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Justin Kleczka
University of Richmond

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by

Justin Kleczka

Honors Thesis

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Advisor: Dr. David North

Abstract

Implementing event-study analysis, I find that President Trump's tweets about publicly traded companies cause daily abnormal returns of 0.25% in a company's stock in the same direction as the sentiment of the tweet: positive tweets increase abnormal returns by 0.25% on the day's end, while negative tweets will cause -0.25% abnormal returns.

Additionally, I find that President Trump's company-specific tweets increase the daily abnormal trading volume and volatility of a company's stock by 19%, regardless of tweet sentiment. For abnormal returns and abnormal trading volume, the effects of President Trump's tweets do not last multiple days after a tweet. However, company stocks experience persistent higher volatility up to four days after President Trump tweets about them.

When breaking the sample into subsets, I find that President Trump's positive sentiment company-specific tweets have an asymmetrically stronger impact on a company's abnormal returns and abnormal trading volume than that of negative sentiment company-specific tweets. For most measures, President Trump's Twitter influence increases greatly when he tweets about a company during U.S. market trading hours. Outlier robust regressions confirm that the main abnormal returns results are not driven by outliers, while the results for volume and volatility appear to be inflated by outliers.

Because this type of stock market influence causes persistent increased volatility and has potential to be abused, I recommend that lawmakers consider limiting the scope of presidents' ability to tweet about publicly traded companies.

Introduction

In the past decade, social media has evolved into both a form of personal expression and a mode of reporting real-time news. Millions of Twitter users every day look to friends, celebrities, and influencers for news and opinions. As social media occurs in real-time, it should be no surprise that it correlates to financial markets, which also operate in real-time.

President Trump coming into a position as one of the most important people in the world during the dawn of worldwide social media usage provides ample opportunities to study how social media plays a role in the world and, in particular, the stock market. On July 1, 2017, President Trump tweeted "My use of social media is not Presidential - it's MODERN DAY PRESIDENTIAL." As he said himself, Donald Trump's embrace of social media as a world leader is truly modern and unprecedented; he has tweeted over 16,000 times since becoming President-Elect on November 9, 2016 — much more than any other world leader.

Because President Trump is so unique in his Twitter usage as President of the United States, his tweets have already been the subject of a number of studies including two that highlight his effect on the U.S. stock market. The first of these studies, by Juma'h and Alnsour (2018), focused on how President Trump's tweets affect the U.S. stock market on a broader level by evaluating tweets containing key financial or economic terms, while also considering how his tweets about specific companies effected the stocks of those companies. Ge, Kurov, and Wolfe (2018) studied specifically how President Trump's tweets about publicly traded companies affect the abnormal returns, abnormal trading volume, volatility, and Bloomberg institutional investor attention of those companies' stocks.

To better understand President Trump's (apparent) influence over stocks, consider an instance when he tweeted (from @realDonaldTrump) about Google on August 19, 2019 at exactly 11:52 a.m. EST.:

> *Wow Report Just Out! Google manipulated from 2.6 million to 16 million votes for*
>
> *Hillary Clinton in 2016 Election! This was put out by a Clinton supporter not a Trump*
>
> *Supporter! Google should be sued. My victory was even bigger than thought!*
>
> *@JudicialWatch*

This tweet is clearly negative towards Google, as President Trump suggests that the company be sued for potentially meddling in the 2016 election. In the immediate moments after this tweet, as depicted in the graph below, the stock price (red line) of Google (ticker = GOOGL) dropped significantly, and the volume (blue bars) skyrocketed.

It can be argued that, in this particular instance, President Trump was not the sole driver of Google's total day stock price and volume swings; surely, the subject matter of the news report played a role in the movement of Google's stock over the course of the entire day. Keep in mind, however, that the report that President Trump references was released earlier in the morning well before President Trump's tweet. Therefore, the specific timing of Google's stock price and volume movements shows how, at the very least, President Trump contributed to the intraday movements of Google's stock price and volume. In the matter of two minutes after President Trumps' negative tweet, the price of Google dropped $4 and the volume increased by about 26,000 more trades than the prior two minutes.

GOOGL Minute-by-Minute Last Trade Price and Volume
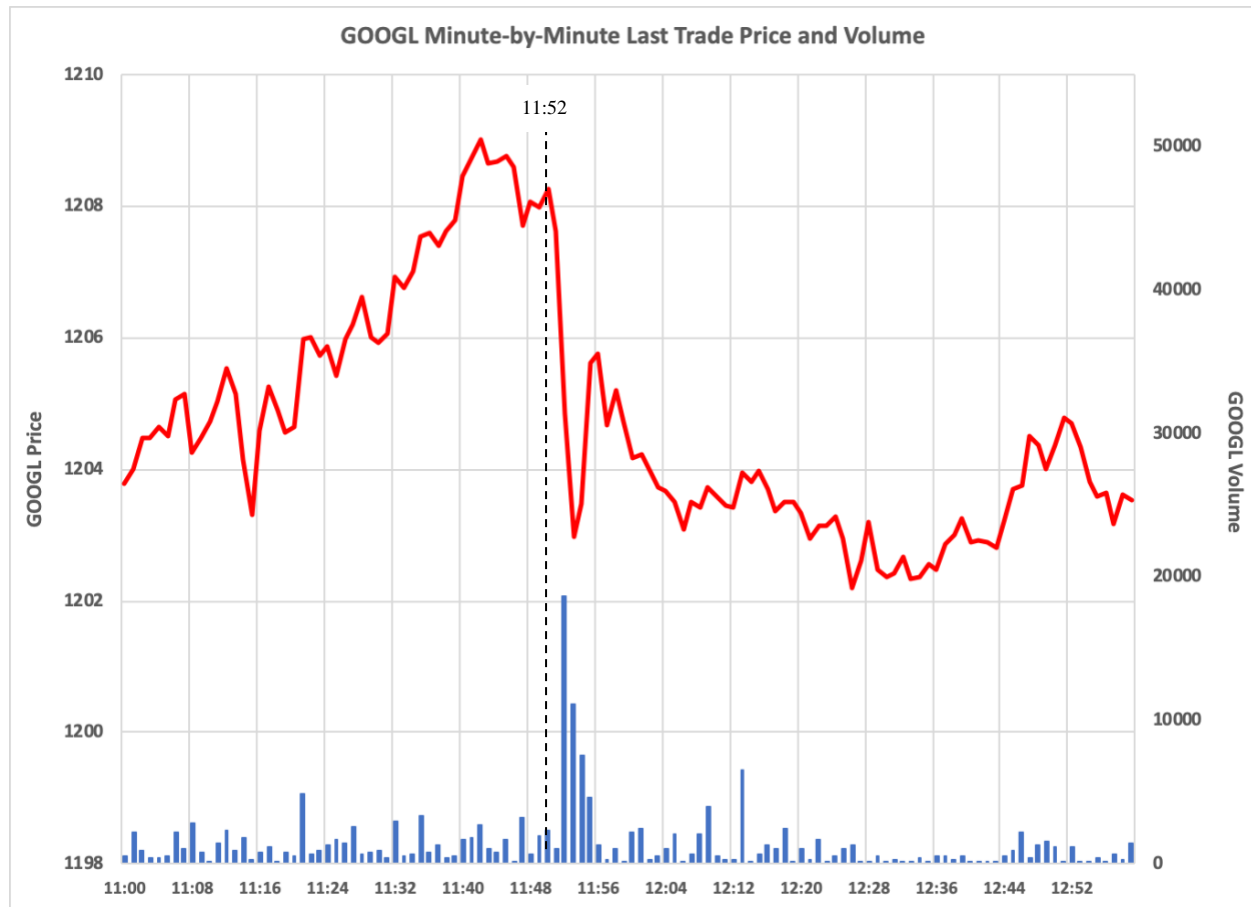
Motivated to understand President Trump's Twitter influence in a comprehensive manner and clear up the divisive results between Juma'h et al.'s and Ge et al.'s studies, I will be replicating Ge et al.'s study, excluding the "Bloomberg institutional investor attention" variable that they included in their analysis. From there, I will run tests on an extended within-sample time period to incorporate more of President Trump's company-specific tweets during his presidency. Finally, using this expanded sample data, I will conduct numerous sensitivity analyses to extract as many insights into President Trump's Twitter influence as possible.

