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Stock Market Reactions to Presidential Statements: Evidence from Company-Specific Tweets

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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 July 31, 2017 that include the name of a publicly traded company. 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. The initial impact of the presidential tweets on stock prices appears to dissipate over the next few trading days. Overall, the results show that investors pay attention to presidential company-specific statements even when such statements have no lasting effect on shareholder value.

Keywords: Twitter, company-specific statements, President Trump, stock price, trading volume, volatility, investor attention, event study
JEL classification: G12, G14

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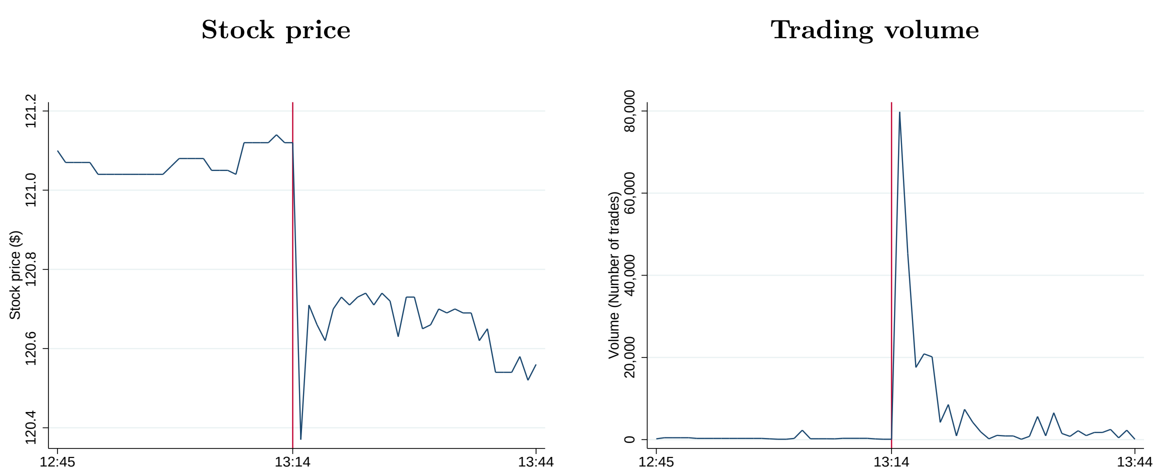
1 Introduction

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. 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. An interesting question, therefore, arises whether the President's company-specific statements affect the stock market. To motivate our inquiry, Figure 1 shows an example of the impact on the price and trading volume of Toyota's American Depositary Receipts (ADRs) in the 60-minute window around a tweet about Toyota. The figure suggests that the trading volume spiked and price dropped by more than one dollar after the tweet.

Figure 1: Toyota ADRs on January 5, 2017



The figure shows the price and trading volume of Toyota ADRs in the 60-minute window around 13:14 on January 5, 2017 when then President-elect Trump tweeted: *"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."* The figure is constructed using minute-by-minute transaction data from Genesis Financial Technologies.

While no systematic inferences can be drawn from this figure, it is possible that investors react to such company-specific statements. We posit that the statements may be understood by investors to include some information relevant to future company fundamentals because the President can enact measures affecting these companies via executive orders and other means. In other words, the presidential tweets may themselves form unexpected news events that could move the stock market. If that is the case, the stock market may react in an identical way as when facing public news releases studied by, for example, Chan (2003) and Vega (2006).

We review all tweets from November 9, 2016 to July 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 investor attention. We also find that the impact was stronger before the presidential inauguration on January 20, 2017. During the pre-inauguration period, the tweets on average move the company stock price by approximately 1.14 percent and increase trading volume, volatility and institutional investor attention by approximately 47, 0.32 and 51 percentage points, respectively, on the day of the tweet. The impact on the stock price appears to be reversed by price movements on the following days.

We contribute to the literature in two ways. First, previous literature shows that news moves the stock market (for example, Chan, 2003 and Vega, 2006); we systematically document and analyze the stock market impact of a new kind of news – statements about individual companies made by the highest-ranking government official in the largest economy in the world – that has not been studied in the previous literature. This contributes to our understanding of what drives stock market activity and to the discussion in the finan-

[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 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.

cial press about trading around President Trump's tweets.[2] Given that government officials' public statements are constantly monitored and interpreted by the stock market, such an analysis also has important policy implications.

