Do Investors Care about Presidential Company-Specific Tweets?*

Qi Ge † Alexander Kurov ‡ Marketa Halova Wolfe §

First Draft: March 20, 2017

This Draft: August 8, 2018

Forthcoming, *Journal of Financial Research*

Abstract

When the President of the United States tweets, do investors respond? We analyze the impact of tweets from President Trump's official Twitter accounts from November 9, 2016 to December 31, 2017 that include names of publicly traded companies. We find that these tweets move company stock prices and increase trading volume, volatility, and institutional investor attention, with a stronger impact before the presidential inauguration. There is some evidence that the initial impact of the presidential tweets on stock prices is reversed on the next few trading days.

Keywords: Twitter, company-specific statements, President Trump, stock price, trading volume, volatility, investor attention, event study

JEL classification: G12, G14

---

*We thank the editors, an anonymous referee, Margaret J. Lay, seminar participants at Hamilton College and Skidmore College, and session participants at the 2017 Liberal Arts Macro Workshop for helpful suggestions. We also thank Chen Gu and Kun Zhou for research assistance. The opinions in this paper are those of the authors and do not necessarily reflect the views of Skidmore College or West Virginia University.

†Assistant Professor, Department of Economics, Skidmore College, Saratoga Springs, NY 12866, Phone: +1-518-580-8302, Email: qge@skidmore.edu

‡Professor, Department of Finance, College of Business and Economics, West Virginia University, P.O. Box 6025, Morgantown, WV 26506, Phone: +1-304-293-7892, Email: alkurov@mail.wvu.edu

§Assistant Professor, Department of Economics, Skidmore College, Saratoga Springs, NY 12866, Phone: +1-518-580-8374, Email: mwolfe@skidmore.edu

I Introduction

Donald J. Trump, elected the 45th President of the United States on November 8, 2016, has frequently utilized the social media platform Twitter as his primary communication channel. Some of President Trump's Twitter messages included statements about specific companies. These tweets have attracted considerable attention in the financial press. The discussion about the impact of the tweets has, however, been inconclusive. For example, Wang (2016) reports that the Lockheed Martin stock price dropped after President Trump tweeted about the company on December 22, 2016 "*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!*", and numerous sources, for example, Peltz (2017), describe attempts at creating algorithms for trading around President Trump's tweets, but Kaissar (2017) cautions that the impact of the presidential tweets on stock prices may not be predictable.

The impact of such company-specific statements is not clear *a priori*. On the one hand, the stock market may consider the tweets as information relevant to future company fundamentals. As one of the most powerful persons in the world (Ewalt, 2016 and Gibbs, 2017), the President of the United States holds a unique position with broad powers to influence policy relevant to companies, such as government contracts, trade tariffs, and government bailouts. The President's company-specific statements may then be understood by investors to include information relevant to future company fundamentals because the President can enact measures affecting these companies via executive orders and other means. For example, the above tweet about the cost overrun by the military contractor Lockheed Martin may be understood by investors as increasing the likelihood of the government contract being canceled, which would negatively affect future profitability of the company. Thus, presidential tweets may themselves form unexpected news events that could move the stock market. The stock market may then react in an identical way as when facing public news releases studied by, for example, Chan (2003) and Vega (2006). On the other hand, it is possible that the tweets are only noise without information relevant to company fundamentals. For example, the above tweet about Lockheed Martin may be understood by investors as only an empty threat that will not lead to contract cancellation. The market may, therefore, not react to the tweets, or the reaction may be only temporary. Temporary effects have been shown in numerous contexts. For example, Greene and Smart (1999) show that analyst coverage of companies in a Wall Street Journal column creates only a temporary pressure on stock prices by raising uninformed noise trading. Tetlock (2007) shows that the effect of media pessimism on the stock market reverses over the following trading week. Barber and Odean (2008) point out that attention is a scarce resource and show that individual investors buy stocks that catch their attention. It is possible that President Trump's tweets direct investors' attention to the company mentioned in the tweet. The resulting demand shock may then temporarily push the price away from fundamentals; however, this mispricing is corrected in the subsequent days as the attention fades.

We review all tweets from November 9, 2016 to December 31, 2017 posted on `@POTUS` and `@realDonaldTrump` Twitter accounts used by President Trump, document the tweets that include the name of a publicly traded company[1] and analyze their impact on the company stock price, trading volume, volatility, and institutional investor attention. We find that the tweets move the company stock price and increase trading volume, volatility, and institutional investor attention.[2] We also find that the impact was stronger before the presidential

[1]This dataset of company-specific tweets is unique. For comparison, we reviewed tweets in Twitter accounts used by former President Barack Obama, the only other president that utilized Twitter: `@POTUS44` from inception in May 2015 through January 2017 and `@BarackObama` from February 2016 through January 2017. The `@BarackObama` account shows no tweets naming public companies. The `@POTUS44` account shows only one tweet about Lehman Brothers on September 15, 2015 mentioning the bankruptcy of the company that occurred in 2008 and one tweet mentioning Shell on May 28, 2015 in response to a tweet from another Twitter user who wrote about this company.

[2]Wagner, Zeckhauser, and Ziegler (2017) study reactions of individual stock prices in the days and weeks after the 2016 presidential election and document numerous interesting findings such as the outperformance of high-beta stocks and high-tax firms. The findings in our paper show a reaction on the day of the tweet, which is in addition to the reaction documented by Wagner et al. (2017).

inauguration on January 20, 2017. During the pre-inauguration period, the tweets on average move the company stock price by approximately 1.21 percent and increase trading volume, volatility, and institutional investor attention by approximately 47, 0.34, and 45 percentage points, respectively, on the day of the tweet. There is also some evidence that the impact on the stock price is reversed by price movements on the following days.

Our paper contributes to the growing literature on the role of social media in the stock market. Previous research has extensively studied the role of traditional media in the stock market; recent papers examine the role of newspaper coverage (Fang & Peress, 2009), local newspapers (Engelberg & Parsons, 2011), and writing by specific journalists (Dougal, Engelberg, Garcia, & Parsons, 2012). The rise and popularity of social media utilizing real-time information delivery and social networking have understandably attracted scholarly attention and extended our understanding of the media's role in the stock market. Numerous studies examine how the stock market is affected by the number of messages in social media (for example, posts by finance industry professionals and regular users of China's social network Sina Weibo in Zhang, An, Feng, & Jin, 2017)[3] or investor sentiment that is derived using textual analysis of a large number of messages in online investment forums (for example, Chen, De, Hu, & Hwang, 2014), Facebook posts (for example, Karabulut, 2013 and Siganos, Vagenas-Nanos, & Verwijmeren, 2014), and Twitter feeds (for example, Azar & Lo, 2016, Bartov, Faurel, & Mohanram, 2017, Bollen, Mao, & Zeng, 2011, and Sprenger, Sandner, Tumasjan, & Welpe, 2014). Our study advances this social media literature by carefully examining the context and content of messages posted by one user – the highest-ranking government official in the largest economy in the world. The stock market impact of comments

[3]The paper by Zhang et al. (2017) is similar to our study because it also analyzes the impact of social media posts by influential individuals. Our study differs from Zhang et al. (2017) in two ways. First, Zhang et al. (2017) study the impact of posts by finance professionals whereas our study focuses on the President of the United States who has broad powers to influence policy relevant to the companies. Second, Zhang et al. (2017) use the number of posts to measure the impact on the stock market whereas our study carefully analyzes the context and content of each tweet.

about specific companies by the President of the United States has not been studied in previous literature; Twitter provides a unique opportunity for this study because it streamlines the data collection process by comprehensively recording all presidential comments made in this media platform with precise timing of when the comments were posted.

II Twitter Data

Table 1 lists all tweets from `@realDonaldTrump` and `@POTUS` Twitter accounts used by President Trump that include the name of a publicly traded company.[4] The `@realDonaldTrump` account with approximately 43 million followers is President Trump's personal account. This account was used during the presidential campaign, and it continues to be used after the elections.[5] The tweets containing names of specific companies are almost always posted on this account. Only three tweets containing the names of specific companies are posted on the `@POTUS` account, the official account of the President of the United States with approximately 21 million followers that became available to President Trump after inauguration on January 20, 2017.[6] We include these three tweets from the `@POTUS` account in our analysis for completeness.

The sample period is from November 9, 2016 to December 31, 2017. November 9, 2016 is the beginning of the sample period because the presidential election took place on November 8, 2016. The first company-specific tweet appears on November 17, 2016. The last one appears on December 29, 2017.

[4]We exclude tweets that mention media companies, such as CNN (owned by Time Warner Inc) and New York Times (owned by the New York Times Company) because their impact on the stock market is complicated by President Trump's relationship with media.

[5]While there was some uncertainty at the beginning of President Trump's term whether his social media posts should be considered official presidential statements, this debate was put to rest during a press conference on June 6, 2017 by Sean Spicer, then White House Press Secretary, who confirmed that President Trump's tweets are "official statements" (Spicer, 2017).

[6]Tweets created by President Obama were archived into `@POTUS44` account.

Most of the tweets were posted outside of the United States stock market trading hours – in the early morning, in the evening, on weekends or holidays – such as a tweet about Rexnord on December 2, 2016 at 22:06. Therefore, in order to analyze the impact of the tweets, we use daily stock prices, trading volume, volatility, and investor attention following previous literature that also used daily data (for example, Demirer & Kutan, 2010 and Zhang et al., 2017). Tweets that occur after the closing of the stock market at 16:00 Eastern Time, on weekends or during holidays, are, therefore, assigned to the next trading day because that is the day when investors in the U.S. stock market would be able to trade on the tweets.

When multiple tweets about the same company occur on the same day, the daily data combine their effects. These tweets can happen over several hours (for example, tweets about Carrier on November 29 and 30, 2016) or within a few minutes when a message is split into multiple tweets (for example, tweets about SoftBank on December 6, 2016), which arises from the character restriction that Twitter imposes on the tweet length.[7] Table 1 shows how multiple tweets are combined into a single event in our study.

