it occurs before the market opens. When traders are doing their pre-open research, they may take extra precaution with a negative tweet that just occurred in case it leads to a broader market downturn. However, the results differ when looking at tweets that occur after the market, partially discrediting this hypothesis and increasing the likelihood of the first scenario.

Intraday Timeframes

Figure 5 summarizes the regression results for tweet sentiment value on the VXX and SPY. What we see is that for 1 and 2 minutes after the tweet, the R Squared is the highest and P-values are at their lowest. These reverse 5 minutes after the tweet, with P-Values becoming very high and R Squared values very low. This suggests that between 1 and 2 minutes after President Trump tweets, investors are making trades based on the sentiment value of the tweet for both positive and negative tweets. However, beyond 2 minutes after the tweet it appears that investors are no longer basing their trades on the sentiment value of President Trump's Tweets. By 1 hour after the tweet, there is almost no evidence between returns on VXX and SPY and the sentiment value of the tweets. It should, however, be noted how powerful the relation is in the first 2 minutes. The regression model used for this analysis is just a univariate regression (Model : $Y_{t+n} = X_t + U_{t+n}$) and it is able to account for a surprisingly large amount of the change in the VXX and SPY. For the VXX, this model accounts for about 40% of the return in the index value after 2 minutes and for SPY it accounts for about 60% of the return after 2 minutes. When this is paired with the relatively low p-values (P-value $\leq$ 0.1 for both SPY and VXX after 2 minutes), it suggests that the president's twitter account is a very important factor for investors when trading VXX and SPY.

Figure 5: Regression results (intraday)

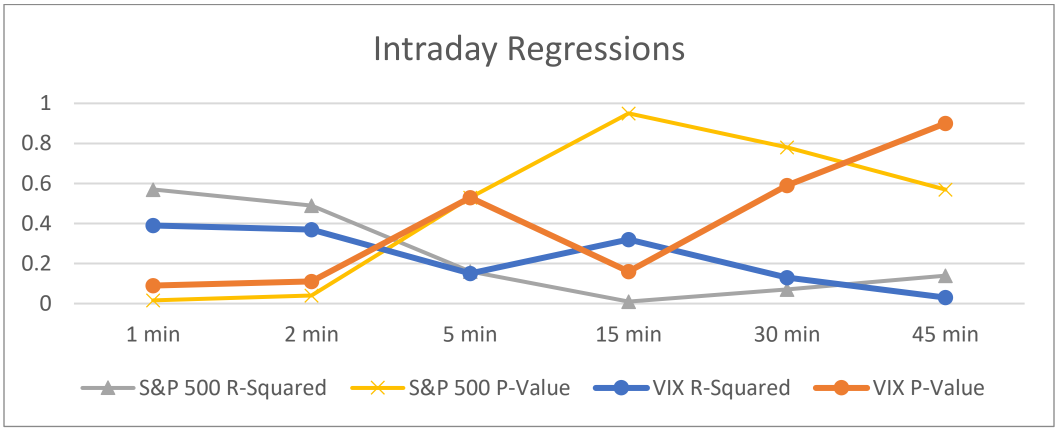
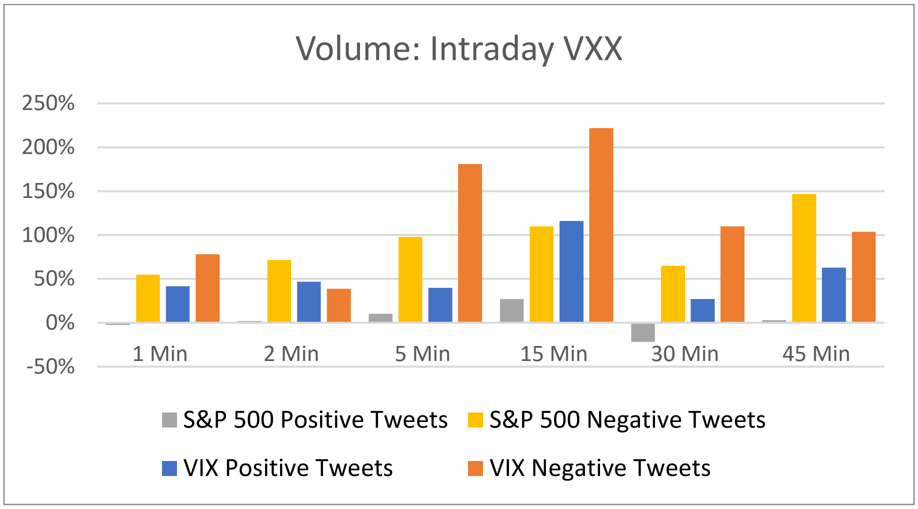


