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

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

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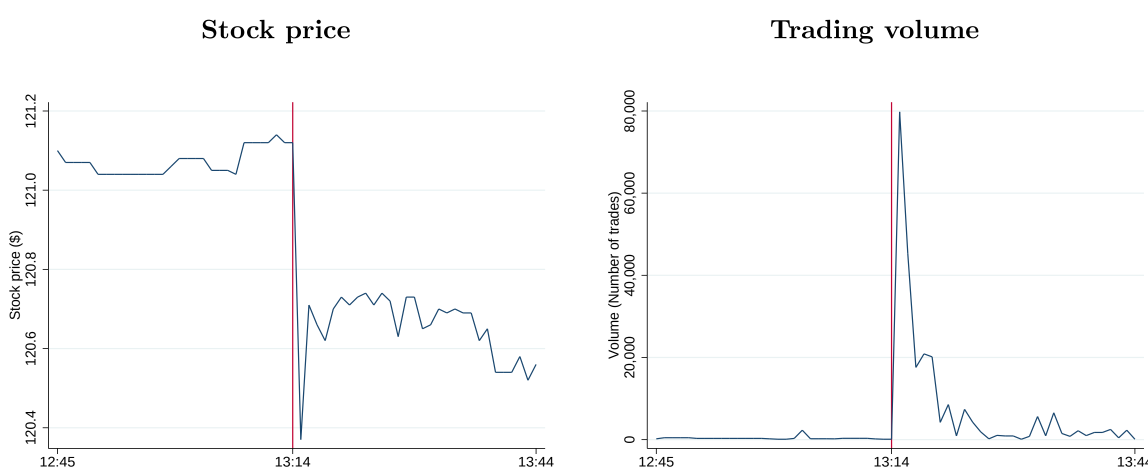
1 Introduction

Donald J. Trump, elected the 45th President of the United States on November 8, 2016, has frequently utilized 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 or other means. In other words, the presidential tweets may themselves be 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, therefore, further hypothesize that the presidential statements about specific companies will result in market reactions in returns, trading volume, volatility, and investor attention.

We review all tweets from November 9, 2016 to February 28, 2017 posted on `@POTUS` and `@realDonaldTrump` Twitter accounts used by President Donald Trump, document the tweets that include a name of a publicly traded company[1] and analyze their impact on the company stock price, trading volume, volatility, and 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 1.15 percent and increase trading volume, volatility and institutional investor attention by approximately 48, 0.34 and 52 percentage points, respectively, on the day of the tweet.

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. Given that government officials' public statements are constantly monitored and interpreted by the stock market,

[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.

such an analysis 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 largest social network Sina Weibo in Zhang, An, Feng, & Jin, 2017)[2] and *investor sentiment* 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 Section 3 and discuss future research questions in Section 4.

[2]Zhang et al. (2017) is similar to our study because they also analyze 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.

2 Twitter Data

Table A1 lists all tweets from `@realDonaldTrump` and `@POTUS` Twitter accounts[3] that include the name of a publicly traded company from November 9, 2016 to February 28, 2017.[4] November 9, 2016 is the beginning of the sample period because the presidential election took place on November 8, 2016.[5] The first company-specific tweet appears on November 17, 2016. The last one appears on February 17, 2017.

Most of the tweets were posted outside of the U.S. 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, to analyze the impact of the tweets, we use daily stock prices, trading volume, volatility, and investor attention.[6] 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 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

[3]`@POTUS` with approximately 16 million followers is the official Twitter account of the U.S. President 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 27 million followers is President Trump's personal account. All but four tweets in our sample were posted on `@realDonaldTrump`.

[4]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.

[5]We also analyze then-candidate Trump's company-specific tweets from the year preceding the presidential election (November 9, 2015 - November 8, 2016). We find that 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 pre-election tweets and results are available upon request.

[6]Intraday data is useful for analyzing the impact of news events and has been used in numerous studies (for example, Balduzzi, Elton, & Green, 2001, Andersen, Bollerslev, Diebold, & Vega, 2003, and Kurov, Sancetta, Strasser, & Wolfe, 2017). Since it is not possible to use intraday data to analyze President Trump's company-specific tweets because the stock market is closed when most of the tweets are posted, we follow previous literature that used daily data (for example, Demirer & Kutan, 2010 and Zhang et al., 2017).