Second, our paper also 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, 2016, Bollen, Mao, & Zeng, 2011, and Sprenger, Sandner, Tumasjan, & Welpe, 2014). These papers do not consider the context and content of the social media messages. Our study seeks to advance this social media literature by *carefully examining the context and content of messages posted by one user* – the President of the United States.

We describe our Twitter data in Section 2, present methodology and empirical results in

[2]The discussion in the financial press about trading around President Trump's tweets has 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, but Kaissar (2017) cautions that the impact of the presidential tweets on stock prices may not be predictable.

[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 people. 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.

Section 3, conduct robustness checks in Section 4 and discuss future research questions in Section 5.

2 Twitter Data

Table A1 lists all tweets from `@realDonaldTrump` and `@POTUS` Twitter accounts[4] that include the name of a publicly traded company from November 9, 2016 to July 31, 2017.[5] 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 July 20, 2017.

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 stock market closes at 16:00 Eastern Time, on weekends or holidays, are, therefore, assigned to the next trading day because that is the day when investors 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 140-character restriction that Twitter imposes on the tweet length. Table A1

[4] `@POTUS` with approximately 20 million followers is the official Twitter account of the President of the United States that became available to President Trump after his inauguration on January 20, 2017. Tweets created by President Obama were archived into `@POTUS44` account. `@realDonaldTrump` with approximately 38 million followers is President Trump's personal account. All but three tweets in our sample were posted on `@realDonaldTrump`.

[5] We exclude tweets about 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.

shows how multiple tweets are combined into a single event in our study.

We classify the tweets as positive or negative based on the tone that President Trump expressed towards the company.[6] Previous studies of social media impact on the stock market analyze a large number of messages from numerous users; therefore, the analysis in those studies 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 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. (2016) 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. In contrast, 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 to determine whether the tone is positive or negative.

In terms of content, the tweets are of several types as indicated in the Content column in Table A1. Most of them pertain to election campaign promises: about jobs, controlling government costs, and the Affordable Care Act. To determine the tone of the tweets related to jobs (tweet events #1-5, 7, 12-20, 26-29 and 31-34), we base the classification on the election campaign promise of keeping jobs in the United States and bringing them back from other countries as stated in, for example, the 2016 Republican primary debate in South

[6] Our sample does not contain any days with both positive and negative tweets about the same company.

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 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 in the United States or bringing them back from other countries (for example, tweets about Ford on November 17, 2016), we classify it as positive. If a tweet criticizes a company for moving jobs out of the United States (for example, a tweet about Rexnord on December 2, 2016), we classify it as negative. 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).

To determine the tone of the tweets related to controlling government costs (tweet events #6, 10 and 11), we base the classification on the election promises of reducing government costs as stated in, for example, the 2016 Republic 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 it as negative. If the tweet suggests that a company may reduce the government's costs, we classify it as positive (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 tweet related to the Affordable Care Act (tweet event #30), we base the classification on the negative campaign towards 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, NV on October 19, 2016*, 2016). Since the tweet is commenting on losses incurred by a health insurance company due to the Affordable Care Act, we classify it as negative.

Four tweets (tweet events #21-24) are about President Trump's meetings with chief executive officers (CEOs); since these tweets express a positive tone about the companies, we classify them as positive. Two tweets (tweet events #8 and 9) are complimenting the CEO of ExxonMobil who became the Secretary of State; since the tweets express a positive tone, we classify them as positive. One tweet (tweet event #25) 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. The Code column shows the classification with -1 and 1 representing negative and positive tweets, respectively.[7]

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 34 events (combining 45 tweets).[8] Eight are classified as negative, and 26 are classified as positive.[9]

3 Empirical Strategy and Results

Section 3.1 reports the impact of the tweets on company stock returns, trading volume, volatility, and investor attention. Section 3.2 documents how the impact varies between the pre- and post-inauguration periods. Section 3.3 shows that the impact on the stock price on the day of the tweet is reversed on the following days.

[7]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, and disadvantageous if it forgoes the cost savings from relocating to a country with lower production cost.

[8]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.

[9]We present a robustness check in Section 4 showing that negative and positive tweets to not differ in their impact on the stock market.