As stated in Section I, we analyze the impact of the tweets on the company stock price, trading volume, volatility, and investor attention. Following previous literature described in more detail in Section III.A, the impact on trading volume, volatility, and investor attention is not directional because tweets can increase trading volume, volatility, and investor attention regardless of the tweets' tone. The impact on stock price, however, is directional because tweets that have a positive (negative) tone are expected to increase (decrease) the price. Therefore, we have to classify the tone of the tweets as positive or negative.

We take two approaches to classifying the tone of the tweets. First, since our study focuses on social media messages posted by one user, we are able to carefully analyze the specific context and content of each tweet. In particular, we analyze each tweet to determine whether President Trump expressed positive or negative tone toward the company.[8] Second, we apply

[7]The tweet length was limited to 140 characters until November 7, 2017 when it was expanded to 280 characters.

[8]There are no days that include multiple tweets with positive and negative tones about the same company.

a textual analysis utilizing the Google Cloud Natural Language API (Google API hereafter), a cutting edge tool that utilizes machine learning to reveal the meaning of the text and infer the underlying sentiment. Consistent with previous literature,[9] we also conduct additional textual analysis using the Loughran and McDonald (2011) lexicon and the National Research Council Canada Sentiment and Emotion Lexicon. Because the textual analysis using the Google API and the lexicons agrees with our context-based classification, we report this alternative classification method in the Appendix as a robustness check.

We analyze the content of each tweet in the context of previous statements that President Trump repeatedly made during the election campaign about the topics of the tweets: keeping jobs and manufacturing in the United States and bringing them back from other countries, controlling government costs, repealing the Affordable Care Act, and lowering drug prices. To determine the tone of the tweets related to jobs and manufacturing (tweet events #1-5, 7, 12-22, 28, 30-33, 35-40, and 44-47 denoted by "Jobs" in the Content column in Table 1), we base the classification on the election campaign of keeping jobs and manufacturing in the United States and bringing them back from other countries as stated in, for example, the 2016 Republican primary debate in South Carolina: *"I'm going to bring jobs back from China. I'm going to bring jobs back from Mexico and from Japan, where they're all every country*

[9] Previous studies of social media impact on the stock market analyze a large number of messages from numerous users. The analysis in those studies, therefore, has to depend on algorithms that extract overall sentiment from that "big data" and cannot take into account the specific context and actual content of the individual messages. For example, Chen et al. (2014) use a negative words list compiled by Loughran and McDonald (2011) and a methodology of using the fraction of negative words proposed by Tetlock, Saar-Tsechansky, and Macskassy (2008) to analyze the Seeking Alpha investment-related website articles and comments about the articles. Karabulut (2013) and Siganos et al. (2014) use the Gross National Happiness index constructed by Facebook based on positive and negative words in the status updates of Facebook users. Azar and Lo (2016) use a polarity score based on the positive, negative, and objective meanings in a tweet. Bartov et al. (2017) use four measures to classify tweets as positive or negative including the negative words list compiled by Loughran and McDonald (2011) and an enhanced classifier produced by Narayanan, Arora, and Bhatia (2013). Bollen et al. (2011) use the OpinionFinder, a software tool for analyzing polarity of sentences, and Google-Profile of Mood States for measuring mood in six dimensions.

throughout the world now Vietnam, that's the new one." (*Republican Candidates Debate in Greenville, South Carolina on February 13, 2016*, 2016). Therefore, if a tweet commends a company for keeping jobs and/or manufacturing in the United States or bringing them back from other countries (for example, tweets about Ford on November 17, 2016), we classify the tone as positive toward the company and denote it with 1 in the Code column. If a tweet criticizes a company for moving jobs and/or manufacturing out of the United States (for example, a tweet about Rexnord on December 2, 2016), we classify the tone as negative toward the company and denote it with -1 in the Code column. The rationale for this classification is based on repeated threats to punish companies by measures, such as an import tax (for example, a tweet about General Motors on January 3, 2017). Note that this textual analysis classification focuses on the tone of the tweet rather than potential economic impacts that are likely to be complex. For example, a decision to keep a plant in the United States may be advantageous for a company if the company is able to negotiate incentives, such as tax breaks or reduced regulation, or disadvantageous if it forgoes the cost savings from relocating to a country with lower production costs.[10]

To determine the tone of the tweets related to controlling government costs (tweet events #6, 10, 11, and 48), we again base the classification on the election campaign. In this case, the election campaign focused on reducing government costs as stated in, for example, the 2016 Republican primary debate in Texas: *"...Now, the wall is $10 billion to $12 billion, if I do it. If these guys do it, it'll end up costing $200 billion... Mexico will pay for the wall."* (*Republican Candidates Debate in Houston, Texas on February 25, 2016*, 2016). Therefore, if the tweet criticizes a company for providing goods and services to the government at high cost (for example, a tweet about Boeing on December 6, 2016), we classify the tone as negative

[10] Whether companies actually benefit and face costs as described in the tweets remains to be seen. There is some evidence that firms do benefit and face costs. For example, Waldmeir (2016) reports that Carrier was able to negotiate a tax break for keeping jobs in the United States, and Capaccio and Cirilli (2017) report that Boeing entered negotiations with President Trump to reduce the Air Force One cost. However, other policies such as the border tax have not been implemented.

toward the company. If the tweet notes that a company may reduce the government's costs, we classify the tone as positive toward the company (for example, a tweet about Boeing on December 22, 2016). Again, the rationale for this classification is based on threats to punish companies by measures, such as canceling government orders (for example, a tweet about Boeing on December 6, 2016).

To determine the tone of the tweets related to the Affordable Care Act (tweet events #29, 34, and 41), we base the classification on the election campaign against this legislation as stated in, for example, the third presidential candidate debate in Nevada: *"And one thing we have to do: Repeal and replace the disaster known as Obamacare."* (*Presidential Debate in Las Vegas, Nevada on October 19, 2016*, 2016). Because the tweets are related to health insurance companies exiting from the Affordable Care Act health exchange, we classify the tone as positive toward the companies since President Trump considers being a part of the health exchange as negative.

To determine the tone of the tweets related to drug prices (tweet events #42 and 43), we base the classification on the election campaign against the high cost of drugs as stated, for example, in a campaign rally in New Hampshire widely reported in the media (Krauskopf, 2016). Since these tweets are criticizing a pharmaceutical company for high drug prices, we classify the tone as negative toward the company.

In addition to the above tweets related to the presidential campaign, there are seven other tweets. Six tweets (tweet events # 8-9 and 23-26) are about company chief executive officers (CEOs). Tweets # 8-9 are complimenting the CEO of ExxonMobil who became the Secretary of State. Tweets # 23-26 comment on successful meetings with CEOs. All of these tweets express a positive tone toward the companies and we, therefore, classify them as positive. One tweet (tweet event #27) criticizes a retail company for dropping the fashion line of Ivanka Trump, President Trump's daughter; since the tweet expresses a negative tone about the company, we classify it as negative.

If a tweet mentions more than one company, such as a tweet about General Motors and Walmart on January 17, 2017, the tweet is listed twice to capture the impact on both companies. This is important especially when a tweet is positive about one company and negative about another company, such as a tweet about Lockheed Martin (negative) and Boeing (positive) on December 22, 2016. Our dataset then includes the entire population of President Trump's company-specific tweets with a total of 48 events (combining 59 tweets).[11] Eleven are classified as having a negative tone toward the company, and 37 are classified as having a positive tone toward the company.[12]

III Empirical Strategy and Results

Section III.A reports the impact of the tweets on company stock returns, trading volume, volatility, and investor attention. Section III.B documents how the impact varies between the pre- and post-inauguration periods. Section III.C analyzes whether the impact on the stock price on the day of the tweet is reversed in the following days.

A Stock Market Reactions to Presidential Tweets

We study the impact of the tweets on four variables: company stock returns, trading volume, volatility, and investor attention. To measure the impact on returns, we obtain daily closing stock prices, $C_{i,t}$,[13] and compute the holding period return for each company i as $R_{i,t} = \frac{C_{i,t}-C_{i,t-1}}{C_{i,t-1}}$, stated in percentage. Table 2 reports the summary statistics. We compute excess return as the return in excess of risk-free return, RF_t, i.e., $ER_{i,t} = R_{i,t} - RF_t$. We estimate the Fama and French (1993) three-factor model. This model uses OLS to regress the excess return on the stock market return, RM_t, minus RF_t, small-minus-big market capitalization,

[11] Some companies were tweeted about more than once, such as General Motors on January 3 and January 24. We verify that there is no difference in impact between the first and subsequent tweets.

[12] We present a robustness check in Section IV.B showing that negative and positive tweets to not differ in their impact on the stock market.

[13] The company stock data are from Bloomberg.

SMB_t, and high-minus-low book-to-market ratio, HML_t:[14]

$$ER_{i,t} = \beta_0 + \beta_1(RM_t - RF_t) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{i,t}. \tag{1}$$

Since the parameters of this model change over time, we estimate them using a rolling window of 126 trading days (about six months). MacKinlay (1997) recommends that the estimation and event windows do not overlap. Therefore, we use data up until day $t-1$ to estimate the betas for day t. We then compute the abnormal return, stated in percentage, during our sample period as follows:[15]

$$AR_{i,t} = ER_{i,t} - [\widehat{\beta_0} + \widehat{\beta_1}(RM_t - RF_t) + \widehat{\beta_2} SMB_t + \widehat{\beta_3} HML_t]. \tag{2}$$

Controlling for the stock market return is especially important since the overall market rose during our sample period.