expressed towards the company.[7] Previous studies of social media impact on the stock market typically 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 tends to ignore the 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 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), and 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 a *specific set* of social media messages posted by *one user*, we are able to carefully analyze the 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 (#1-5, 7, 12-20, 26 and 27) and controlling government costs (#6, 10 and 11). To determine the tone of the tweets related to jobs, we base the classification on the election campaign promise of keeping jobs in the U.S. 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 throughout the world now Vietnam, that's the new one."* (*Republican*

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

Candidates Debate in Greenville, South Carolina on February 13, 2016, 2016). Therefore, if a tweet commends a company for keeping jobs in the U.S. 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 U.S. (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).[8] To determine the tone of the tweets related to controlling government costs, 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). Four tweets (#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 (#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 (#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,

[8] The rationale for our classification is also consistent with market analysts' view (for example, DeCambre, 2017) that investors likely trade on campaign promises.

respectively.[9,10]

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 27 events (combining 34 tweets). Six are classified as negative, and 21 are classified as positive.[11]

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 shows how the impact varies between the pre- and post-inauguration periods. Section 3.3 discusses how the presidential tweets relate to other news.

3.1 Stock Market Reactions to Presidential Tweets

We obtain daily closing stock prices, $C_{i,t}$,[12] 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

[9] 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 U.S. 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.

[10] Following prior related social media studies, we also perform a standard textual analysis as a robustness check for our classification method. Specifically, we consider three alternative textual analysis methods: the lexicon compiled by Loughran and McDonald (2011), the NRC Sentiment and Emotion Lexicons compiled by the National Research Council Canada, and the Google Cloud Natural Language API (Google API hereafter). The results from this robustness check, particularly from Google API that utilizes machine learning models to reveal the meaning of the text and infer the underlying sentiment instead of simply matching the exact wording from a lexicon, agree with the classification of tones for most of our tweets and provide strong support for the applicability and accuracy of our classification method. Detailed results of this lexicon robustness check are available upon request.

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

[12] The company data are from Yahoo Finance. RF_t, RM_t, SMB_t and HLM_t are from Kenneth French's website.

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)[13] 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:

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

Table 1: Summary Statistics

	Return	Absolute Value Return	Abnormal Return	Absolute Value Abnormal Return	Abnormal Trading Volume	Volatility	Abnormal Institutional Investor Attention
Median	0.108	0.726	-0.030	0.644	-0.061	0.863	0.000
Mean	0.144	1.068	-0.011	0.956	0.080	1.037	0.249
Minimum	-10.280	0.000	-10.195	0.001	-0.814	0.000	0.000
Maximum	9.682	10.280	7.086	10.195	10.858	14.587	1.000
Std Dev	1.574	1.165	1.437	1.072	0.726	0.791	0.433

This table shows the summary statistics for return $R_{i,t} = (C_{i,t} - C_{i,t-1})/C_{i,t-1}$, its absolute value, abnormal return from equation (2), its absolute value, 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 February 28, 2017. There are 75 days and 15 companies. The resulting number of panel observations is 1,125.

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.[14] We then compute the abnormal return during our sample period as follows:

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

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:

[13]Results using the Fama and French (2015) five-factor model are similar.

[14]Results with excess returns using data from January 1, 2016 to February 28, 2017 are almost identical.

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

where θ_i accounts for the fixed effects and $T_{i,t}$ is the Twitter variable described in Section 2.[15] There are 75 days and 15 companies. The resulting number of panel observations is 1,125. 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.

The top panel of Table 2 reports the impact of the tweets in the full sample period from November 9, 2016 to February 28, 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 0.78 percent. This is an economically meaningful effect because the median daily absolute return and absolute abnormal return are approximately 0.73% and 0.64%, respectively, per Table 1.[16]

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 $J = 5$.[17] We then estimate a fixed effects panel model:

[15]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.

[16]We also analyze whether the impact of the presidential tweets is permanent or temporary. We repeat the above analysis while including lags of the Twitter variable: $AR_{i,t} = \gamma_0 + \sum_{j=0}^{J} \gamma_j T_{i,t-j} + \theta_i + \upsilon_{i,t}$, where $J = 5$ to control for weekly patterns. We conduct a test of the sum of the coefficients on the lagged terms. This sum is negative and statistically significant, which suggests the impact that presidential tweets have on the returns on the day of the tweet is reversed on the following days. However, 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). The sum of the coefficients is still negative but no longer statistically significant. Therefore, while there is some evidence that the effect of tweets on returns is temporary, this result appears to be driven by outliers.