Literature Review

A number of behavioral finance research studies have explained the link between Twitter sentiment and the stock market on a large scale (over a million tweets evaluated). Ranco et al. (2015) show that tweet sentiment polarity peaks about a particular stock imply the direction of cumulative abnormal returns for that stock. In other words, when numerous people are tweeting strong sentiments about a company, the stock price of that company will move in the direction of the sentiment of those tweets: positive tweets imply gains in stock prices, while negative tweets imply decreases in stock prices. Similarly, Li et al. (2018) analyzed over 1.2 million tweets that incorporated specific hashtags of publicly traded companies. They found that periods of high-volume strongly-positive tweets about a company signify positive daily abnormal returns, but that relationship does not hold at an intraday level (15-minute intervals). This suggests that it takes the course of an entire trading day for public Twitter sentiment about a company to be reflected in the abnormal returns of the company's stock.

Another large-scale study regarding Twitter sentiment and the stock market was conducted by Nofer and Hinz in 2015. These researchers hypothesized that the Twitter sentiment of an entire area reflects the mood of the investors of that area, and the mood of investors impacts stock market returns. Instead of attempting to test this hypothesis on a global scale, Nofer and Hinz focused on Germany and its stock market index, the DAX. Twitter mood was determined by key-word identification using the WAST method, detailed in their paper. They found that, when weighting tweets by follower count, social mood is predictive of returns in the DAX and these returns last until the end of the next trading day (the end of the day after tweet mood is determined).

Less research into the link between Twitter sentiment and the stock market exists at the microeconomic level. Shutes et al.'s (2016) study shows how popular financial microbloggers often cause abnormal returns for stocks they tweet about. Specifically, they found that these microbloggers, such as @Scaramucci and @dougkass, cause statistically significant changes in daily abnormal returns of stocks they tweet about 29.7% of the time. Sul, Dennis, and Yuan (2014) demonstrate results consistent with Ranco et al. (2015) and Li et al. (2018), with an additional key insight: tweets by users with larger follower counts have a stronger impact on changes in abnormal returns than tweets by users with lower follower counts. Logically, this makes sense, as the information disseminated by users with many followers will reach a wider audience.

My research covers one of the most-followed tweeters in the world, Donald Trump, and investigates how he alone may impact the stock market, much like a financial microblogger. The two closest related papers to my research have been briefly mentioned in the Introduction. Juma'h and Alnsour (2018) collected a sample of President Trump's tweets containing economic or financial keywords as well as tweets about publicly traded companies. Then, they implemented interday event-study analysis to determine what effects President Trump's tweets have on major U.S. stock market indexes and the specific companies he tweets about. They found that President Trump has no effect on the performance of U.S. indexes nor the companies he tweets about.

Contrary to Juma'h and Alnsours's (2018) results, Ge et al. (2018) show that President Trump's company-specific tweets do have significant effects on daily abnormal returns, abnormal trading volume, and volatility of company stocks he tweets about. The potential driver of the difference between Juma'h and Alnsour's results and Ge et al.'s results could be the fact

that Juma'h and Alnsour included company-specific tweets from the beginning of 2016 — well before President Trump was elected president. Meanwhile, Ge et al. focused specifically on President Trump's company-specific tweets from the time of his election, November 9, 2016, through July 31, 2017. Considering the contradictory results, this suggests that investors are not motivated to base decisions off of Donald Trump's tweets himself, but, rather, are driven to make decisions off the sentiment of tweets of the person holding the title President of the United States. In other words, I conjecture that a person's position of power is more relevant to his/her social media stock market influence than the person himself or herself.

Ge et al. (2018) serves as the basis of my own research. I seek to replicate their study, then build upon their research with a larger sample of tweet events and new methods.

Data Collection

To begin, I searched the Trump Twitter Archive for instances in which President Trump (@realDonaldTrump) tweeted the name of a publicly traded company between November 9, 2016 and December 31, 2019. As the name implies, the Trump Twitter Archive is a data repository of all of Donald Trump's tweets. The final sample included 257 company-specific tweet observations. Included in this sample are tweets about a subsidiary of a publicly traded company. Tweets about subsidiaries are evaluated based on changes in the stock of the parent company. For example, on July 11, 2019 President Trump tweeted a positive sentiment about Sikorsky, an aircraft manufacturing company. Because Sikorsky is owned by Lockheed Martin, a publicly traded company, this tweet was treated as if it were directed at Lockheed Martin.