3.1 Stock Market Reactions to Presidential Tweets

We obtain daily closing stock prices, $C_{i,t}$,[10] and compute the holding period return for each company i as $R_{i,t} = \frac{C_{i,t} - C_{i,t-1}}{C_{i,t-1}}$. Table 1 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 standard Fama-French three-factor model (Fama & French, 1993) using OLS regressing the excess return on the stock market return, RM_t, minus RF_t, small-minus-big market capitalization, SMB_t, and high-minus-low book-to-market ratio, HML_t:[11]

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

Table 1: Summary Statistics

	Return	Absolute Value Return	Abnormal Return	Absolute Value Abnormal Return	Abnormal Trading Volume	Volatility	Abnormal Institutional Investor Attention
Median	0.064	0.619	−0.025	0.563	−0.070	0.781	0.000
Mean	0.091	0.905	0.015	0.821	0.058	0.933	0.252
Minimum	−10.842	0.000	−10.432	0.000	−0.870	0.000	0.000
Maximum	10.531	10.842	10.134	10.432	16.456	14.587	1.000
Std Dev	1.357	1.015	1.244	0.934	0.676	0.659	0.434

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 volume $AV_{i,t} = (V_{i,t} - V_{Avrg,t})/V_{Avrg,t}$, volatility computed as the square root of variance from equation (5) multiplied by 100, and abnormal institutional investor attention. Returns are in percentages. The sample period is from November 9, 2016 to July 31, 2017. There are 181 days and 19 companies. The resulting number of panel observations is 3,439.

MacKinlay (1997) recommends that the estimation and event windows do not overlap. Therefore, we use data from January 1, 2016 to November 8, 2016 when estimating equation (1) to ensure that the estimation of excess returns is not affected by the events in the sample period. We then compute the abnormal return during our sample period as follows:[12]

[10] The company data are from Yahoo Finance.

[11] 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 are similar.

[12] Results with abnormal returns that are based on factor loadings estimated using data from January 1, 2016 to July 31, 2017 are almost identical.

$$AR_{i,t} = ER_{i,t} - [\widehat{\beta}_0 + \widehat{\beta}_1(RM_t - RF_t) + \widehat{\beta}_2 SMB_t + \widehat{\beta}_3 HML_t]. \tag{2}$$

Controlling for the stock market return is especially important since the overall market rose during our sample period. Finally, we estimate a fixed effects panel model:

$$AR_{i,t} = \gamma_0 + \gamma_1 T_{i,t} + \theta_i + \upsilon_{i,t}, \tag{3}$$

where θ_i accounts for the company-specific fixed effects and $T_{i,t}$ is the Twitter variable described in Section 2.[13] There are 181 days and 19 companies. The resulting number of panel observations is 3,439. The Twitter variable represents President Trump's positive (negative) tone expressed towards the company, which potentially adds positive (negative) information to the fundamentals of the involved company. We posit that statements that are positive (negative) about a company will increase (decrease) the company stock price, i.e., we expect γ_1 to be positive.

Table 2 reports the impact of the tweets in the full sample period from November 9, 2016 to July 31, 2017. Column (1) shows the impact on abnormal returns. The positive coefficient indicates that the stock price tends to rise (fall) if the tweet is positive (negative). The tweets on average move the stock price by approximately 0.64 percent. This is an economically meaningful effect because the median daily absolute return and absolute abnormal return are approximately 0.62% and 0.56%, respectively, per Table 1.

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 $J = 5$.[14] We then estimate a fixed effects panel model:

[13] 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.

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

Table 2: Impact of Presidential Tweets: Full Sample

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	0.635***	0.331***	0.220**	0.376***
	(0.203)	(0.111)	(0.095)	(0.071)

ATV and AIIA stand for abnormal trading volume and abnormal institutional investor attention, respectively. 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 July 31, 2017. There are 181 days and 19 companies. The resulting number of panel observations is 3,439. This includes all 34 tweet events listed in Table A1.

$$AV_{i,t} = \delta_0 + \delta_1 |T_{i,t}| + \phi_i + \varepsilon_{i,t}, \tag{4}$$

where ϕ_i accounts for the company-specific fixed effects. 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 33 percentage points compared to the average trading volume on the previous five days.

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

$$\hat{\sigma}_{it}^2 = (H_{it} - C_{it})(H_{it} - O_{it}) + (L_{it} - C_{it})(L_{it} - O_{it}), \tag{5}$$

where O_{it}, C_{it}, H_{it}, and L_{it} are the opening, closing, high, and low prices in natural log for 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. We estimate a fixed effects panel model similar to equation (4) that also includes the first lag of volatility to account for volatility persistence. Similarly 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 0.78% and 0.93%, respectively, in Table 1. Therefore, an average increase of 0.22 percentage points is economically meaningful.