To measure the impact on trading volume, we compute the abnormal trading volume, $AV_{i,t}$, as the difference between the trading volume $V_{i,t}$ and the mean trading volume of the previous five days divided by the mean trading volume of the previous five days to control for intra-week volume pattern similar to Joseph, Wintoki, and Zhang (2011): $AV_{i,t} = \frac{V_{i,t} - V_{Avrg,t}}{V_{Avrg,t}}$ where $V_{Avrg,t} = \frac{\Sigma_1^J V_{i,t-j}}{J}$ and $J = 5$.[16]

To measure volatility of prices, we use the Rogers and Satchell (1991) range-based estimator of volatility computed as:

$$\hat{\sigma}_{it}^2 = (H_{it} - C_{it})(H_{it} - O_{it}) + (L_{it} - C_{it})(L_{it} - O_{it}), \tag{3}$$

where O_{it}, C_{it}, H_{it}, and L_{it} are the opening, closing, high, and low prices in natural log for

[14] RF_t, RM_t, SMB_t, and HLM_t data are from Kenneth French's website. We verify that results using the Fama and French (2015) five-factor model and a single-factor market model are similar.

[15] Results with abnormal returns that are based on factor loadings estimated using the entire period from January 1, 2016 to December 31, 2017 are very similar.

[16] The results with the full sample average as well as with $J = 22$, i.e., 22-day moving average, are similar.

company i on day t, respectively. We take the square root of this estimated variance and multiply the resulting standard deviation by 100 to express it in percentage terms.

To measure investor attention, we use the Bloomberg institutional investor attention measure described in Ben-Rephael, Da, and Israelsen (2017).[17] Bloomberg tracks how many times Bloomberg users read articles and search for information about each company using the company ticker. Bloomberg records hourly counts, compares the counts in the recent eight hours to those in the previous 30 days and assigns a score of 0, 1, 2, 3, and 4 if the average of the last eight hours is less than 80%, between 80% and 90%, between 90% and 94%, between 94% and 96%, or higher than 96% of the hourly counts in the previous 30 days, respectively. The maximum hourly score for each calendar day is the daily score shown on Bloomberg. Following Ben-Rephael et al. (2017), we construct a binary measure of abnormal investor attention that equals 1 if the score equals 3 or 4, and 0 otherwise, so that the abnormal investor attention captures the right tail of the investor attention distribution, and a value of 1 represents an investor attention shock.

We then estimate a fixed effects panel model for abnormal returns:

$$AR_{i,t} = \gamma_0 + \gamma_1 T_{i,t} + \theta_i + \tau_d + \upsilon_{i,t}, \tag{4}$$

where θ_i accounts for the company-specific fixed effects, τ_d accounts for day-of-week fixed effects proxied by indicator variables for the trading days in a week, and $T_{i,t}$ is the Twitter variable described in Section II.[18] There are 287 days and 27 companies. The resulting

[17]As an alternative measure of investor attention, we use the number of tweets about each company calculated by Bloomberg based on data from Twitter and StockTwits, a social media site for sharing ideas among investors, traders, and entrepreneurs. The results (available upon request) are similar to those based on the Bloomberg institutional investor attention measure. Other papers, such as Da, Engelberg, and Gao (2011), use Google Trends search volume data as a measure of investor attention. We do not use Google Trends data because many observations are missing for the companies in our sample.

[18]In contrast to studies analyzing scheduled announcements that have to subtract market's expectations from the actual announcement to compute the announcement's unexpected component, our empirical strategy does not involve subtracting the expectations because the tweets are unscheduled and unexpected.

number of panel observations is 7,749. As described in Section II, the Twitter variable represents the positive (negative) tone expressed by President Trump toward the company. If President Trump's tweets affect the company stock price, we expect γ_1 to be positive because positive (negative) information about the company will increase (decrease) the stock price.

Table 3 reports the impact of the tweets in the full sample period from November 9, 2016 to December 31, 2017. Column (1) shows the impact on abnormal returns. The positive coefficient indicates that the stock price tends to increase (decrease) if the tweet is positive (negative). The tweets on average move the stock price by approximately 0.80 percent. This is an economically meaningful effect because the median daily absolute return and absolute abnormal return are approximately 0.64% and 0.58%, respectively, per Table 2.

Next, we estimate a fixed effects panel model for abnormal trading volume:

$$AV_{i,t} = \delta_0 + \delta_1 |T_{i,t}| + \phi_i + \mu_d + \varepsilon_{i,t}, \tag{5}$$

where ϕ_i and μ_d account for the company-specific, and day-of-week fixed effects, respectively. We use the absolute value of the Twitter variable because we expect the tweets to increase the trading volume regardless of whether their tone is positive or negative. This means that we expect δ_1 to be positive. Column (2) reports the results. We find that the tweets on average increase trading volume by approximately 39 percentage points compared to the average trading volume on the previous five days.

In Column (3), we estimate a fixed effects panel model in equation (5) where we use volatility rather than trading volume as the dependent variable. Similar to trading volume and consistent with previous literature (for example, Neuhierl, Scherbina, & Schlusche, 2013), we expect an increase in volatility driven by President Trump's tweets regardless of their tone. Recall that volatility is measured by the standard deviation of daily returns multiplied by 100. Its median and mean values are 0.83% and 0.97%, respectively, in Table 2. Therefore, an average increase of 0.31 percentage points is economically meaningful.

Finally, we estimate a panel probit model of the abnormal investor attention on the absolute value of the Twitter variable, $|T_{i,t}|$, with indicator variables for individual stocks. Following previous literature on investor attention including Ben-Rephael et al. (2017), we expect the presidential tweets, regardless of their tone, to raise investor attention. Column (4) reports the marginal effects. The tweets (both positive and negative) on average increase the probability of abnormal investor attention by 40 percentage points, suggesting that the tweets capture investors' attention.

One potential concern about specifications (4) and (5) is that the results could be driven by unobserved company-specific events that occurred prior to the tweets. These events could be unrelated to the topic of President Trump's tweets (for example, unrelated news about company earnings) or related to the topic of President Trump's tweets (for example, if President Trump's tweets are merely reactions to news about these companies from television and other news sources). Therefore, we follow Tetlock (2007) and include in our specification five lags of abnormal returns, abnormal trading volume, volatility, and abnormal investor attention to account for the possibility that President Trump and investors were responding to the same recent attention-grabbing events. This augmented specification also accounts for persistence that has been documented for volatility and trading volume (for example, Fleming & Kirby, 2011). For abnormal returns, for example, the specification becomes:

$$AR_{i,t} = \gamma_0 + \gamma_1 T_{i,t} + \gamma_2 L5(AR_{i,t}) + \gamma_3 L5(AV_{i,t}) + \gamma_4 L5(\hat{\sigma}_{it}) + \gamma_5 L5(AIIA_{i,t}) + \theta_i + \tau_d + \upsilon_{i,t}, \quad (6)$$

where $L5$ is a lag operator that transforms the variable into a row vector of its five lags. For example, $L5(AR_{i,t})$ denotes $L5(AR_{i,t}) = (AR_{i,t-1}, AR_{i,t-2}, AR_{i,t-3}, AR_{i,t-4}, AR_{i,t-5})$. Correspondingly, γ on the lagged terms represents a vector of coefficients.

Table 4 reports results from these full specifications. We find that for all four dependent variables the results are similar to those reported in Table 3. This suggests that the results in Table 3 are not driven by investors systematically responding to attention-grabbing events that took place on trading days prior to the presidential tweets. We come back to this point with an additional robustness check in Section IV.C. For the remainder of the paper, our analyses and discussions are based on the specifications that include the full set of lagged abnormal returns, abnormal trading volume, volatility, and abnormal institutional investor attention.[19]

To gauge the potential wealth creation or destruction as a result of the presidential tweets, we multiply the abnormal return of each firm on the day of the tweet by the Code variable. We then multiply this sign-adjusted abnormal return by that firm's market capitalization on the previous business day.[20] The mean (median) impact of a tweet amounts to $949 million ($364 million), an economically significant impact.[21] The mean impact of presidential tweets on firm value is statistically different from zero at 1% significance level based on both the t-test and the signed rank test.

B Pre- vs. Post-Inauguration

Our sample comprises two distinct periods: from the election to the inauguration (November 9, 2016 to January 19, 2017) and from the inauguration to the end of our sample period (January 20, 2017 to December 31, 2017). We analyze whether the impact of tweets differs between the periods. We repeat the analysis in Section III.A while including an indicator variable, I_t, equal to 1 if the event falls into the post-inauguration period and 0 otherwise, and a term interacting the Twitter variable with this indicator variable. For example, for

[19] Note that the relatively low R^2 values in our tables follow from our choice of the time-series regression approach. The tweets are fairly rare events and, therefore, they may not explain behavior of the dependent variables over the whole sample period. In spite of this, we prefer the time-series regression approach (rather than the event study regression approach) because it allows us to include control variables such as lagged values of the dependent variables and days of the week to be consistent with previous literature.

[20] In this calculation, we include only firms with common stock data in the CRSP database. For example, this calculation excludes firms with American Depositary Receipts such as Toyota. 22 of the 27 firms in our sample are included in this calculation. This means that 42 out of 48 events are included in this calculation.

[21] In addition, we separately compute the economic impact of positive and negative tweets and find that the mean (median) economic impact amounts to $931 million ($364 million) for positive tweets and $1,004 million ($335 million) for negative tweets.

abnormal returns we estimate:

$$AR_{i,t} = \gamma_0 + \gamma_1 T_{i,t} + \gamma_2 L5(AR_{i,t}) + \gamma_3 L5(AV_{i,t}) + \gamma_4 L5(\hat{\sigma}_{it}) + \gamma_5 L5(AIIA_{i,t}) + \gamma_6 I_t + \gamma_7 T_{i,t} * I_t + \theta_i + \tau_d + \upsilon_{i,t}, \quad (7)$$

where θ_i and τ_d account for the company-specific and day-of-week fixed effects, respectively, and γ on the lagged terms again represents a vector of coefficients. Table 5 presents the results.[22] The coefficient on the Twitter variable, γ_1, measures the impact during the pre-inauguration period. The signs on the coefficients for all four dependent variables are the same as in the full sample period, indicating that the tweets move the variables in the same direction in the pre-inauguration period as in the full sample period. The magnitude of the coefficients is larger than in the full sample period. For example, the tweets on average move the company stock price by approximately 1.21 percent compared to 0.80 percent in the full sample period.