A number of company-specific tweets were excluded from this sample. Following Ge et al.'s precedent, tweets about major media conglomerates, such as The New York Times, Sinclair

Broadcast Group, and Tribune Media were excluded. This decision stems from President Trump's complicated relationship with "the media"; the attention that President Trump brings to these media companies, regardless of sentiment, is linked to each company's revenue, as increased attention increases advertisement viewership. This relationship muddles the intended research area of this study, especially considering that tweets about mass media conglomerates make up an overwhelming majority of all his company-specific tweets.

Tweets directed at companies that are not traded on U.S. exchanges were also excluded, as American investors — presumably the majority of people basing investment decisions off of President Trump's tweet sentiment — generally lack consistent access to foreign exchanges or over-the-counter financial markets. Additionally, instances in which President Trump retweeted tweets that include the name of a publicly traded company, or when he himself tweeted a picture/logo of a publicly traded company, were also excluded. Furthermore, tweets that include the name of a company coincidentally are excluded from the sample. An example of a tweet excluded for this reason is the following tweet from October 8, 2019:

> *I think that Crooked Hillary Clinton should enter the race to try and steal it away from Uber Left Elizabeth Warren. Only one condition. The Crooked one must explain all of her high crimes and misdemeanors including how & why she deleted 33000 Emails AFTER getting "C" Subpoena!*

Despite the capitalization of "Uber," in this context the word clearly functions as an adjective describing the extremity of Elizabeth Warren's democratic views, as opposed to referencing the ride-sharing company.

Every instance in which President Trump tweeted about a country, a dummy variable representing the tweet, "TW," was assigned a non-zero number on the market trading day for the

corresponding company stock. Positive tweets were given a "1" on the dummy variable, and negative tweets were given a "-1." For days in which President Trump did not tweet about a company, the dummy variable was "0." Tweets during U.S. market trading hours (9:30 a.m. - 4:00 p.m. EST) were simply assigned to the TW variable on day of the tweet. Tweets after-market trading hours were assigned to the TW variable on the next trading day, as investors looking make decisions based off these tweets would only be able to do so the next time they are able to make trades. Often, President Trump tweets about a particular company multiple times within hours or even minutes of each other. When multiple tweets are supposed to be assigned to the same date, the Twitter dummy variable does not change to reflect these occurrences, as a dummy variable cannot be scaled up or down to indicate the number of occurrences. Rather, the unscaled dummy variable captures the effects of multiple tweets assigned to the same day: in theory, the changes to abnormal returns, abnormal trading volume, and volatility should compound to reflect multiple tweet occurrences. In other words, if President Trump tweets negatively about Google twice on the same day, his effect on Google's stock should (in theory) double. This conjecture was tested, and the results are explained in Section VIII of the Results. Considering the instance of multiple tweets assigned to the same day, the total number of "tweet events" in my sample —all the times a dummy variable was assigned to a trading day — is 209. This number results from 34 instances in which multiple tweets were assigned to the same trading day.

The final sample included these 209 tweet events, spanning 57 companies and 790 days, Three companies, Andeavor, Aetna, and Time Warner Cable have shortened estimation windows because they were delisted before the end of the estimation period. Altogether, this amounts to 44,052 total panel observations.

The chart below depicts the publicly traded companies that received the most tweet events. In this sample, Amazon is the top recipient of President Trump's attention with 26 tweet events — ten more than the second most-frequently tweeted company, Twitter. President Trump has often criticized Amazon for exploiting the Federal Post Office system. Additionally, President Trump has taken issue with Amazon's connection to the Washington Post, one of many "Fake News" entities that he has warred with.

Most Tweeted Companies		
Company	Ticker	Total Tweets
Amazon	AMZN	26
Twitter	TWTR	16
Facebook	FB	14
General Motors	GM	14
Google	GOOGL	12
Ford	F	10
Apple	AAPL	10

The technique used to investigate how an individual could influence stocks is called "event study analysis", which is the overarching method of this research. See Khotani and Warner (2007) and Binder (1997) for a broader explanation of event-study analysis and its various facets. My specific event study analysis requires daily closing, opening, high, and low stock prices along with daily total volume: this data came from Bloomberg.

An additional component of my event study analysis is broad stock market data, required for abnormal returns calculations. The Fama-French 3-factors, the standard for most event study analyses, were used as the broad-market controls in this study, and this data came directly from

Fama and French's official website. These variables will be explained in more detail in the Methodology.

Sentiment Classification

As mentioned in the Data Collection Section, tweets are assigned to a corresponding market trading day as a positive or negative one on dummy variable, "TW." In the most general form, the sentiment of each tweet is determined by the tone expressed by President Trump towards the company mentioned in that tweet. Sentiment was determined by myself because the tweet sample was manageable enough for detailed analysis of context and content of each tweet. This serves to reduce errors that come from computer-programmed textual analysis, which cannot effectively account for tweet context. General guidelines to determining President Trump's company-specific tweet sentiment were set by Ge et al. (2018):

1. Tweets regarding a company potentially creating (decreasing) jobs in the US are classified as positive (negative). This includes instances in which President Trump reports that a specific building, factory, facility, or business segment will remain operating in the U.S., close permanently, or move to another country.

2. Tweets regarding a company costing the US government money are classified as negative.

3. Tweets about companies incurring losses due to the Affordable Care Act are graded as negative.

4. Tweets about meetings with CEOs are graded as positive.

My sentiment classification procedure follows the aforementioned guidelines by Ge et al. and lays out additional guidelines necessary for classifying tweets that did not fall under their standards. These additional guidelines are as follows:

5. Accusing a company of propagating "Fake News" discredits that company for poor journalistic practices (even if the news is not actually "fake"). Therefore, President Trump's accusations of a company promoting "Fake News" are graded as negative towards that company. Amazon, with its connection to the Washington Post, has frequently been a recipient of these accusations. Conversely, instances where President Trump lauds as a company for eliminating "Fake News" are graded positive, considering that the company appears to be taking action to improve its journalistic practices.

6. Tweets concerning silenced conservative voices from a platform are graded as negative toward the company of that platform for similar reasons to Guideline #5.

   o Example: A tweet from May 3, 2019

   The wonderful Diamond and Silk have been treated so horribly by Facebook. They work so hard and what has been done to them is very sad - and we're looking into. It's getting worse and worse for Conservatives on social media!

   o This tweet is graded as negative towards Facebook

7. Thanking a company for a particular action is graded positively.

8. Mentioning a company-sponsored arena is a positive sentiment toward that company.

   o Example: A tweet from October 15, 2019

   Join me in Dallas, Texas (October 17th) at the American Airlines Center! #KAG2020

   o This tweet is graded as positive towards American Airlines

- o Rationale: President Trump's willingness to participate in events in a company-sponsored arena suggest that he passively accepts what the company stands for. Furthermore, these tweets are a form of free advertising for the company, which reflects positively on that company.