To measure investor attention, we use the Bloomberg institutional investor attention (IIA) described in Ben-Rephael, Da, and Israelsen (2017). Bloomberg tracks how many times Bloomberg users read articles and search for information about each company. Bloomberg records hourly counts, compares the counts in the recent eight hours to 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%, 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 IIA that equals 1 if IIA equals 3 or 4, and 0 otherwise, so that the abnormal IIA captures the right tail of the IIA distribution, and a value of 1 represents an IIA shock. We estimate a panel probit model of the abnormal IIA on the absolute value of the Twitter variable, $|T_{i,t}|$, with dummies 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 institutional investor attention. Column (4) reports the marginal effects. The tweets (both positive and negative) on average increase the probability of abnormal IIA by 38 percentage points, suggesting that the tweets capture institutional investors' attention.

3.2 Pre- vs. Post-Inauguration

Our sample comprises two distinct periods: from the election to inauguration (November 9, 2016 to January 19, 2017) and from the inauguration to the end of our sample period (January 20, 2017 to July 31, 2017). We analyze whether the impact differs between the periods. We repeat the analysis in Section 3.1 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 abnormal returns we estimate:

$$AR_{i,t} = \alpha_0 + \alpha_1 T_{i,t} + \alpha_2 I_t + \alpha_3 T_{i,t} * I_t + \varphi_i + \nu_{i,t}, \tag{6}$$

where φ_i accounts for the company-specific fixed effects. Table 3 presents the results. The coefficient on the Twitter variable, α_1, measures the impact during the pre-inauguration period. The signs on the coefficients for all four 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. Furthermore, the coefficients are higher than those in the full sample period. For example, the tweets on average move the company stock price by approximately 1.14 percent compared to 0.64 percent in the full sample period.

Table 3: Impact of Presidential Tweets: Pre- and Post-Inauguration

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	1.139***	0.473***	0.323***	0.507***
	(0.248)	(0.148)	(0.121)	(0.101)
Post-inauguration	−1.199***	−0.356	−0.351*	−0.269*
interaction term	(0.419)	(0.223)	(0.197)	(0.148)
Coefficient sum	−0.061	0.117	−0.027	0.238**
	(0.339)	(0.167)	(0.155)	(0.109)

ATV and AIIA stand for abnormal trading volume and abnormal institutional investor attention, respectively. 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 July 31, 2017. There are 181 days and 19 companies. The resulting number of panel observations is 3,439. This includes all 34 tweet events listed in Table A1 with 20 and 14 tweet events in the pre- and post-inauguration events, respectively. The last row reports the sum of the coefficients on the Twitter variable and the post-inauguration interaction term.

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 α_3 indicates that the post-inauguration impact is lower than in the pre-inauguration period. This is indeed the case in all four variables, although this coefficient estimate is not statistically significant for abnormal trading volume. The last row of Table 3 shows the sum of the coefficients on the Twitter variable and the post-inauguration interaction term. For returns, volatility and abnormal volume, this sum is not statistically significant, indicating that the tweets have no discernible effect on these variables in the post-inauguration period.

Two potential explanations exist for the market reaction diminishing after the inauguration. First, the informational content of President Trump's tweets has changed. Second, Twitter was the primary communication channel with the market before inauguration. Other channels such as presidential executive orders, memoranda, and press releases have been in effect since the inauguration. These channels could lessen the Twitter impact if investors consider them more influential.

For the second explanation, we review all presidential executive orders, memoranda, and press releases from the post-inauguration period (January 20, 2017 - July 31, 2017). We do not find any presidential executive orders or memoranda that include a name of publicly traded company. We find only one press release that mentions a company from our sample: a press release about ExxonMobil on March 6, 2017 (The White House, 2017). Therefore, information about 33 out of 34 of our events appears to have been communicated solely via the tweets in our sample. This leaves the first explanation as the likelier explanation for the diminishing market reaction.[15] 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 about specific companies took the market by surprise, but the market has grown accustomed to them and does not react as strongly any more.