The post-inauguration interaction term tests whether the difference between the pre- and post-inauguration results is statistically significant. A negative sign on the coefficient γ_7 indicates that the impact of the tweets is lower in the post-inauguration period than in the pre-inauguration period. This is indeed the case for the coefficient estimate on abnormal returns. The coefficient sum reports the sum of the coefficients on the Twitter variable and the post-inauguration interaction term and shows the impact in the post-inauguration period. Overall, the results indicate that although investors may still be paying attention to the tweets, the impact on stock price has lessened in the post-inauguration period.

Two potential explanations exist for the decline in market reaction after the inauguration. First, the information content of President Trump's tweets has changed. Second, in addition to Twitter and public appearances, such as speeches that were already available

[22]Estimating specifications in Table 4 separately for the pre-inauguration and post-inauguration subsamples produces results similar to those in Table 5; estimating both periods jointly in Table 5 allows us to show the statistical significance of changes in the impact after the inauguration.

to then President-elect Trump before inauguration, other communication channels with the markets, such as presidential executive orders, memoranda, and press releases, have become available since inauguration. These channels could lessen the Twitter impact if investors consider them more influential. We review all presidential executive orders, press releases, and memoranda from the post-inauguration period (January 20, 2017 - December 31, 2017). We do not find any presidential executive orders that include a name of publicly traded company. We find only two press releases (The White House (2017c) and The White House (2017d) about ExxonMobil and Broadcom Limited on March 6, 2017 and November 2, 2017, respectively) and two memoranda (The White House (2017a) and The White House (2017b) about Keystone XL and Dakota Access pipelines owned by Energy Transfer Partners and TransCanada Corp, respectively, on January 24, 2017) that mention companies from our sample. This may be because presidential executive orders, press releases, and memoranda are official channels vetted by other cabinet members or White House staff as opposed to coming directly from President Trump. Since information about 44 out of our 48 events appears to have been communicated solely via the tweets in our sample,[23] the explanation of the new communication channels lessening the Twitter's influence does not appear to contribute to the market reaction changing after inauguration.

This leaves the first explanation as the likelier explanation for the changing market reaction. Changes in the informational content of the tweets could be due to the nature of the tweets changing or the fact that the initial presidential tweets (by then President-elect) about specific companies took the market by surprise because his predecessor, President Obama, did not post company-specific tweets. Therefore, President Trump's tweets were likely unexpected attention-grabbing events. After some time, however, investors might have grown accustomed to the tweets and do not react as strongly any more. This is a plausible explanation in view of the delays in implementing the presidential campaign objectives, such

[23]This conclusion comes with the caveat that company-specific statements could have been made via other means that we were unable to find.

as imposing a border tax on imports and repealing the Affordable Care Act.

C Do Tweets Have a Permanent Effect on Stock Returns?

Section III.A shows that President Trump's tweets move the company stock price on the day of the tweet. However, investors may initially overreact or underreact to presidential tweets. Price reversals have been documented in numerous studies. For example, Greene and Smart (1999) show that analyst coverage of companies in a Wall Street Journal column creates only a temporary pressure on price by raising uninformed noise trading. Tetlock (2007) shows that the effect of media pessimism on the stock market reverses over the following trading week. Barber and Odean (2008) point out that attention is a scarce resource and show that individual investors buy stocks that catch their attention. Tetlock (2011) shows that investors react to stale news, resulting in temporary stock price movements.

To test for continuing price adjustment on the following days, we repeat the analysis of Section III.A while including lags of the Twitter variable:

$$AR_{i,t} = \gamma_0 + \sum_{j=1}^{J} \gamma_j T_{i,t+1-j} + \gamma_7 L5(AR_{i,t}) + \gamma_8 L5(AV_{i,t}) + \gamma_9 L5(\hat{\sigma}_{it}) + \gamma_{10} L5(AIIA_{i,t}) + \theta_i + \tau_d + \upsilon_{i,t} \quad (8)$$

where we use $J = 6$ to control for weekly patterns, and γ on the lagged terms again represents a vector of coefficients.[24]

Column (1) of Table 6 reports the results. The coefficient on the contemporaneous term is of the same sign with similar magnitude and statistical significance as the one reported in Table 4. We do find some evidence toward price reversal. The test of the sum of the coefficients on the contemporaneous and lagged terms is not statistically significant, suggesting that the initial impact on the day of the tweet is reversed on the following days. In addition, the test of the sum of the coefficients on the lagged terms is negative and statistically

[24] We verify that using longer lags does not affect the results.

significant at 10% level, again suggesting that there is some reversal of the initial price effect.

We note that only the third lag is statistically significant on its own. This is an unexpected result that could be driven by outliers. Therefore, we repeat the analysis with the Huber (1973) outlier robust regression (M-estimation) and present the results in Column (2). The third lag is no longer significant, which suggests that its statistical significance in Column (1) is driven by outliers. The results of the tests of coefficient sums share the same directions with the OLS results, although the sum of the coefficients on the lagged terms is no longer significant.

We, therefore, conclude that there is some evidence that the effect of tweets on returns is temporary. It is possible that President Trump's tweets direct investors' attention to the company. The resulting demand shock may then temporarily push the price away from fundamentals; however, this mispricing is corrected in the following days as the investor attention fades. The market response on the day of the tweet likely represents an overreaction. This is also consistent with Seasholes and Wu (2007) who show that individual investors buy stocks as a result of attention-grabbing events and rational traders profit from this attention-caused buying.

IV Robustness Checks

We already noted in Section II that our results are robust to alternative classifications of the tweet tone. We also noted in Section III.A that our results for returns are robust to using the market-adjusted return and the Fama and French (2015) five-factor model (rather than the three-factor model based on Fama and French (1993)) as well as estimating factor loadings in equation (1) using the entire period from January 1, 2016 to December 31, 2017. We also confirmed that the results for trading volume are robust to computing the abnormal trading volume using the full sample average as well as the 22-day moving average that accounts for monthly volume patterns (rather than five-day moving average that accounts for weekly volume patterns). We verified that the impact of tweets on investor attention is similar when an alternative measure of investor attention (the number of tweets about each company calculated by Bloomberg based on data from Twitter and StockTwits) is used. Furthermore, we re-estimated all specifications using standard errors double-clustered by firm and time, as suggested in Petersen (2009). The results of these robustness checks are similar and available upon request. This section presents additional robustness checks. Section IV.A verifies that our results are not driven by outliers, Section IV.B shows that the results do not differ between positive and negative tweets, and Section IV.C considers a potential effect of other news.

A Outlier-Robust Regression

Our analysis employs the entire population of President Trump's 48 company-specific tweet events. In this sense, our study follows other studies that use samples of similar sizes. For example, Brooks, Patel, and Su (2003) analyze the effect of 21 industrial accidents, and Lamont and Thaler (2003) analyze the effect of 18 stock carve-outs. We conduct two robustness checks to verify that our results in Sections III.A and III.B are not influenced by outliers.

First, we repeat the analysis of Sections III.A and III.B with the Huber (1973) outlier robust regression (M-estimation). Table 7 reports the results for the full sample period in the top panel and for the pre-inauguration and post-inauguration periods in the bottom panel.[25] The results for returns, trading volume, and volatility are qualitatively similar to those from the least squares panel regression reported in Tables 4 and 5. We also find that, after accounting for outliers, the market response to presidential tweets is significantly stronger in all three variables in the pre-inauguration period. Overall, the results from the outlier

[25]The Huber (1973) outlier robust regression (M-estimation) does not apply to nonlinear regression models, such as the panel probit model that we use for estimating the impact on abnormal investor attention. Therefore, Table 7 reports results only for returns, trading volume, and volatility.

robust regression show that our findings are not driven by outliers. In spite of this, we prefer reporting the least squares results in Sections III.A and III.B because that methodology uses a panel estimation accounting for the correlation of errors across firms whereas the outlier robust regression in Table 7 uses indicator variables for individual companies.

Second, as an additional robustness check, we winsorize variables at 1% and 99%. We winsorize only abnormal returns, abnormal trading volume, and volatility because the institutional investor attention variable only takes on values of 0 and 1. We repeat the analysis of Tables 4 and 5. The coefficients on the Twitter variable show the same sign as well as similar magnitude and statistical significance as in Tables 4 and 5, again suggesting that our results are not driven by outliers. These results are available upon request.

B Asymmetries between Positive and Negative Tweets

Several previous papers studying the impact of media on the stock market find that negative sentiment in the media is especially related to the stock market activity. For example, Tetlock (2007) uses data from a Wall Street Journal column to show that high pessimism in the media predicts a downward pressure on the stock market prices that reverses during the next few days, and abnormally high or low pessimism predicts high stock market trading volume. Chen et al. (2014) show that the fraction of negative words in the Seeking Alpha investment-related website articles and comments about the articles negatively predict stock returns. Therefore, we test whether negative and positive tweets in our sample differ in their impact on returns, trading volume, volatility, or investor attention.

We repeat the analysis of Section III.A while including a term interacting the Twitter variable with an indicator variable equal to 1 if the tweet is negative and 0 otherwise. Table 8 reports the results. Although the response appears to be larger in positive tweets (an increase of 0.93% in returns) than negative tweets (a decrease of 0.37% in returns computed as the sum of the Twitter variable and interaction term coefficients), the difference (measured by the interaction term) is not statistically significant. With the caveat of a small sample size (because only eleven tweet events are classified as negative), this result suggests that negative and positive tweets do not differ in their impact. This result is similar to Williams (2015) who finds that the reaction to good and bad earnings news becomes asymmetric only in times of high ambiguity measured by large increases in the VIX. The VIX was relatively low during our sample period (the daily average of approximately 11 compared to, for example, the daily average of approximately 19 during the period from January 1990 to December 2017).