9. References to a company in regards to a particular tool or platform are graded positively for reasons similar to that of Guideline #9.

   - o Example: A tweet from September 9, 2017

     FLORIDA- Visit FloridaDisaster.org/info to find shelters road closures & evacuation routes. Helpful Twitter list …

   - o Twitter, offering a helpful list feature, is graded as positive in this example.

10. If President Trump reports on positive (negative) news about a company, the tweet is graded positively (negatively).

    - o Example: A tweet from November 1, 2019

      Wow a blowout JOBS number just out adjusted for revisions and the General Motors strike 303000. This is far greater than expectations. USA ROCKS!

    - o General Motors is graded as negative in this example.

    - o Rationale: In this particular example, President Trump is reporting on positive news: great jobs number. However, his reference to the GM strike reminds his followers that GM has been undergoing issues with its labor force, which, before revisions, would negatively impact the jobs numbers.

11. Tweets regarding a company suffering from tariffs are classified as negative because it is implied that the company will lose (or has lost) profits. Tweets about a company avoiding

tariffs by maintaining business operations in the US are graded as positive for the same

reasons as Guideline #1 .

- o Example: A tweet from July 26, 2019

  Apple will not be given Tariff waiver or relief for Mac Pro parts that are made in

  China. Make them in the US no Tariffs!

- o This tweet is graded as negative towards Apple.

12. Instances where President Trump condemns a company for not paying adequate taxes to

the U.S. government are graded as negative for reasons similar to Guideline #2.

- o Example: A tweet from March 29, 2018

  I have stated my concerns with Amazon long before the election. Unlike others,

  they pay little or no taxes to state and local governments…

- o This tweet is graded as negative towards Amazon.

Methodology

I.   Abnormal Returns

The steps for determining daily abnormal stock returns are as follows. First, I find the excess

returns (ER$_{it}$) of company "i" at day "t." Excess returns are defined as the daily returns ("R") of a

stock, $R_{i,t} = \frac{C_t - C_{t-1}}{C_{t-1}}$, subtracted by the Risk Free alternative (RF$_t$), where "C" stands for daily

closing price. RF$_t$ is a component of Fama-French 3 factors and stands for the one-month

Treasury Bill rate.

The excess returns are calculated for a pre-sample period (January 1, 2016 through

November 8, 2016) and within-sample period (November 9, 2016 through December 31, 2019)

for all stocks in the sample. The pre-sample excess returns are regressed on Fama-French's 3-
Factor model components:

$$ER_{i,t} = \beta_0 + \beta_1(RM_t - RF_t) + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_{i,t}$$

Where, $\varepsilon_{i,t}$ represents the error component of the regression. RM_t represents the market return for a given day,
specifically, the returns of all companies represented in the NASDAQ and NYSE exchanges. SMB_t represents the
difference between small and big market capitalization stocks performance. HML_t stands for the difference in high
and low book-to-market ratio stock performance. RM_t, RF_t, HML_t, and SMB_t are defined in detail in Fama & French
(1993).

The beta coefficients from the pre-sample ER regression are used to calculate abnormal returns

(AR) for each company in the within-sample period. The pre-sample betas are used for within

sample calculations to prevent event returns from influencing the measures of normal returns

(Mackinlay, 1997). Within-sample abnormal returns are calculated as follows:

$$AR_{i,t} = ER_{i,t} - [\beta_0 + \beta_1(RM_t - RF_t) + \beta_2 SMB_t + \beta_3 HML_t]$$

Finally, the abnormal returns for each stock over the within-sample time period (the period

containing the 209 tweet events graded and assigned to the TW dummy variable) are used in a

fixed effects panel model:

$$1) \quad AR_{i,t} = \alpha_0 + \alpha_1 TW_{i,t} + \varphi_i + \upsilon_{i,t}$$

where φ_i accounts for the company-specific fixed effects and $\upsilon_{i,t}$ is an error component of the regression.

The coefficient on TW is the main object of focus for most parts of this research, as it explains

how abnormal returns of a company are affected (if at all) by President Trump's tweets about

that company.

II.   Abnormal Trading Volume

To estimate President Trump's Twitter impact on a company's trading volume, first, a

company's five-day average trading volume ($V_{avg,i,t}$) is calculated: $V_{avg,i,t} = \frac{\sum_1^j V_{i,t-j}}{j}$, where

"j" equals 5. Using the five-day average controls for intraweek trading fluctuations. The

abnormal trading volume (ATV) calculation is as follows: $ATV_{i,t} = \frac{V_{i,t} - V_{avg,i,t}}{V_{avg,i,t}}$. Finally, a fixed

effects panel model is estimated in which ATV is regressed on the absolute value of TW.

Consistent with past literature, the rationale for using the absolute value of TW stems from the

concept that, regardless of tweet sentiment, the trading volume will increase. Logically, those

basing decisions off of President Trump's tweets will react with increased buying or increased

selling, which both lead to increased trading volume. The fixed effects panel model looks as

follows:

$$2)\ \ ATV_{i,t} = \delta_0 + \delta_1|TW_{i,t}| + \theta_i + \mu_{i,t}$$

Where, θ_i represents company-specific fixed effects and $\mu_{i,t}$ represents the error term.

III.   Volatility

Following Ge et al.'s method, I chose to calculate a company's daily variance using Rogers

and Satchell's (1991) range-based calculation:

$$\sigma 2_{i,t} = (H_{i,t} - C_{i,t})*(H_{i,t} - O_{i,t}) + (L_{i,t} - C_{i,t})*(L_{i,t} - O_{i,t})$$

Where $H_{i,t}$ stands for a company's highest trading price of the day, C_i stands for the closing price, $L_{i,t}$ stands for the

lowest price of the day, and $O_{i,t}$ stands for opening price.

To express volatility in percentage terms, I take the square root of $\sigma 2_{i,t}$ and multiply it by

100. Finally, this volatility variable is regressed in a fixed effect panel model equivalent similar

to regression 2:

$$3)\ \text{Volatility}_{i,t} = \phi_0\ + \phi_1|\text{TW}_{i,t}\ |+ \eta_i + \omega_{i,t}$$

Where η_i represents individual company fixed effects and $\omega_{i,t}$ represents the error component of the regression.