[17]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

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
<u>Full Sample</u>				
Twitter variable	0.778***	0.408***	0.191	0.462**
	(0.262)	(0.129)	(0.122)	(0.082)
<u>Pre- and Post-Inauguration</u>				
Twitter variable	1.150***	0.478***	0.344**	0.520***
	(0.284)	(0.155)	(0.142)	(0.102)
Post-inauguration	−1.433**	−0.273	−0.603**	−0.197
interaction term	(0.659)	(0.278)	(0.281)	(0.176)
Coefficient sum	−0.283	0.205	−0.259	0.324**
	(0.594)	(0.230)	(0.243)	(0.145)

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 February 28, 2017. There are 75 days and 15 companies. The resulting number of panel observations is 1,125. This includes all 27 tweet events listed in Table A1 with 20 and 7 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.

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

where ϕ_i accounts for the 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 41 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. However, Column (3) suggests that the tweets do not have a significant effect on volatility in the full sample.

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 the 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 46 percentage points, suggesting that the tweets capture institutional investors' attention.

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 IIA. We repeat the above analysis 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 February 2017). While this finding comes with the caveat of a small sample size (because only six events are classified as negative), it underscores that the markets are paying attention to President Trump's tweets whether they are positive or negative in tone. These results are available upon request.

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 February 28, 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 fixed effects. The bottom panel of Table 2 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. The impact on volatility is now significant. Recall that volatility is measured by standard deviation of daily returns multiplied by 100. Its median and mean values are 0.86% and 1.04%, respectively, in Table 1. Therefore, an average increase of 0.34 percentage point is economically meaningful. For the other three variables, the coefficients are higher than those in the full sample period. For example, the tweets on average move the company stock price by approximately 1.15 percent compared to 0.78 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 α_3 indicates that the post-inauguration impact is lower than in the pre-inauguration period. This is the case in all four variables although only the return and volatility show statistical significance, which could partially be due to a small sample size: only seven of the 27 events in Table A1 occurred after inauguration.

The last row of Table 2 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.

Three potential explanations exist for the market reaction diminishing after the election. 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. Third, some of the post-inauguration tweets were posted on the `@POTUS` account, which may differ in impact from the `@realDonaldTrump` account since the accounts differ in the number and perhaps even characteristics of the followers.

To test the third explanation, we repeat the analysis in Section 3.1 while including a term interacting the Twitter variable with an indicator variable equal to 1 if the tweet was posted on the `@POTUS` account. These results, available upon request, indicate that the difference between the impact of tweets posted in the `@realDonaldTrump` and `@POTUS` accounts is not statistically significant at 5% level.[18] For the second explanation, we review all presidential executive orders, memoranda, and press releases from the post-inauguration period (January 20, 2017 - February 28, 2017). We do not find any presidential executive orders, memoranda, or press releases that include a name of publicly traded company.[19] This leaves the first explanation as the most likely explanation for the diminishing 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 about specific companies took the market by surprise, but the market has since grown accustomed to them and does not react as strongly.

3.3 What Is 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,[20] a leading provider of financial and economic news with more than 30,000 sources ranging from traditional media to websites and blogs. While thirteen of our presidential tweet events do not appear to be responding to preceding related news events, we find that fourteen tweet events could be responses to preceding related news

[18] This test comes with a small sample caveat because only three tweets were posted on the `@POTUS` account.

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

[20] 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.

events.[21] This finding is not surprising because the President of the United States does not tweet in a vacuum. However, in the tweet events that may be responses to preceding related news events, a question arises whether the observed stock market reaction is driven by these news rather than the tweets. While the daily data does not allow us to fully separate these two effects, there is anecdotal evidence indicating that President Trump's tweets generate an additional 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 appeared to generate an additional reaction as shown in Figure 1. In the future, if a larger population of tweets occurs during the stock market trading hours, it will be interesting to analyze this additional stock market reaction more systematically.

4 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 investor attention. We also find that the impact was stronger before the presidential inauguration on January 20, 2017. 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 announcements can potentially instantly 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

[21] 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.

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. This will also be helpful to isolate the effect of the presidential tweets from a possible effect of related news events.

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

This table lists tweets from `@realDonaldTrump` and `@POTUS` Twitter accounts that include the name of a publicly traded company from November 9, 2016 to February 28, 2017. Time is Eastern Time. # shows how multiple tweets combine into a single event when tweets occur on the same day. Code classifies the tweets as negative (-1) or positive (1) following the methodology described in Section 2. The total number of events is 27.

[a] The tweet was posted during the U.S. stock market trading hours on business days from 9:30 to 16:00. 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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