3.3 Do Tweets Have a Permanent Effect on Stock Returns?

Section 3.1 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.[16] To test for continuing price adjustment on the following days, we repeat the analysis of Section 3.1 while including lags of the Twitter variable:

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

[16]For example, Tetlock (2007) shows that the effect of media pessimism on the stock market reverses over the following trading week.

$$AR_{i,t} = \gamma_0 + \sum_{j=0}^{J} \gamma_j T_{i,t-j} + \theta_i + \upsilon_{i,t}, \tag{7}$$

where $J = 5$ to control for weekly patterns.[17]

Column (1) of Table 4 reports the results. The coefficient on the contemporaneous term is of the same sign, magnitude and statistical significance as the one reported in Table 2. We then conduct a test of the sum of the coefficients on the contemporaneous and lagged terms. This sum is not statistically significant, suggesting that the initial impact on the day of the tweet is reversed on the following days. We also conduct a test of the sum of the coefficients on the lagged terms and report the results in the last row. This sum is negative and statistically significant, again suggesting that the impact is reversed on the following days.

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 an 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. Correspondingly, the sum of the lag terms continues to be negative but is no longer statistically significant. However, the sum of the coefficients on the contemporaneous and lagged terms continues to be statistically insignificant, again suggesting that the impact is reversed on the following days. Therefore, there is evidence that the effect of tweets on returns is temporary. The market response on the day of the tweet likely represents an overreaction.

4 Robustness Checks

We already noted in Section 3.1 that our results for returns are robust to using the Fama-French five-factor model based on Fama and French (2015) (rather than the three-factor

[17]We verified that using longer lags does not affect the results.

Table 4: Analysis of Possible Market Underreaction or Overreaction to Tweets

	(1) OLS	(2) Outlier Robust Regression
Contemporaneous	0.680***	0.457***
	(0.196)	(0.156)
Lag 1	−0.217	−0.076
	(0.198)	(0.157)
Lag 2	0.148	0.002
	(0.197)	(0.157)
Lag 3	−0.561**	−0.118
	(0.197)	(0.157)
Lag 4	−0.103	−0.081
	(0.198)	(0.157)
Lag 5	−0.181	−0.162
	(0.196)	(0.156)
Sum of contemporaneous	−0.235	0.022
& lag coefficients	(0.392)	(0.342)
Sum of lag coefficients	−0.914**	−0.436
	(0.367)	(0.316)

The dependent variable is the daily abnormal return. 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 July 31, 2017. There are 181 days and 19 companies. The resulting number of panel observations is 3,439. This includes all 34 tweet events listed in Table A1. 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; in parentheses we show the standard errors of these coefficient sums.

model based on Fama and French (1993)) and estimating factor loadings in equation (1) using price data from January 1, 2016 to July 31, 2017 which includes our sample period (rather than price data from January 1, 2016 to November 8, 2016 which excludes our sample period). We also noted 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). This section presents additional robustness checks. Section 4.1 discusses an alternative method for classifying the tweet tone, Section 4.2 verifies that our results are not driven by outliers, Section 4.3 shows that the results do not differ between positive and negative tweets, and Section 4.4 considers the potential effect of other news.

4.1 Alternative Method for Classifying the Tweet Tone

In Section 2, we describe how we carefully classify the tone of each tweet as positive or negative based on the tweet's content and context. In contrast, previous social media studies that analyze a large number of messages from numerous users have to depend on algorithms and lexicons to extract an overall sentiment from that "big data." As a robustness check of our classification method, we perform a textual analysis comparable to those used in previous studies. We utilize the Google Cloud Natural Language API (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.[18] We apply the Google API algorithm to each tweet in our sample and compare the resulting predicted tones with our classification. The results from this robustness check agree with our classification for 85% of our tweets and provide strong support for the applicability and accuracy of our classification method.

Indeed, our classification gains further support once we take into account the context and content of the 15% of tweets for which the classification based on the Google API 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 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 further demonstrates the importance of considering the context and content of the social media messages, especially those with

[18] Google Cloud Natural Language API (`https://cloud.google.com/natural-language/`) represents the cutting-edge effort in textual analysis based on adaptive machine learning technology and advanced language understanding system. In contrast, standard textual analyses employed in related studies that examine large numbers of 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), which may not be readily and accurately adapted to the language usage in Twitter.

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 (positive) and Boeing (negative) 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!*" Detailed results of this tweet tone classification robustness check are available upon request.