IV.   Other Considerations

As researchers Beck and Katz point out in a 1994 paper, a number of issues arise with OLS

fixed effects models that deal with cross-sectional time series data. Particularly, cross-sectional

heteroscedasticity distorts true standard errors of coefficient estimates. Therefore, my regression

results will be expressed using Beck and Katz's method of correcting standard errors of panel

data, unless otherwise stated.

Because the coefficient on the TW variable is the most-important part of each regression, the

corresponding null and alternative hypotheses of importance are $H_0 : \alpha_1 = 0$ and $H_1 : \alpha_1 \neq 0$. The

coefficient from the AR regressions is illustrated here as an example, but the coefficient on TW

is the important consideration for all three regressions (AR, ATV, and Volatility). When the

coefficient on TW is significant to at least the 10% level, the null hypothesis can be rejected, and

thus, President Trump's company-specific tweets have a proven impact on companies' AR,

ATV, and/or Volatility.

Below are summary statistics of the full sample abnormal returns, abnormal trading

volume, and abnormal volatility.

Summary Statistics				
	ER	AR	ATV	Volatility
Min	-0.271	-0.293	-0.862	0.071
Median	-0.005	-0.005	-0.064	1.014
Mean	-0.005	-0.005	0.042	1.198
Max:	0.197	0.193	17.352	14.587

Results

I.   Replication of Ge et al.

To begin, I attempted to replicate the major findings of Ge et al.'s research. The results of the my replication study compared to Ge et al.'s findings are depicted in Table 1 of the Appendix. These tests were estimated based on the fixed effects panel model described in the Methodology. Both samples contains the same 34 tweet events about 19 companies that total 3,439 panel observations.

The results of my replication test nearly identically matched those of Ge et al's study. Both results show that a positive (negative) tweet about a company causes an increase (decrease) in a company's abnormal returns by about 0.6%. This is economically meaningful when considering that a 0.6% change in stock price could amount to hundreds of million dollars in changes to that company's market capitalization. Additionally, both tests show that President Trump's company-specific tweets increase ATV by about 33% and volatility by about 20%.

II.   Analysis with Full Sample

The same methods described in the Methodology and implemented in the replication study were applied to the expanded sample of panel data spanning 209 tweet events (257 total tweets), 57 companies (3 with shortened estimation windows), and 790 days, totaling 44,053 panel observations. The results of these tests are depicted in the first row of Table 2 of the Appendix.

It appears that, within this 790 day sample period, President Trump's company-specific tweets still carry power to them, causing a 0.25% increase (decrease) in daily abnormal returns when a tweet about a company is positive (negative). Additionally, ATV and volatility remain strongly influenced by President Trump's tweets: both measures increase by about 19% when

President Trump tweets about a company. Although these results are all lower in magnitude than the results of Ge et al.'s study, they are still economically significant for the same aforementioned reasons.

There are a number of potential explanations as to why President Trump's Twitter influence seems to have weakened in comparison to Ge et al's study. Firstly, President Trump's company-specific tweets may have lost their novelty in the public eye as people grew more accustomed to seeing him tweet as President of the U.S. Secondly, people may have lost trust in President Trump's words and/or sentiments. PolitiFact, a non-partisan group that grades verifiable claims made by prominent American politicians, reports that, as of April 19, 2020, 69% of 796 graded claims of President Trump were "Mostly False," "False," or "Pants on Fire" (outlandishly false). Certainly, the public could have grown tired with the President's copious amount of false claims, and correspondingly lost trust in the veracity of his Twitter sentiments. With this in mind, my results capture a broader, more accurate representation of President Trump's Twitter influence, accounting for more total tweets and a longer time period in which investors were able to become more acclimated to his Twitter behavior.

III.   Testing for Asymmetry

To decompose more specific effects of President Trump's tweets, a number of tests were performed with restricted samples of the Twitter dummy variable, TW. First, the fixed effect panel regressions described in the Methodology were conducted on only the 103 positive tweets (with the same 44,053 total panel observations). The results in second row of Table 2 show that positive tweets correspond to a statistically significant 0.42% change in abnormal returns, which is about 0.17% higher than the results of the full sample test. President Trump's positive tweets

also cause higher changes in ATV and lower changes to volatility compared to the full sample results.

This same process was repeated on the 106 negative tweets in the sample, and the results are also shown in Table 2. Notice how the coefficient on TW in the AR test lost its significance. Whereas Ge et al. (2018) found no significant difference in market reactions to positive and negative tweets, my results suggest that there is a difference: it appears that investors are not as strongly driven to base investment decisions off negative company-specific tweets as they are to base investment decisions off positive company-specific tweets.

All the aforementioned tests included tweets that were tweeted after market trading hours and assigned to the next day under the assumption that these tweets would affect stock trading the next time trading is available. I believe that the effect of tweets *not* after market trading hours would have a weaker effect on abnormal returns, abnormal trading volume, and volatility, because investors are more likely to forget about President Trump's tweets when they have to wait a period of time before making trades. Therefore, I hypothesize that tweets *during* market hours (what I will call "intraday tweets"), when investors reacting to tweets can immediately make trades, would have a stronger effect on stock the three stock variables of interest. The regression to test this hypothesis is different from the others in that only intraday tweets were given a "1" or "-1" for the Twitter dummy variable, and the rest were given a "0." Altogether, there were 64 intraday tweet events. The results are depicted in the Table 3 of the Appendix. ATV and volatility are higher magnitudes in this test than the full sample test, which partially confirm my conjecture. Contrary to my conjecture, however, the coefficient on the AR variable was not significant, which suggests that, in general, President Trump's intraday tweets have no effect on stock's abnormal returns.

I surmise that the lack of significance on the AR variable could derive from asymmetries between effects of positive intraday tweets compared to negative intraday tweets. So, I conducted tests on subsets of positive (28) and negative (36) tweets. These results are depicted in the bottom two rows of Table 3. Considering the highly significant value of 0.8% on the AR variable in the positive only intraday tweet test and the non-significant value on the TW coefficient in the negative intraday tweet regression, it does appear that asymmetries exist in the effects of President Trump's intraday tweets.