Figure 6 shows the change in SPY and VXX trading volume after President Trump tweets from his accounts. This graph shows that, in general, trading volumes for the SPY and VXX increase after both positive and negative tweets from the President; sometimes up to a 200% increase. The data suggests that negative tweets tend to increase trading volumes more than positive tweets, which should be expected as generally volumes increase when uncertainty increases. It is also interesting to overlay the volume figures with the earlier regression stats. When keeping the regression conclusions in mind, 1 and 2 minutes after the tweet should show the highest relationship to the tweet sentiment value. However, when looking at the volume results, the largest changes in volume come 5 and 15 minutes after the tweet. When pairing these with figures 7 and 8, which shows the returns on the VXX and SPY, it starts to paint a clearer picture of trading strategies used by investors.

Figure 6: Change in Trading Volume (intraday)



Figures 7 and 8 show that 1 and 2 minutes after tweets, negative tweets cause and increase in uncertainty (VXX increases and SPY decreases) and positive tweets cause a decrease in uncertainty (VXX decrease and SPY increase). However, after that, it looks like we start to see some of the opposite effects. Figure 8 shows that 5 minutes after a negative tweet there is a relatively large increase in the SPY, an unexpected result. This also appears in figure 7 where 5 and 15 minutes after a negative tweet there is a relatively large decrease in the VXX. On their own, these results are confusing, but when paired with the returns, trading volume, and regression stats it makes more sense. For example, with SPY we see that for the first 2 minutes investors are trading based on the sentiment of the tweet. However, at 5 minutes, the R Squared values are cut in half, trading volumes increase (especially for negative tweets), and returns completely retrace. This suggests that some traders may be overreacting to the news of the tweet within the first 2 minutes and then other investors are coming in and taking advantage of that market overreaction. This is even more prominent in VXX trading when looking at 15 minutes after a negative tweet.

Figure 7: Returns on VXX (Intraday)

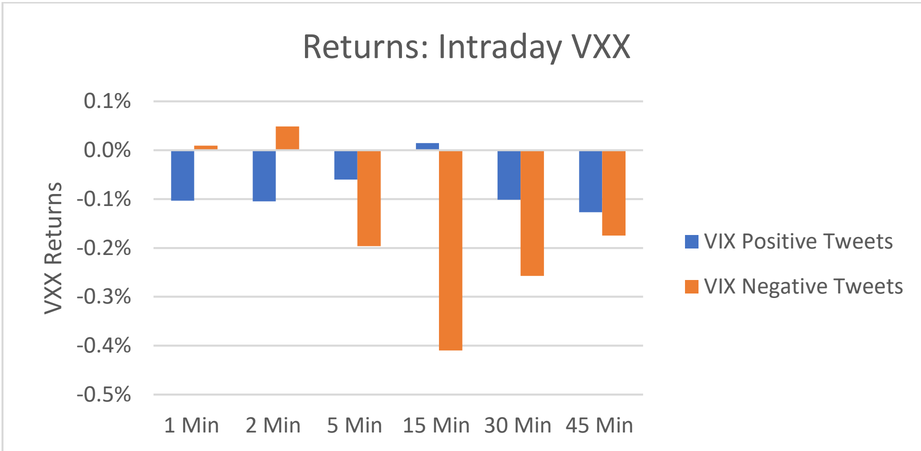
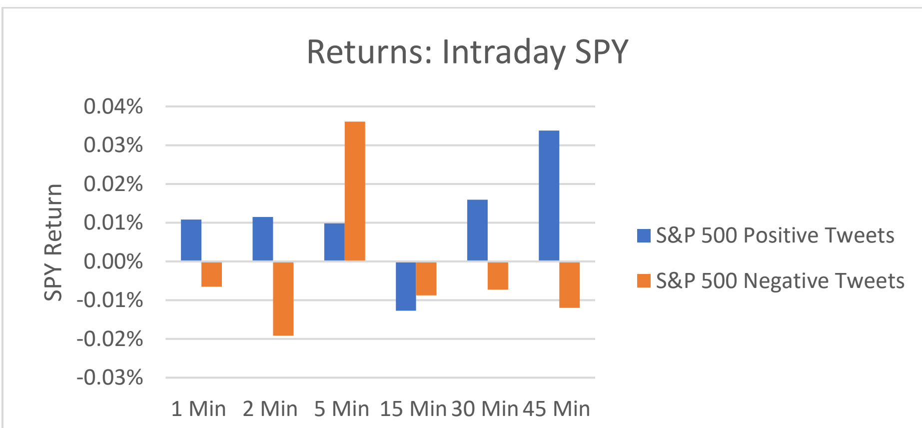