4.2 Outlier-Robust Regression

Our analysis employs the entire population of President Trump's 34 company-specific tweet events.[19] In this robustness check, we verify that our results in Sections 3.1 and 3.2 are not influenced by outliers. We repeat the analysis of Sections 3.1 and 3.2 with an outlier robust regression (M-estimation). Table 5 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.[20] The results for returns, volume and volatility are qualitatively similar to the results from the least squares panel regression reported in Tables 2 and 3. Overall, the results from the outlier robust regression show that our findings are not driven by outliers. In spite of this, we prefer reporting the least squares results in Sections 3.1 and 3.2 because that methodology uses a panel estimation accounting for the correlation of errors across firms whereas the outlier robust regression in Table 5 uses indicator variables for individual companies.

4.3 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,

[19] In this sense, our study follows other studies that used 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.

[20] The outlier robust regression (M-estimation) does not apply to nonlinear regression models, such as the probit model that we use for estimating the impact on AIIA. Therefore, Table 5 reports results only for returns, trading volume, and volatility.

Table 5: Impact of Presidential Tweets - Outlier Robust Regression

	(1) Abnormal Return	(2) ATV	(3) Volatility
Full Sample			
Twitter variable	0.458***	0.252***	0.267***
	(0.158)	(0.059)	(0.053)
Pre- and Post- Inauguration			
Twitter variable	0.838***	0.387***	0.359***
	(0.206)	(0.077)	(0.070)
Post-inauguration	−0.641**	−0.269**	−0.301***
interaction term	(0.320)	(0.120)	(0.108)
Coefficient sum	0.197	0.118	0.058
	(0.246)	(0.091)	(0.083)

This table reports the outlier robust regression (M-estimation). ATV stands for abnormal trading volume. 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 July 31, 2017. There are 181 days and 19 companies. The resulting number of panel observations is 3,439. This includes all 34 tweet events listed in Table A1 with 20 and 14 tweet events in the pre- and post-inauguration events, respectively. The last row reports the sum of the coefficients on the Twitter variable and the post-inauguration interaction term.

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 IIA. We repeat the analysis of Section 3.1 while including a term interacting the Twitter variable with an indicator variable equal to 1 if the tweet is negative and 0 otherwise. We find 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 low during our sample period (the daily average of approximately 12 compared to, for example, the daily average of approximately 20 during the period from January 1990 to July 2017). While this finding comes with the caveat of a small sample size (because only eight tweet events are classified as negative), it suggests that the markets pay attention to President Trump's tweets no matter whether they are positive or negative in tone. The results are reported in Table 6.

Table 6: Test of Asymmetric Effect of Negative and Positive Tweets

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	0.766***	0.294**	0.236**	0.357***
	(0.230)	(0.118)	(0.101)	(0.081)
Negative tweet dummy	−0.550	0.155	−0.069	0.075
interaction term	(0.534)	(0.281)	(0.238)	(0.159)

ATV and AIIA stand for abnormal trading volume and abnormal institutional investor attention, respectively. 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 July 31, 2017. There are 181 days and 19 companies. The resulting number of panel observations is 3,439. This includes all 34 tweet events listed in Table A1.

4.4 Tweets as Reactions to Related News

A variety of media (for example, Gajanan, 2017) has commented that President Trump's tweets are reactions to news from television and other news sources. We, therefore, research whether this is the case for our population of company-specific tweets. 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.[21] While fifteen of our presidential tweet events do not have preceding related news events, we find that the other nineteen tweet events could perhaps be responses to preceding related news events.[22] It is not surprising to find that some tweet events coincide with preceding related

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

[22]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.

news events because the President of the United States does not tweet in a vacuum. We, therefore, test whether the results shown in Table 2 hold for the sub-sample of tweet events that were not preceded by any related news events using the empirical specifications from Section 3.1. Table 7 presents the estimated coefficients. With the exception of Column (2), the results show that when the President's tweets are the original news, the magnitude of their impact is larger than when the tweets are responses to preceding news events. While this analysis is subject to the small-sample caveat, the fact that the results hold for this sub-sample indicates that President Trump's tweets indeed generate a reaction in the stock market.[23]

This conclusion is strengthened by the fact that even in tweets where there appear to be preceding related events, there is evidence indicating that President Trump's tweets generate a reaction in the stock market. For example, the tweet about Toyota on January 5, 2017 was preceded by a series of news about Toyota that appeared in the media in the preceding days, but the tweet still generated a reaction as shown in Figure 1.