IV.   Time-Based Interaction Effects

I found it important to investigate how President Trump's influence may have changed between different time periods. The regressions that I constructed have a slightly different structure than those described in the Methodology:

$$AR_{i,t} = \alpha_0 + \alpha_1 TW_{i,t} + \alpha_2 I_{i,t} + \alpha_3(TW_{i,t} *I_{i,t}) + \varphi_i + \upsilon_{i,t}$$

$$ATV_{i,t} = \delta_0 + \delta_1|TW_{i,t}| + \delta_2 I_{i,t} + \delta_3(|TW_{i,t}|*I_{i,t}) + \theta_i + \mu_{i,t}$$

$$Volatility_{i,t} = \phi_0 + \phi_1|TW_{i,t}| + \phi_2 I_{i,t} + \phi_3(|TW_{i,t}|*I_{i,t}) \eta_i + \omega_{i,t}$$

Where, $I_{i,t}$ represents a dummy variable for a time period and the last two variables of each regression represent company fixed effects and error terms, respectively. The coefficients on $(TW_{i,t} *I_{i,t})$ represents the interactions effect; in other words, this coefficient shows how (if at all) a tweet during a particular time period affects the magnitide of President Trump's Twitter influence.

The first time period I decided to test was the difference between tweets from Ge et al.'s sample and my full sample. Remember, Ge et al.'s sample contains President Trump's 31 company-specific tweet events from November 9, 2016 through July 31, 2017. My sample

covers 209 company-specific tweet events from November 9, 2016, through December 31, 2019. The aforementioned regressions were implemented with the inclusion of a "1" on the "I" dummy variable for days in the panel occurring after this July 31, 2017.

The results of this test are depicted in the first row of Table 4. There is no statistical significance for the coefficients of the interaction effects on AR and Volatility, suggesting that President Trump's Twitter influence did not change between my sample and Ge et al.'s for these two variables. However, the coefficient on ATV significantly increases by 7% when a tweet occurs during the Post-Ge et al. time period. This result suggests that investors actually began paying *more* attention to President Trump's tweets over the time period of August 1, 2017 through Dec 31, 2019. Perhaps this result is driven by an increase in President Trump's Twitter followers and press coverage in that period.

Additionally, I decided to test for a difference before and after President Trump's inauguration. Following the previously described interaction effect methodology, a "1" was given to panel observations after Trump's inauguration (January 20, 2017) and assigned to the "I" variable. The results of these interaction effect regressions are represented in the bottom row of Table 4. These results show that President Trump's influence on abnormal returns in the post-inauguration period are much lower than that of his pre-inauguration period. In the Literature Review, I surmised that investors are more likely to make decisions when a person, such as Donald Trump, attains more power than they normally do. These results suggest that my conjecture is not necessarily true, as President Trump had a higher influence on stocks *before* he was inaugurated, which was before his presidency (and the power that comes with it) officially began.

V.   Tweets as Reaction to Related News

Ge et. al (2018) used Factiva to determine which of President Trump's tweets are a reaction to "related news" and which are "original" in content. They determined that 19 out of 34 tweets were reactions to related news and the rest were original. Then, they found that the original tweets cause changes to AR and volatility that are greater in magnitude than the effects of his tweets in reaction to related news.

I find that determining what counts as "related news" and what does not is a blurry line: on Factiva, one can find "news" about nearly any large company on nearly any day, and trying to link this news to the content of President Trump's tweets can be complicated. This research paper is more interested in confirming or rejecting the idea that President Trump's tweets could be a reaction to related news than it is interested in trying to determine asymmetric effects between related news tweets and original tweets. To accomplish the task of identifying whether or not President Trump's tweets are generally a reaction to related news, I tested the Twitter dummy variable as if it were tweeted by President Trump one through five days earlier, and regressed this in a fixed effects panel model:

$$AR_{i,t} = \beta_0 + \beta_1 TW_{i,t} + \beta_2 TW_{i,t-1} + \beta_3 TW_{i,t-2} + \beta_4 TW_{i,t-3} + \beta_5 TW_{i,t-4} + \beta_6 TW_{i,t-5} + \phi_i + \varepsilon_{i,t}$$

$$ATV_{i,t} = \alpha_0 + \alpha_1 |TW_{i,t}| + \alpha_2 |TW_{i,t-1}| + \alpha_3 |TW_{i,t-2}| + \alpha_4 |TW_{i,t-3}| + \alpha_5 |TW_{i,t-4}| + \alpha_6 |TW_{i,t-5}| + \gamma_i + \nu_{i,t}$$

$$Volatility_{i,t} = \delta_0 + \delta_1 |TW_{i,t}| + \delta_2 |TW_{i,t-1}| + \delta_3 |TW_{i,t-2}| + \delta_4 |TW_{i,t-3}| + \delta_5 |TW_{i,t-4}| + \delta_6 |TW_{i,t-5}| + \eta_i + \mu_{i,t}$$

Where the last two variables of each regression represent company fixed effects and an error component, respectively.

The outcome of these tests are shown in Table 6 of the Appendix. The significant coefficients on the one-day lag suggests that, indeed, there is some sort of event, or "news," that influences a stock the day before Trump tweets about that stock. This does not affect the rest of the interpretations of my research, as it can be argued that these "news" events are fully incorporated

into a stock's price by the following day, as per the Efficient Market Hypothesis (Fama, 1970).

Therefore, the significant coefficients on Trump's tweets *on the day of the tweet* suggest that

Trump's tweets themselves are new "news" that elicits a market response.

VI.   Persistence of President Trump's Twitter Effects

The findings up until this section show the power that President Trump wields over

company's stock abnormal returns, abnormal trading volume, and volatility over the single day

in which investors are able to make trades off his tweets. However, it may be that President

Trump's influence lasts more than a single day. To test this, I set up a model similar to that of

Section V, except with the Twitter variable placed each of five days after the tweet event. These

regressions look as follows:

$$AR_{i,t} = \beta_0 + \beta_1 TW_{i,t} + \beta_2 TW_{i,t+1} + \beta_3 TW_{i,t+2} + \beta_4 TW_{i,t+3} + \beta_5 TW_{i,t+4} + \beta_6 TW_{i,t+5} + \phi_i + \varepsilon_{i,t}$$

$$ATV_{i,t} = \alpha_0 + \alpha_1 |TW_{i,t}| + \alpha_2 |TW_{i,t+1}| + \alpha_3 |TW_{i,t+2}| + \alpha_4 |TW_{i,t+3}| + \alpha_5 |TW_{i,t+4}| + \alpha_6 |TW_{i,t+5}| + \gamma_i + \nu_{i,t}$$

$$Volatility_{i,t} = \delta_0 + \delta_1 |TW_{i,t}| + \delta_2 |TW_{i,t+1}| + \delta_3 |TW_{i,t+2}| + \delta_4 |TW_{i,t+3}| + \delta_5 |TW_{i,t+4}| + \delta_6 |TW_{i,t+5}| + \eta_i + \mu_{i,t}$$

Where the last two variables of each regression represent company fixed effects and an error component,

respectively.