C Tweets as Reactions to Related News

We already mentioned in Section III.A a potential concern about the results from specifications (4) and (5) being driven by unobserved company-specific events that occurred prior to the tweets. These events could be unrelated to the topic of President Trump's tweets (for example, unrelated news about company earnings) or related to the topic of President Trump's tweets (for example, if President Trump's tweets are merely reactions to news about the companies from television and other news sources). In specification (6), we included five lags of abnormal returns, trading volume, volatility, and investor attention to account for the possibility that President Trump and investors are responding to the same recent attention-grabbing events that took place on trading days prior to the presidential tweets. In this section, we provide another robustness check.

We conduct a comprehensive search for any company-specific news on or before the day of the tweets using the Factiva Global News Database, a leading provider of financial and economic news with more than 30,000 sources ranging from traditional media to websites and blogs. The search interval is as follows: 1) if the tweet was posted during trading hours, the search interval ranges from three business days prior to the tweet to the day of the tweet; 2) if the tweet was posted outside trading hours or within two hours from the end of trading hours, the search interval ranges from three business days prior to the tweet to the business day following the tweet.[26]

While 18 of our presidential tweet events do not have preceding related news events, we find that the other 30 tweet events could perhaps be responses to preceding related news events,[27] which is not surprising because the President of the United States does not tweet in a vacuum. We, therefore, repeat the analysis from Section III.A for each of these two subsamples. This analysis controls for events not only on days prior to the presidential tweet but also earlier in the day on the day of the tweet.

Table 9 presents the estimated coefficients. Regardless of whether the President's tweets are preceded by related news, we find significant market responses in all four columns. While this analysis is subject to the small-sample caveat, the fact that the results hold for the subsample of tweets that are not preceded by related news indicates that President Trump's tweets indeed generate a reaction in the stock market.[28]

V Conclusion

We analyze the impact of presidential tweets about specific companies. We document that the tweets move stock prices and increase trading volume, volatility, and institutional investor attention. We also find that the impact was stronger before the presidential inauguration on January 20, 2017. There is some evidence that the impact on the stock price on the

[26] Details about the Factiva news database searches are available upon request.

[27] Another potential scenario is the presidential tweets attracting news coverage, which in turn leads to the stock market reaction. This is not an issue for us because the purpose of our paper is to identify the overall market impact of the tweets including the impact due to subsequent media coverage of the tweets.

[28] As a separate check, we analyze then candidate Trump's company-specific tweets from the year preceding the presidential election (November 9, 2015 - November 8, 2016). These tweets have no statistically significant effect on stock prices, trading volume, volatility, or investor attention. The lack of market reaction may be due to pre-election polls repeatedly favoring candidate Hillary Clinton as documented by, for example, Zurcher (2016) or due to the candidates not possessing powers to implement policy and the market believing that the election promises will not be fulfilled. These results suggest that it is the presidential tweets that drive the market reaction. These pre-election tweets and results are available upon request.

day of the tweet is reversed by price moves on the following days. These findings raise the policy question of whether it is optimal for high-ranking government officials to communicate industrial policy by making statements about specific companies since such statements can potentially instantly create or wipe out hundreds of millions of dollars in shareholder value.

This topic lends itself to further research when a larger population of presidential tweets becomes available. Future research could investigate whether certain industry or firm-level attributes make the tweets particularly influential. For example, some industries may be more influenced by the tweets due to their dependence on government contracts (such as the defense industry) or bailouts (such as the automobile industry). Likewise, the size of the targeted company could play a role in explaining the stock market reaction. Also, if more tweets occur during the stock market trading hours, a comprehensive analysis of intraday data will reveal high-frequency moves that are likely to be interesting. Finally, as Twitter is becoming more popular, it will be interesting to compare the impact of the tweets by the President of the United States to tweets by other politicians and celebrities.

References

Azar, P. D., & Lo, A. W. (2016). The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Twitter feeds. *The Journal of Portfolio Management*, *42*(5), 123–134.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, *21*(2), 785-818.

Bartov, E., Faurel, L., & Mohanram, P. S. (2017). Can Twitter help predict firm-level earnings and stock returns? *The Accounting Review (in press).*

Begley, S. (2017). Trump wasn't always so linguistically challenged. What could explain the change? *STAT*, May 23, 2017. Retrieved on November 15, 2017, from `www.statnews.com`.

Ben-Rephael, A., Da, Z., & Israelsen, R. D. (2017). It depends on where you search: Institutional investor attention and underreaction to news. *The Review of Financial Studies*, *30*(9), 3009–3047.

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

Brooks, R. M., Patel, A., & Su, T. (2003). How the equity market responds to unanticipated events. *The Journal of Business*, *76*(1), 109–133.

Capaccio, T., & Cirilli, K. (2017). Trump talks on Air Force One cost make progress, Boeing CEO says. *Chicago Tribune*, January 17, 2017. Retrieved on February 10, 2018, from www.chicagotribune.com.

Chan, W. S. (2003). Stock price reaction to news and no-news: Drift and reversal after headlines. *Journal of Financial Economics*, *70*(2), 223–260.

Chen, H., De, P., Hu, Y. J., & Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies*, *27*(5), 1367–1403.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, *66*(5), 1461–1499.

Demirer, R., & Kutan, A. M. (2010). The behavior of crude oil spot and futures prices around OPEC and SPR announcements: An event study perspective. *Energy Economics*, *32*(6), 1467–1476.

Dougal, C., Engelberg, J., Garcia, D., & Parsons, C. A. (2012). Journalists and the stock market. *The Review of Financial Studies*, *25*(3), 639–679.

Engelberg, J. E., & Parsons, C. A. (2011). The causal impact of media in financial markets. *The Journal of Finance*, *66*(1), 67–97.

Ewalt, D. M. (2016). The world's most powerful people 2016. *Forbes*, December 14, 2016. Retrieved on July 1, 2017, from www.forbes.com.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stock and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22.

Fang, L., & Peress, J. (2009). Media coverage and the cross-section of stock returns. *The Journal of Finance*, *64*(5), 2023–2052.

Fleming, J., & Kirby, C. (2011). Long memory in volatility and trading volume. *Journal of Banking & Finance*, *35*(7), 1714–1726.

Gibbs, N. (2017). The 100 most influential people in the world 2017. *Time*, April 20, 2017. Retrieved on July 1, 2017, from `www.time.com`.

Greene, J., & Smart, S. (1999). Liquidity provision and noise trading: Evidence from the "Investment Dartboard" column. *The Journal of Finance*, *54*, 1885-1899.

Huber, P. J. (1973). Robust regression: Asymptotics, conjectures and Monte Carlo. *Annals of Statistics*, *1*(5), 799–821.

Joseph, K., Wintoki, M. B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting*, *27*(4), 1116–1127.

Kaissar, N. (2017). Trump's tweets aren't stock tips. *Bloomberg*, January 24, 2017. Retrieved on January 24, 2017, from `www.bloomberg.com`.

Karabulut, Y. (2013). Can Facebook predict stock market activity? *Working Paper*.

Krauskopf, L. (2016). Trump drug cost comments raise new risks for pharma stocks. *Reuters*, January 26, 2016. Retrieved on November 14, 2017, from `www.reuters.com`.

Lamont, O. A., & Thaler, R. H. (2003). Can the market add and subtract? Mispricing in tech stock carve-outs. *Journal of Political Economy*, *111*(2), 227-268.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, *66*(1), 35–65.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, *35*(1), 13–39.

Narayanan, V., Arora, I., & Bhatia, A. (2013). Fast and accurate sentiment classification using an enhanced Naive Bayes model. In Yin H. et al. (Ed.), *Intelligent Data Engineering and Automated Learning - IDEAL 2013.* Heidelberg: Springer.

Neuhierl, A., Scherbina, A., & Schlusche, B. (2013). Market reaction to corporate press releases. *Journal of Financial and Quantitative Analysis*, *48*(4), 1207–1240.

Peltz, J. F. (2017). When Trump tweets, Wall Street trades - instantly. *Los Angeles Times*, January 16, 2017. Retrieved on November 22, 2017, from `www.latimes.com`.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), 435–480.

Presidential Debate in Las Vegas, Nevada on October 19, 2016. (2016). Retrieved on September 8, 2017, from `http://www.presidency.ucsb.edu/ws/index.php?pid=119039`.

Republican Candidates Debate in Greenville, South Carolina on February 13, 2016. (2016). Retrieved on July 1, 2017, from `www.presidency.ucsb.edu/ws/index.php?pid=111500`.

Republican Candidates Debate in Houston, Texas on February 25, 2016. (2016). Retrieved on July 1, 2017, from `www.presidency.ucsb.edu/ws/index.php?pid=111634`.

Rogers, L., & Satchell, S. (1991). Estimating variance from high, low and closing prices. *The Annals of Applied Probability*, *1*(4), 504-512.

Seasholes, M. S., & Wu, G. (2007). Predictable behavior, profits, and attention. *Journal of Empirical Finance*, *14*(5), 590-610.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2014). Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior & Organization*, *107*(B), 730–743.

Spicer, S. (2017). *Press Conference of White House Press Secretary on June 6, 2017.*

Retrieved on July 1, 2017, from `www.c-span.org`.

Sprenger, T. O., Sandner, P. G., Tumasjan, A., & Welpe, I. M. (2014). News or noise? Using Twitter to identify and understand company-specific news flow. *Journal of Business Finance & Accounting*, *41*(7-8), 791–830.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), 1139–1168.

Tetlock, P. C. (2011). All the news that's fit to reprint: Do investors react to stale information? *The Review of Financial Studies*, *24*(5), 1481–1512.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, *63*(3), 1437–1467.