5 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. The impact on the stock price on the day of the tweet appears to be reversed by price moves on the following days. These findings raise the question of whether it is optimal for high-ranking government officials to communicate industrial policy pertaining to specific companies via Twitter where unexpected statements can potentially instantly

[23] As a separate check, we analyze the 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 IIA. 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.

Table 7: Subsets 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	0.740***	0.302*	0.472***	0.466***
	(0.260)	(0.181)	(0.124)	(0.094)
<u>Tweets preceded by related news</u>				
Twitter variable	0.549*	0.350**	0.019	0.373***
	(0.300)	(0.136)	(0.132)	(0.081)

ATV and AIIA stand for abnormal trading volume and abnormal institutional investor attention, respectively. 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 full sample period is from November 9, 2016 to July 31, 2017. The number of days is 181. The number of companies is 8 and 16 in the top and bottom panels resulting in 1,448 and 2,896 panel observations including 15 and 19 tweet events listed in Table A1, respectively.

create or wipe out 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). A tweet about Nordstrom on February 8, 2017 provides anecdotal evidence that this may be the case. The trading volume spiked, but after an initial dip the stock price increased in spite of the tweet being negative about the company. This may be due to the company operating in the retail industry that does not depend on government contracts or bailouts. Likewise, the size of the targeted company could play a role in explaining the stock market reaction.

Finally, 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 based on the anecdotal evidence about Toyota and Nordstrom.

Table A1: 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 (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 (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 (UTX)	11/29/16	2:50	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 (UTX)[a]	11/30/16	13:21	Great interview on foxandfriends by SteveDoocy w/ Carrier employee-who has a message for #PEOTUS realDonaldTrump & #VPEOTUS mike_pence.	3	Jobs	1
Carrier (UTX)[a]	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 (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 (UTX)[a]	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)[a,b]	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)[a,b]	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	Dep’t of State	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	Dep’t of State	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)[a]	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)[a,b]	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)[a]	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)[a]	01/17/17	12:55	Same as above.	19	Jobs	1

Bayer AG (BAYN)[b]	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
Ford (F)	01/24/17	19:46	Great meeting with Ford CEO Mark Fields and General Motors CEO Mary Barra at the WhiteHouse today.	21	CEOs	1
General Motors (GM)	01/24/17	19:46	Same as above.	22	CEOs	1
Harley-Davidson (HOG)[a,c]	02/02/17	12:56	Great meeting with @harleydavidson executives from Milwaukee, Wisconsin at the @WhiteHouse.	23	CEOs	1
Harley-Davidson (HOG)[a,c]	02/03/17	13:26	#ICYMI- Remarks by President Trump Before Meeting with Harley-Davidson Executives and Union Representatives:	24	CEOs	1
Nordstrom (JWN)[a,c]	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!	25	Ivanka Trump	-1
Intel (INTC)[a]	02/08/17	14:22	Thank you Brian Krzanich, CEO of @Intel. A great investment ($7 BILLION) in American INNOVATION and JOBS! #AmericaFirst	26	Jobs	1
Boeing (BA)[c]	02/17/17	6:38	Going to Charleston, South Carolina, in order to spend time with Boeing and talk jobs! Look forward to it.	27	Jobs	1
ExxonMobil (XOM)	03/06/17	16:19	'President Trump Congratulates Exxon Mobil for Job-Creating Investment Program'	28	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!	28	Jobs	1
ExxonMobil (XOM)	03/06/17	18:49	There is an incredible spirit of optimism sweeping the country right nowwe're bringing back the JOBS!	28	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.	28	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!	28	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!	29	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'	30	Obamacare	-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.	31	Jobs	-1
Corning (GLW)	07/20/17	23:31	Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning, Merck & Pfizer:	32	Jobs	1
Merck (MRK)	07/20/17	23:31	Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning, Merck & Pfizer:	33	Jobs	1
Pfizer (PFE)	07/20/17	23:31	Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning, Merck & Pfizer:	34	Jobs	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 July 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 where the tweet on the first day occurred after the stock market closed at 16:00). Code classifies the tweets as negative (-1) or positive (1) following the methodology described in Section 2. The total number of events is 34.

[a] 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 holidays.

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

[c] The tweet was posted on the `@POTUS` Twitter account. Other tweets were posted on the `@realDonaldTrump` account. Tweet #25 was posted on the `@realDonaldTrump` account and retweeted from the `@POTUS` account.

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