The results of these tests are shown in Table 5. The coefficients for both AR and ATV show

no significance in the days following President Trump's company-specific tweets; this suggests

that the effect of President Trump's company-specific tweets does not last more than a day, for

these two variables. The coefficient on volatility, however, is statistically significantly for up to

four days after a tweet, which suggests that President Trump's company-specific tweets cause

persistently high volatility in the company's stocks. Peculiarly, the coefficient on the two-day lag

isn't significant in the volatility regression while the coefficients on the three and four-day lag

variables are significant. In case these strange results came from outliers, I conducted M-

Estimation on the volatility regression using the method described in the next section. The test results did not clear up the peculiar findings regarding volatility.

VII.   Robust Regressions

To make sure that the results of my main findings are not driven by outliers, all the tests of Section I were redone with the Huber method of M-Estimation (also known as Outlier Robust Estimation). This method fits a model using iterated re-weighted least squares, weighting observations with low residuals higher than observations with high residuals. These regressions do not incorporate panel-corrected standard errors, as the estimation method does not allow for correcting of cross-sectional heteroscedasticity (Ge et al., 2018).

The results of the M-Estimation are reported in Table 7. Abnormal returns are nearly unchanged by outliers compared to the full sample results of Table 2. However, ATV and volatility are 6% and 13%, respectively, compared to the results of 19% each for the full sample; it appears that these two variables are inflated in magnitude by outliers. Additionally, the outlier robust regressions performed on the positive and negative tweet subsets all seem to be strongly influence in magnitude and/or significance by outliers.

As an alternative robustness test, two-way fixed effects regressions were implemented to control for each company and *day* in the panel data. Controlling for time-based effects is somewhat redundant, as the method of calculating abnormal returns already controls for time-based effects that impact the entire stock with the use of the Fama-French 3 factors. However, there is still value in the time-based control variables, as non-stock market events could influence any given day of trading, and the abnormal trading volume and volatility variables do not have market-wide controls built into their calculations.

The two-way fixed effects tests follow the same structure as the one-way fixed effects described in the Methodology, with the addition of dummy variables for each of the 790 days of the estimation period. The results of these tests are shown in Table 8. We see that the results are nearly equivalent to those of the one-way fixed effects regressions.

VIII.   Tests that Yielded No Significant Results

With a large sample size of company-specific tweets events and companies, 209 and 57, respectively, it was possible to conduct tests that could elucidate more detailed insights into President Trump's Twitter influence. Unfortunately, all of these tests that I will describe yielded no significant insights. However, the lack of significant results of these tests is a result of itself: President Trump's Twitter influence on company's stocks is universal and not limited to particular situations, company characteristics, or tweet interactions.

I began by creating dummy variables for each company based on market capitalization. I expected to find that President Trump's company-specific tweets have greater influence over small cap stocks – companies with under $2 billion market capitalization. Smaller cap stocks are generally traded less than any other cap size, and I figured that President Trump's action of bringing these companies to the limelight would create massive swings in all measures, relative to stocks with larger market capitalizations. To my surprise, the tests did not support this hypothesis: it appears that market cap of a company does not change how President Trump's company-specific tweets impact abnormal returns, abnormal trading volume, and volatility of stocks.

Similarly, I thought there would be insights extracted from fixed effects regressions with interaction effects tested for the sectors of each company. I categorized each company based on

its sector listed in its company profile on Yahoo Finance. I believe that the Sector-based interaction effects yielded no significant results due to many sectors having very few Twitter events assigned to them, such as the Utilities sector which only had on one company and two tweet events in the sample.

Additionally, I hypothesized that President Trump's approval rating would reflect the public's trust in his word, and, thus, reflect how strongly investors would react to his company-specific tweets. Specifically, I expected that President Trump's tweets when he had an approval rating above his median (as of December 31, 2019) would have a stronger impact on stocks than tweets below the median. Approval rating data was collected by FiveThirtyEight, which averages approval ratings from numerous pollers and adjusts the data based on political bias, poll quality, and sample size. Likewise, I thought that tweets above the median amount of interactions (favorites and retweets) would correspond to higher magnitude abnormal stock movements. Fixed effects regressions yielded no significant results for interaction effects for instances in which President Trump tweeted about a company while having an above median approval rating, above median favorites, or above median retweets.

In the Introduction, I mentioned that instances when multiple company-specific tweets were assigned to the same company on the same day, President Trump's effects would compound on those particular days. This was tested using the regressions of the Methodology on a subset of "multiple tweet instances" as a replacement for TW. A "1" was given to this variable for days with multiple positive tweets assigned to them. A "-1" was assigned to days when multiple negative tweets were targeted at a company. There were no instances that had one or more positive tweets and one of more negative tweets occurring on the same day. Additionally, I expected tweets that occurred over the weekend, which were assigned to the next trading day

(usually a Monday or Tuesday) would have weaker results because investors lack access to financial markets and would be more likely to forget about the tweet by the next time they trade. To my surprise, these results of "multiple tweets" and "weekend tweets" subset tests remained consistent with my full sample results, showing that President Trump's company-specific Twitter influence is not withheld to any particular timing.

Conclusions

Firstly, this study successfully replicates Ge et al's (2018) results, showing that their work is to be trusted and valued. Additionally, this paper expands on the work of Ge et al. by extending the sample size of tweets and trying new types of sensitivity analyses that unveil insights into the ways in which President Trump exhibits power over the stocks of publicly traded companies that he tweets about. I find that, in general, when President Trump tweets positively (negatively) about a company, he will create positive (negative) abnormal returns in that company's stock of 0.25% by the end of the trading day. Similarly, whenever President Trump tweets about a company, regardless of sentiment, he increases the abnormal trading volume and volatility of that company's stock by about 19%. Furthermore, I find that positive tweets have an asymmetrically stronger impact on stocks than negative tweets. The effects of President Trump's tweets on a company's AR and ATV do not last more than one day, while the effects on volatility last up to four days.

This paper also adds to the general literature of social media event-study sentiment analysis. There is now more evidence that individuals alone, particularly ones of high power and prestige like a president, are alone able to affect the stocks of publicly traded companies worth billions of dollars.