The White House. (2017a). Memorandum of January 24, 2017 Construction of the Dakota Access Pipeline. *Federal Register*, *82*(18). Retrieved on March 26, 2017, from `www.whitehouse.gov`.

The White House. (2017b). Memorandum of January 24, 2017 Construction of the Keystone XL Pipeline. *Federal Register*, *82*(18). Retrieved on March 26, 2017, from `www.whitehouse.gov`.

The White House. (2017c). President Trump congratulates Exxon Mobil for job-creating investment program. *The White House Press Release*, March 6, 2017. Retrieved on September 13, 2017, from `www.whitehouse.gov`.

The White House. (2017d). Remarks by President Trump in jobs announcement. *The White House Press Release*, November 2, 2017. Retrieved on February 8, 2018, from `www.whitehouse.gov`.

Vega, C. (2006). Stock price reaction to public and private information. *Journal of Financial*

Economics, *82*(1), 103–133.

Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2017). Company stock reacts to the 2016 election shock: Trump, taxes and trade. *Mossavar-Rahmani Center for Business & Government Associate Working Paper Series*.

Waldmeir, P. (2016). Carrier to get up to $7m in state aid from jobs deal with Trump. *Financial Times*, December 1, 2016. Retrieved on February 10, 2018, from `www.ft.com`.

Wang, C. (2016). Lockheed Martin shares take another tumble after Trump tweet. *CNBC*, December 22, 2016. Retrieved on June 21, 2017, from `www.cnbc.com`.

Williams, C. D. (2015). Asymmetric responses to earnings news: A case for ambiguity. *The Accounting Review*, *90*(2), 785-817.

Zhang, Y., An, Y., Feng, X., & Jin, X. (2017). Celebrities and ordinaries in social networks: Who knows more information? *Finance Research Letters*, *20*(February), 153–161.

Zurcher, A. (2016). US election: Is Trump or Clinton going to win? *BBC News*, November 7, 2016. Retrieved on July 1, 2017, from `www.bbc.com`.

Table 1: List of Tweets

Company & Ticker	Date	Time	Tweet	#	Content	Code
Ford (F)	11/17/16	21:01	Just got a call from my friend Bill Ford, Chairman of Ford, who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico	1	Jobs	1
Ford (F)	11/17/16	21:15	I worked hard with Bill Ford to keep the Lincoln plant in Kentucky. I owed it to the great State of Kentucky for their confidence in me!	1	Jobs	1
Carrier[a] (UTX)	11/24/16	10:11	I am working hard, even on Thanksgiving, trying to get Carrier A.C. Company to stay in the U.S. (Indiana). MAKING PROGRESS - Will know soon!	2	Jobs	1
Carrier[a] (UTX)	11/29/16	22:40	I will be going to Indiana on Thursday to make a major announcement concerning Carrier A.C. staying in Indianapolis. Great deal for workers!	3	Jobs	1
Carrier[a] (UTX)	11/29/16	22:50	Big day on Thursday for Indiana and the great workers of that wonderful state.We will keep our companies and jobs in the U.S. Thanks Carrier	3	Jobs	1
Carrier[a] (UTX)[b]	11/30/16	14:51	RT @DanScavino Great interview on foxandfriends by SteveDoocy w/ Carrier employee- who has a message for #PEOTUS realDonaldTrump & #VPEOTUS mike_pence.	3	Jobs	1
Carrier[a] (UTX)[b]	11/30/16	15:00	Its not uncommon for a Republican to be pro-business. But President-elect Donald Trump showed Tuesday night hes pro-worker, too, by saving 1,000 jobs at the Carrier plant in Indiana.	3	Jobs	1
Carrier[a] (UTX)	11/30/16	22:48	Look forward to going to Indiana tomorrow in order to be with the great workers of Carrier. They will sell many air conditioners!	4	Jobs	1
Carrier[a] (UTX)[b]	12/01/16	09:38	Getting ready to leave for the Great State of Indiana and meet the hard working and wonderful people of Carrier A.C.	4	Jobs	1
Rexnord (RXN)	12/02/16	22:06	Rexnord of Indiana is moving to Mexico and rather viciously firing all of its 300 workers. This is happening all over our country. No more!	5	Jobs	-1
Boeing (BA)	12/06/16	8:52	Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!	6	Cost control	-1

SoftBank (SFTBY)[b,c]	12/06/16	14:09	Masa (SoftBank) of Japan has agreed to invest $50 billion in the U.S. toward businesses and 50,000 new jobs....	7	Jobs	1
SoftBank (SFTBY)[b,c]	12/06/16	14:10	Masa said he would never do this had we (Trump) not won the election!	7	Jobs	1
ExxonMobil (XOM)	12/11/16	10:29	Whether I choose him or not for "State"- Rex Tillerson, the Chairman & CEO of ExxonMobil, is a world class player and dealmaker. Stay tuned!	8	CEOs	1
ExxonMobil (XOM)	12/13/16	6:43	I have chosen one of the truly great business leaders of the world, Rex Tillerson, Chairman and CEO of ExxonMobil, to be Secretary of State.	9	CEOs	1
Boeing (BA)	12/22/16	17:26	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!	10	Cost control	1
Lockheed Martin (LMT)	12/22/16	17:26	Same as above.	11	Cost control	-1
General Motors (GM)	01/03/17	7:30	General Motors is sending Mexican made model of Chevy Cruze to U.S. car dealers-tax free across border. Make in U.S.A.or pay big border tax!	12	Jobs	-1
Ford (F)[b]	01/03/17	11:44	"@DanScavino: Ford to scrap Mexico plant, invest in Michigan due to Trump policies"	13	Jobs	1
Ford (F)	01/04/17	8:19	Thank you to Ford for scrapping a new plant in Mexico and creating 700 new jobs in the U.S. This is just the beginning - much more to follow	14	Jobs	1
Toyota (TM)[b,c]	01/05/17	13:14	Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! Build plant in U.S. or pay big border tax.	15	Jobs	-1
Fiat Chrysler (FCAU)	01/09/17	9:14	It's finally happening - Fiat Chrysler just announced plans to invest $1BILLION in Michigan and Ohio plants, adding 2000 jobs. This after...	16	Jobs	1
Fiat Chrysler (FCAU)	01/09/17	9:16	Ford said last week that it will expand in Michigan and U.S. instead of building a BILLION dollar plant in Mexico. Thank you Ford & Fiat C!	16	Jobs	1
Ford (F)	01/09/17	9:16	Same as above.	17	Jobs	1

General Motors (GM)[b]	01/17/17	12:55	Thank you to General Motors and Walmart for starting the big jobs push back into the U.S.!	18	Jobs	1
Walmart (WMT)[b]	01/17/17	12:55	Same as above.	19	Jobs	1
Bayer AG (BAYN)[c]	01/18/17	8:00	"Bayer AG has pledged to add U.S. jobs and investments after meeting with President-elect Donald Trump, the latest in a string..." WSJ	20	Jobs	1
Energy Transfer Partners L.P.[a] (ETP)[b,e]	01/24/17	12:49	Signing orders to move forward with the construction of the Keystone XL and Dakota Access pipelines in the Oval Office. at The Oval Office	21	Jobs	1
TransCanada Corp.[a] (TRP)[b,e]	01/24/17	12:49	Same as above.	22	Jobs	1
Ford (F)[e]	01/24/17	19:46	Great meeting with Ford CEO Mark Fields and General Motors CEO Mary Barra at the WhiteHouse today.	23	CEOs	1
General Motors (GM)[e]	01/24/17	19:46	Same as above.	24	CEOs	1
Harley-Davidson (HOG)[b,d]	02/02/17	12:56	Great meeting with @harleydavidson executives from Milwaukee, Wisconsin at the @WhiteHouse.	25	CEOs	1
Harley-Davidson (HOG)[b,d]	02/03/17	13:26	#ICYMI- Remarks by President Trump Before Meeting with Harley-Davidson Executives and Union Representatives:	26	CEOs	1
Nordstrom (JWN)[b,e]	02/08/17	10:51	My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person – always pushing me to do the right thing! Terrible!	27	Ivanka Trump	-1
Intel (INTC)[b,e]	02/08/17	14:22	Thank you Brian Krzanich, CEO of @Intel. A great investment ($7 BILLION) in American INNOVATION and JOBS! #AmericaFirst	28	Jobs	1
Aetna (AET)	02/15/17	16:34	Aetna CEO: Obamacare in 'Death Spiral' #RepealAndReplace	29	ACA[f]	1
Boeing (BA)	02/17/17	6:38	Going to Charleston, South Carolina, in order to spend time with Boeing and talk jobs! Look forward to it.	30	Jobs	1
ExxonMobil (XOM)	03/06/17	16:19	'President Trump Congratulates Exxon Mobil for Job-Creating Investment Program'	31	Jobs	1
ExxonMobil (XOM)	03/06/17	16:22	45,000 construction & manufacturing jobs in the U.S. Gulf Coast region. $20 billion investment. We are already winning again, America!	31	Jobs	1
ExxonMobil (XOM)[d]	03/06/17	18:43	There is an incredible spirit of optimism sweeping the country right nowwe're bringing back the JOBS!	31	Jobs	1