Figure 8: SPY Returns (Intraday)



The first 2 minutes go exactly as expected, but then 15 minutes after a negative tweet, trading volume increases by over 200%, R squared values decrease, and we see the largest negative returns of the entire study. These results would coincide with Born, Myers, and Clark's findings that irrational/noise traders are the largest cause of price movements after these tweets. Since they often contain no new information, it is most likely retail traders that overreact to these tweets and then institutional investors quickly spot the overreaction and take the opposite position to correct the market. This hypothesis also coincides with Zhang, Fuehres, and Gloor's findings that lag variables can often cause inverse effects on the indices.

Conclusions and Areas for Further Research

When looking for the impact of President Trump's tweets on the financial markets, it is important to break down the timeframes and the types of tweets being assessed. This study finds that when looking at daily open and close prices, tweets that occur before the market opens have a greater effect on the VXX than tweets that occur after the market closes (Figure 1 vs Figure 2). The data also suggests that negative tweets account for a 0.7% increase in the VXX (P-value 0.03) and positive tweets account for a 0.6% decrease in the VXX (P-value 0.04) when looking at daily open and close values (Figure 3 vs Figure 4). However, it is hard to capture the effect of the President's tweets on a daily timeframe so there was a need to look at intraday values.

When measuring the intraday prices of VXX and SPY, there is high relation and significance with non-neutral tweets both 1 and 2 minutes after the tweet occurs (Figure 5). From 5 minutes to 45 minutes after the tweet, R squared drops and P values increase. The data also shows that all non-neutral tweets increase trading volumes on the VXX and SPY from 1-45 minutes after the tweets, with it peaking around a 200% increase in VXX trading (Figure 6). Returns on the VXX and SPY after non-neutral tweets act as expected for 1 and 2 minutes after the tweets, showing that a negative tweet increases uncertainty (higher VXX, lower SPY), and a positive tweet decreases uncertainty (lower VXX, higher SPY) (Figure 7, 8).

Further research should look to collect more tweets, as an increase in the sample size could show changes in trading patterns throughout President Trump's tenure. Research could also include a comparison of reaction to President Trump's tweets with President Obama's tweets to see if there is any significant difference. The data from this study could suggest that a market overreaction occurs within the first 2 minutes after a tweet, which is then followed by an abrupt correction, however more research should be done to confirm this hypothesis. It may be possible to include analysis of lag variables and the RSI (relative strength index) to show if the VXX and SPY are becoming overbought or oversold right after these tweets occur.

Appendix:

Table A.1: All tweets Outside of market hours (daily)

Regression Statistics				
R Square	0.234			
Standard Error	0.029			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.008	0.003	2.688	0.009
Tweet Sentiment	-0.007	0.003	-2.254	0.027

Table A.2: All tweets before market hours (daily)

Regression Statistics				
R Square	0.339			
Standard Error	0.030			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.011	0.004	2.815	0.007
Tweet Sentiment	-0.011	0.004	-2.793	0.007

Table A.3: All Negative tweets, all hours (daily)

Regression Statistics				
R Square	0.209			
Standard Error	0.033			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.001	0.003	0.152	0.879
Tweet Sentiment	-0.007	0.003	-2.206	0.029

Table A.4: All Positive tweets, all hours (daily)

Regression Statistics				
R Square	0.190			
Standard Error	0.032			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.001	0.003	0.405	0.686
Tweet Sentiment	-0.006	0.003	-2.086	0.039

Bibliography:

Baker, S., Bloom, N., & Davis, S. (2016). Measuring Economic Policy Uncertainty. *THE QUARTERLY JOURNAL OF ECONOMICS*.

Born, Jeffery A. and Myers, David Hobson and Clark, William, Trump Tweets and the Efficient Market Hypothesis (May 24, 2017).

Ge, Q., & Wolfe, M. H. (2017). Stock Market Reactions to Presidential Social Media Usage: Evidence from Company-Specific Tweets. *SSRN Electronic Journal*.

Watt, A., Carvill, C., House, R., Livingston, J., & Williams, J. M. (2017). Trump typhoon: A rhetorical analysis of the Donalds Twitter feed. *2017 IEEE International Professional Communication Conference (ProComm)*.

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 Behavioral Sciences, 26*, 55-62.

Zheludev, I., Smith, R., & Aste, T. (2014). When Can Social Media Lead Financial Markets? *Scientific Reports, 4*(1).