For active investors seeking to profit, the results of this research can impact investment decisions. A prudent investor would consider monitoring President Trump's tweets and buying (shorting) shares of a mentioned company that he tweets positively (negatively) about. It appears that this is already occurring through the use of computer algorithms that automatically trade off of President Trump's tweets. In an interview with marketplace.org, Joe Gits explains that President Trump's tweets are the target of some investment firms. Gits is the owner of Social Media Analytics, a company that collects potential market-moving social media data for investment firms. He explains that computer algorithms for some firms automatically make trades based on President Trump's tweets within seconds of the tweets occurring. Automated trading explains instances such as the one graphed in the Introduction, where minute-over-minute trading volume skyrocketed by 10,000% between the minute of President Trump's tweet and the end of the next minute. Because of the existence of trading algorithms, say Gits, "retail investors" – casual investors who aren't associated with a career in stock trading – are left with much less opportunity to profit off of President Trump's tweets, unless they act extremely quickly (Corban & Ryssdal, 2019). With this in mind, it appears that retail investors looking to achieve consistent profits off of President Trump's tweets should exercise caution, as algorithms may complicate the process.

Finally, this research could be valuable in making policy decisions for presidential social media behavior. President Trump's company-specific tweets greatly increase volatility in the subjects of those tweets, lasting days, which is highly undesirable to owners of the company in question as well as the stock market in general. Additionally, if a president were to comprehend the specific power of his/her company specific tweets that is described in this paper, it could potentially be exploited; he/she could specifically tailor tweets to bargaining and political

advantage. For example, as leverage in negotiations with automotive companies to bring back jobs to the U.S., President Trump could threaten automotive companies with a series of negative tweets that could significantly impact their stock values. A president's knowledge of his/her Twitter influence could also potentially lead to insider trading. For example, President Trump could tell a trusted colleague that he plans on tweeting something positive about a specific company at exactly 11:45 a.m., and that colleague could exploit the short-term abnormal returns of that company by buying its stock beforehand and holding onto it for the rest of the day. With these confounding factors in mind, policy should be considered to restrict the scope of a president's company-specific tweets.

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Appendix

Table 1: Replication			
	AR	ATV	Volatility
Ge et al.			
TW	0.006*** (0.002)	0.331*** (0.111)	0.220*** (0.095)
Replication			
TW	0.006*** (0.002)	0.331*** (0.111)	0.217** (0.098)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 19 companies spanning 181 days with the resulting number of panel observations totaling 3,439. In these tests, there are 34 tweet events

Table 2: Full Sample Tests			
	AR	ATV	Volatility
All Tweets			
TW	0.0025** (0.0011)	0.192*** (0.038)	0.190*** (0.052)
Positive Only			
TW	0.0042*** (0.0016)	0.253*** (0.054)	0.160** (0.070)
Negative Only			
TW	-0.0009 (0.0015)	0.131** (0.054)	0.218*** (0.077)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. The full sample test includes 209 tweet events. The positive only test includes 103 tweet events. The negative only test includes 106 tweet events.

Table 3: Intraday Tests			
	AR	ATV	Volatility
All Tweets			
TW	0.0026	0.254***	0.328***
	(0.0020)	(0.070)	(0.097)
Positive Only			
TW	0.0080***	0.335***	0.383***
	(0.0030)	(0.106)	(0.135)
Negative Only			
TW	0.0017	0.191**	0.285**
	(0.0026)	(0.094)	(0.137)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. The full sample intraday test includes 64 tweet events. The positive only test includes 28 tweet events. The negative only test includes 36 tweet events.

Table 4: Interactions Effects			
	AR	ATV	Volatility
Post Ge Et Al.			
TW	0.0047**	0.199***	0.187***
	(0.0021)	(0.039)	(0.052)
Interaction	-0.0032	0.095**	0.007
	(0.0024)	(0.043)	(0.058)
Post Inauguration			
TW	0.0070**	0.198***	0.190***
	(0.0028)	(0.038)	(0.052)
Interaction	-0.0054*	0.087**	-0.010
	(0.0030)	(0.041)	(0.055)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. The post Ge test includes 165 tweet events. The post inauguration test includes 186 tweet events.

Table 5: Lags of Twitter Variable			
	AR	ATV	Volatility
TW	0.0024^{**}	0.193^{***}	$.0178^{***}$
	(0.0011)	(0.038)	(0.052)
TW_{t+1}	0.0013	0.022	0.121^{**}
	(0.0011)	(0.038)	(0.052)
TW_{t+2}	0.0012	-0.050	-0.007
	(0.0011)	(0.039)	(0.052)
TW_{t+3}	-0.0006	0.033	0.182^{***}
	(0.0011)	(0.039)	(0.052)
TW_{t+4}	-.0006	0.018	0.113^{**}
	(0.0011)	(0.038)	(0.052)
TW_{t+5}	0.0010	-0.034	0.074
	(0.0011)	(0.038)	(0.052)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. Each TW variable consists of 209 tweet events.

Table 6: Testing for Prior News			
	AR	ATV	Volatility
TW	0.0023^{**}	0.176^{***}	0.172^{***}
	(0.0011)	(0.039)	(0.053)
TW_{t-1}	0.0030^{***}	0.168^{***}	0.124^{**}
	(0.0011)	(0.039)	(0.053)
TW_{t-2}	0.0011	0.066^{*}	0.097^{*}
	(0.0011)	(0.039)	(0.053)
TW_{t-3}	0.0005	-0.024	0.027
	(0.0011)	(0.039)	(0.053)
TW_{t-4}	-0.0003	-0.030	0.007
	(0.0011)	(0.039)	(0.053)
TW_{t-5}	0.0015	0.004	0.016
	(0.0011)	(0.039)	(0.053)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. Each TW variable consists of 209 tweet events.

Table 7: Outlier Robust Regressions			
	AR	ATV	Volatility
All Tweets			
TW	0.0024*** (0.0008)	0.061** (0.024)	0.130*** (0.033)
Positive Only			
TW	0.0025** (0.0011)	0.093*** (0.034)	0.074 (0.047)
Negative Only			
TW	-0.0023** (0.0011)	0.033 (0.033)	0.184*** (0.046)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. In this test, there are 209 tweet events.

Table 8: Two Way Fixed Effects			
	AR	ATV	Volatility
TW	0.0020* (0.0011)	0.208*** (0.035)	0.190*** (0.041)

Where *,**, *** represent 10%, 5%, and 1% levels of significance, respectively. "AR" stands for abnormal returns and "ATV" stands for abnormal trading volume. The numbers in parentheses represent panel-corrected standard errors. There are 57 companies spanning 790 days with the resulting number of panel observations totaling 44,052. In this test, there are 209 tweet events.