ExxonMobil (XOM)	03/06/17	22:49	Buy American & hire American are the principles at the core of my agenda, which is: JOBS, JOBS, JOBS! Thank you @exxonmobil.	31	Jobs	1
ExxonMobil (XOM)	03/06/17	22:50	Thank you to @exxonmobil for your $20 billion investment that is creating more than 45,000 manufacturing & construction jobs in the USA!	31	Jobs	1
Charter Communications (CHTR)[b]	03/24/17	13:59	Today, I was thrilled to announce a commitment of $25 BILLION & 20K AMERICAN JOBS over the next 4 years. THANK YOU Charter Communications!	32	Jobs	1
Ford (F)	03/28/17	6:36	Big announcement by Ford today. Major investment to be made in three Michigan plants. Car companies coming back to U.S. JOBS! JOBS! JOBS!	33	Jobs	1
Aetna (AET)	05/04/17	8:28	Death spiral! 'Aetna will exit Obamacare markets in VA in 2018, citing expected losses on INDV plans this year'	34	ACA[f]	1
Rexnord (RXN)	05/07/17	18:58	Rexnord of Indiana made a deal during the Obama Administration to move to Mexico. Fired their employees. Tax product big that's sold in U.S.	35	Jobs	-1
Corning (GLW)[e]	07/20/17	23:31	Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning, Merck & Pfizer: `45.wh.gov/jKxBRE`	36	Jobs	1
Merck (MRK)[e]	07/20/17	23:31	Same as above.	37	Jobs	1
Pfizer (PFE)[e]	07/20/17	23:31	Same as above.	38	Jobs	1
Toyota (TM)[e]	08/04/17	6:02	Toyota & Mazda to build a new $1.6B plant here in the U.S.A. and create 4K new American jobs. A great investment in American manufacturing!	39	Jobs	1
Mazda (MZDAY)[c]	08/04/17	6:02	Same as above.	40	Jobs	1
Anthem (ANTM)	08/08/17	6:59	RT @foxandfriends: Anthem announces it will withdraw from ObamaCare Exchange in Nevada `https://t.co/dOCxeHQKwz`	41	ACA[f]	1
Merck (MRK)	08/14/17	8:54	Now that Ken Frazier of Merck Pharma has resigned from President's Manufacturing Council,he will have more time to LOWER RIPOFF DRUG PRICES!	42	Drug prices	-1
Merck (MRK)	08/14/17	18:09	.@Merck Pharma is a leader in higher & higher drug prices while at the same time taking jobs out of the U.S. Bring jobs back & LOWER PRICES!	43	Drug prices	-1

Amazon (AMZN)	08/16/17	6:12	Amazon is doing great damage to tax paying retailers. Towns, cities and states throughout the U.S. are being hurt - many jobs being lost!	44	Jobs	-1
Andeavor (ANDV)	09/06/17[e]	19:20	Wonderful to be in North Dakota with the incredible hardworking men & women @ the Andeavor Refinery. Full remarks: `http://45.wh.gov/POTUSNorthDakota`	45	Jobs	1
Broadcom (AVGO)[b,e]	11/02/17	15:58	Today, we are thrilled to welcome @Broadcom CEO Hock Tan to the WH to announce he is moving their HQs from Singapore back to the U.S.A.....	46	Jobs	1
Broadcom (AVGO)[e]	11/02/17	16:33	Broadcom's move to America=$20 BILLION of annual rev into U.S.A., $3+ BILLION/yr. in research/engineering & $6 BILLION/yr. in manufacturing.	47	Jobs	1
Amazon (AMZN)	12/29/17	8:04	Why is the United States Post Office, which is losing many billions of dollars a year, while charging Amazon and others so little to deliver their packages, making Amazon richer and the Post Office dumber and poorer? Should be charging MUCH MORE!	48	Cost control	-1

This table lists tweets from `@realDonaldTrump` and `@POTUS` Twitter accounts that include the name of a publicly traded company from November 9, 2016 to December 31, 2017. Time is Eastern Time. # shows how multiple tweets combine into a single event when tweets occur on the same day (or on two consecutive days if the tweet on the first day occurred after the stock market closed at 16:00). Code classifies the tweet tone as negative (-1) or positive (1) for each topic shown in the Content column following the methodology described in Section II and verified with a robustness check using Google Cloud Natural Language API, the Loughran and McDonald (2011) lexicon, and the lexicon compiled by the National Research Council Canada in the Appendix. The total number of events is 48.

[a] This company is a subsidiary of a publicly traded company.

[b] The tweet was posted during the United States stock market trading hours on business days from 9:30 to 16:00. All other tweets were posted in the early morning, in the evening, on weekends, or during holidays.

[c] The stock is traded as an American Depositary Receipt.

[d] The tweet was posted on the `@POTUS` Twitter account. The ExxonMobil tweet on March 6, 2017 was subsequently (six minutes later) posted on the `@realDonaldTrump` account.

[e] The tweet was posted on the `@realDonaldTrump` account and retweeted from the `@POTUS` account. Tweets that are not marked with [d] or [e] were posted only on the `@realDonaldTrump` account.

[f] ACA stands for the Affordable Care Act.

Table 2: Summary Statistics

	Return	Absolute Value Return	Abnormal Return	Absolute Value Abnormal Return	Abnormal Trading Volume	Volatility	Abnormal Institutional Investor Attention
Median	0.076	0.640	−0.027	0.577	−0.077	0.825	0.000
Mean	0.091	0.913	−0.006	0.836	0.055	0.973	0.234
Minimum	−10.842	0.000	−11.545	0.000	−0.962	0.000	0.000
Maximum	13.216	13.216	11.365	11.545	16.437	14.587	1.000
Std Dev	1.343	0.989	1.249	0.928	0.677	0.640	0.423
Observations	7,749	7,749	7,749	7,749	7,749	7,749	7,749

This table shows the summary statistics for return $R_{i,t} = (C_{i,t} - C_{i,t-1})/C_{i,t-1}$, the absolute value of the return, abnormal return from equation (2), the absolute value of the abnormal return, abnormal trading volume $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention, which is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Returns are in percentages. The sample period is from November 9, 2016 to December 31, 2017. There are 287 days and 27 companies. The total number of panel observations is 7,749.

Table 3: Impact of Presidential Tweets: Full Sample without Lagged Control Variables

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	0.799***	0.392***	0.305***	0.400***
	(0.173)	(0.090)	(0.079)	(0.057)
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.004	0.010	0.246	0.072
Observations	7,749	7,749	7,749	7,749

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Pseudo-R^2 is reported for the AIIA. The sample period is from November 9, 2016 to December 31, 2017. There are 287 days and 27 companies. The total number of panel observations is 7,749. This includes all 48 tweet events (combining 59 tweets) listed in Table 1.

Table 4: Impact of Presidential Tweets: Full Sample with Lagged Control Variables

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	0.800***	0.380***	0.239***	0.358***
	(0.168)	(0.086)	(0.073)	(0.059)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.006	0.080	0.317	0.115
Observations	7,749	7,749	7,749	7,749

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Lagged control variables include five lags of abnormal returns, ATV, volatility, and AIIA. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Pseudo-R^2 is reported for the AIIA. The sample period is from November 9, 2016 to December 31, 2017. There are 287 days and 27 companies. The total number of panel observations is 7,749. This includes all 48 tweet events listed in Table 1.

Table 5: Impact of Presidential Tweets: Pre- and Post-Inauguration

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	1.211***	0.474***	0.336***	0.452***
	(0.235)	(0.135)	(0.104)	(0.094)
Post-inauguration	−0.694**	−0.167	−0.197	−0.143
interaction term	(0.331)	(0.175)	(0.144)	(0.121)
Coefficient sum	0.517**	0.306***	0.139	0.309***
	(0.233)	(0.112)	(0.100)	(0.076)
Post-inauguration	0.043	−0.016	−0.067**	0.009
indicator variable	(0.040)	(0.035)	(0.027)	(0.014)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.007	0.081	0.318	0.115
Observations	7,749	7,749	7,749	7,749

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. The post-inauguration indicator variable equals 1 if the event falls into the post-inauguration period and 0 otherwise. The post-inauguration interaction term multiplies the Twitter variable and the post-inauguration indicator variable. *Coefficient sum* reports the sum of the coefficients on the Twitter variable and the post-inauguration interaction term and shows the impact in the post-inauguration period. Lagged control variables include five lags of abnormal returns, abnormal trading volume, volatility, and abnormal institutional investor attention. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Pseudo-R^2 is reported for the AIIA. The sample period is from November 9, 2016 to December 31, 2017. There are 287 days and 27 companies. The total number of panel observations is 7,749. This includes all 48 tweet events listed in Table 1 with 20 and 28 tweet events in the pre- and post-inauguration periods, respectively.

Table 6: Analysis of Possible Market Underreaction or Overreaction to Tweets

	(1) OLS	(2) Outlier Robust Regression
Contemporaneous	0.811***	0.767***
	(0.171)	(0.143)
Lag 1	−0.006	0.030
	(0.174)	(0.144)
Lag 2	0.133	0.051
	(0.174)	(0.144)
Lag 3	−0.444**	−0.141
	(0.174)	(0.144)
Lag 4	−0.085	−0.096
	(0.174)	(0.144)
Lag 5	−0.195	−0.194
	(0.171)	(0.143)
Sum of contemporaneous	0.214	0.417
& lag coefficients	(0.348)	(0.313)
Sum of lag coefficients	−0.597*	−0.350
	(0.325)	(0.289)
Lagged controls	Y	Y
Company fixed effects	Y	Y
Day of week dummies	Y	Y
R^2	0.008	0.006
Observations	7,884	7,884

The dependent variable is the daily abnormal return computed using equation (2) and stated in percentage. The last two rows report the sums of the coefficients on the lagged terms of the Twitter variable with and without the contemporaneous term, respectively. Lagged control variables include five lags of abnormal return, abnormal trading volume computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention, which is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The sample period is from November 9, 2016 to January 8, 2018. There are 292 days and 27 companies. The total number of panel observations is 7,884. This includes all 48 tweet events listed in Table 1.

Table 7: Impact of Presidential Tweets - Outlier Robust Regression

	(1) Abnormal Return	(2) ATV	(3) Volatility
<u>FULL SAMPLE</u>			
Twitter variable	0.765***	0.273***	0.202***
	(0.141)	(0.049)	(0.049)
Lagged controls	Y	Y	Y
Company fixed effects	Y	Y	Y
Day of week dummies	Y	Y	Y
R^2	0.006	0.096	0.311
Observations	7,749	7,749	7,749
<u>PRE- AND POST- INAUGURATION</u>			
Twitter variable	1.142***	0.395***	0.344***
	(0.219)	(0.076)	(0.077)
Post-inauguration interaction term	−0.597**	−0.214**	−0.284***
	(0.286)	(0.100)	(0.100)
Coefficient sum	0.545***	0.181***	0.060
	(0.184)	(0.064)	(0.064)
Post-inauguration indicator variable	0.026	−0.017	−0.055***
	(0.032)	(0.011)	(0.011)
Lagged controls	Y	Y	Y
Company fixed effects	Y	Y	Y
Day of week dummies	Y	Y	Y
R^2	0.006	0.096	0.313
Observations	7,749	7,749	7,749

This table reports the Huber (1973) outlier robust regression (M-estimation). Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, and volatility is computed as the square root of variance from equation (3) multiplied by 100. The post-inauguration indicator variable equals 1 if the event falls into the post-inauguration period and 0 otherwise. The post-inauguration interaction term multiplies the Twitter variable and the post-inauguration indicator variable. *Coefficient sum* in the bottom panel reports the sum of the coefficients on the Twitter variable and the post-inauguration interaction term. Lagged control variables include five lags of abnormal returns, ATV, volatility, and abnormal institutional investor attention (AIIA), which is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. The sample period is from November 9, 2016 to December 31. There are 287 days and 27 companies. The total number of panel observations is 7,749. This includes all 48 tweet events listed in Table 1 with 20 and 28 tweet events in the pre- and post-inauguration periods, respectively.

Table 8: Test of Asymmetric Effect of Negative and Positive Tweets

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	0.928***	0.385***	0.280***	0.310***
	(0.192)	(0.097)	(0.082)	(0.064)
Negative tweet dummy	−0.557	−0.020	−0.181	0.230
interaction term	(0.412)	(0.205)	(0.167)	(0.147)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.007	0.080	0.317	0.115
Observations	7,749	7,749	7,749	7,749

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. The interaction term multiplies the Twitter variable and an indicator variable equal to 1 if the tweet is negative and 0 otherwise. Lagged control variables include five lags of abnormal returns, ATV, volatility, and AIIA. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Pseudo-R^2 is reported for the AIIA. The sample period is from November 9, 2016 to December 31. There are 287 days and 27 companies. The total number of panel observations is 7,749. This includes all 48 tweet events listed in Table 1.

Table 9: Subsamples Based on Whether the Tweet Was Preceded by Related News

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
<u>TWEETS NOT PRECEDED BY RELATED NEWS</u>				
Twitter variable	0.756***	0.361**	0.385***	0.471***
	(0.243)	(0.146)	(0.108)	(0.105)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.015	0.140	0.281	0.140
Observations	2,870	2,870	2,870	2,870
<u>TWEETS PRECEDED BY RELATED NEWS</u>				
Twitter variable	0.806***	0.408***	0.161*	0.309***
	(0.226)	(0.106)	(0.094)	(0.072)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.006	0.095	0.327	0.102
Observations	6,314	6,314	6,314	6,314

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Lagged control variables include five lags of abnormal returns, ATV, volatility, and AIIA. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Pseudo-R^2 is reported for the AIIA. The sample period is from November 9, 2016 to December 31, 2017. The number of days is 287. The number of companies is 10 and 22 in the top and bottom panels resulting in 2,870 and 6,314 panel observations including 18 and 30 tweet events listed in Table 1, respectively.

Appendix: Alternative Tweet Tone Classification Methods

In Section II, we explain that we take two approaches to classifying the tone of the tweets. In the first approach, we carefully analyze the specific context of each tweet and classify the tone of the tweet based on whether the tone expressed by President Trump toward the company is positive or negative in the context of previous statements made by President Trump during the election campaign about the topics of the tweets. In the second approach, we utilize standard lexicons employed in previous literature and the Google Cloud Natural Language API (Google API);[29] we report the results of this alternative classification in this Appendix as a robustness check.

The textual analyses employed in previous studies that examine social media messages are mostly based on matching the exact wording with established words lists, such as the lexicon compiled by Loughran and McDonald (2011) (LM hereafter) and the NRC Sentiment and Emotion Lexicons compiled by the National Research Council Canada (NRC hereafter). Since these lexicons may not be adapted to non-standard language usage, such as President Trump's tweets that have been documented in numerous sources (for example, Begley, 2017), we also use Google API that leverages Google's expertise in big data analytics and machine learning models to reveal the meaning of the text and infer the underlying sentiment. Google API represents a cutting-edge effort in textual analysis based on adaptive machine learning technology and advanced language understanding system.

We apply the the NRC and LM lexicons as well as the Google API algorithm to each tweet in our sample and compare the resulting predicted tones with our classification.[30] We find that our context-based classification described in Section II agrees with the LM and

[29] `https://cloud.google.com/natural-language/`.

[30] For textual analysis of each tweet using the LM and NRC lexicons, we count the number of positive and negative words that are listed in the relevant lexicon, and we compute a score based on the difference between the number of positive and negative words that are matched with the respective lexicon. In contrast, the Google API sentiment score relies on Google's built-in algorithm and ranges from -1.0 (negative) to 1.0 (positive), reflecting the overall emotional leaning of the text.

NRC lexicons and Google API classification in 49 of the 59 tweets (83%) in the sample. This comparison provides strong support for the applicability and accuracy of our classification method.

Our context-based classification gains further support once we take into account the context and content of the ten tweets for which the standard textual analysis differs from our classification. For example, one of the mismatched tweets was tweet #7: "*Masa said he would never do this had we (Trump) not won the election!*" Google API classifies the tweet as exhibiting negative sentiment because of the two negations "never" and "not" contained in the tweet. However, if we take the context and content of the tweet into account, this tweet clearly exhibits a positive tone by the President toward SoftBank because it follows a tweet posted one minute earlier where President Trump commends the company for bringing jobs to the United States: "*Masa (SoftBank) of Japan has agreed to invest $50 billion in the U.S. toward businesses and 50,000 new jobs....*". This demonstrates the importance of considering the context and content of the social media messages, especially those with nonstandard language usage. The limitations of the standard textual analysis algorithms are also evident when analyzing tweets that are positive about one company and negative about another company, such as a tweet about Lockheed Martin (negative) and Boeing (positive) on December 22, 2016: "*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!*" A detailed discussion of the tone classification for all ten mismatched tweets is provided in Table A1.

Table A1: Alternative Tweet Tone Classification Methods

Tweet Event #	Our Classification	LM/NRC/Google API Classifications	Tweet Content & Explanation
#7	1	0/0/-0.1	"*Masa said he would never do this had we (Trump) not won the election!*" Negations such as "never" and "not" may trigger a negative classification from Google API. However, given the context of the tweet, this tweet exhibits a positive tone by the President toward SoftBank because it follows a tweet posted one minute earlier where President Trump commends the company for bringing jobs to the United States: "*Masa (SoftBank) of Japan has agreed to invest $50 billion in the U.S. toward businesses and 50,000 new jobs....*"
#10,#11	-1	0/0/0.2	"*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!*" Google API classifies this tweet with positive sentiment possibly due to positive words such as "tremendous." However, since this tweet pertains to controlling government costs, the tweet exhibits a negative tone toward Lockheed Martin (because of potentially losing the government contract due to high production cost of the F-35 fighter) and a positive tone toward Boeing (because of potentially receiving the government contract).
#12	-1	2/0/0	"*General Motors is sending Mexican made model of Chevy Cruze to U.S. car dealers-tax free across border. Make in U.S.A.or pay big border tax!*" Words such as "free" and "big" indicate a positive sentiment from LM's lexicon. But the context and content of this tweet clearly suggest a negative tone by the President toward General Motors due to its conflict with his campaign promises of keeping and creating jobs and manufacturing in the United States.
#20	1	0/0/0	"*Bayer AG has pledged to add U.S. jobs and investments after meeting with President-elect Donald Trump, the latest in a string..." @WSJ*" All three alternative classification methods assign a neutral sentiment to this tweet. However, this tweet shows President Trump's positive tone toward Bayer because its pledge aligns with the President's campaign promises of keeping and creating jobs and manufacturing in the United States.

Table A1: Alternative Tweet Tone Classification Methods (Continued)

Tweet Event #	Our Classification	LM/NRC/Google API Classifications	Tweet Content and Explanation
#31	1	0/0/0	"*'President Trump Congratulates Exxon Mobil for Job-Creating Investment Program'*" All three alternative classification methods assign a neutral sentiment to this tweet. However, this tweet shows the President Trump's positive tone toward Exxon Mobil because its investment program aligns with the President's campaign promises of keeping and creating jobs and manufacturing in the United States.
#36,37,38	1	0/0/0	"*Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning, Merck & Pfizer: 45.wh.gov/jKxBRE*" All three alternative classification methods assign a neutral sentiment to this tweet. However, this tweet shows the President's positive tone toward Corning, Merck and Pfizer because their investments align with the President's campaign promises of keeping and creating jobs and manufacturing in the United States.
#41	1	0/0/-0.3	"*RT @foxandfriends: Anthem announces it will withdraw from ObamaCare Exchange in Nevada https://t.co/dOCxeHQKwz*" Google API classifies this tweet with negative sentiment possibly due to negative words such as "withdraw." However, since this tweet relates to Anthem's exit from the Affordable Care Act health exchange, it suggests President Trump's positive tone toward Anthem because President Trump considers the Affordable Care Act as negative.

This table lists the tweet events where our tone classification described in Section II does not match the alternative tone classifications discussed in this Appendix. The LM and NRC scores are based on the difference between the number of positive and negative words that are matched with the lexicons from Loughran and McDonald (2011) and National Research Council Canada Sentiment, respectively. The Google API sentiment score relies on Google Cloud Natural Language API's built-in algorithm and ranges from -1.0 (negative) to 1.0 (positive), reflecting the overall emotional leaning of the text. The tweet event numbers correspond to those in Table 1.