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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 speci c companies. These tweets have attracted considerable attention in the nancial press. The discussion about the impact of the tweets has, however, been inconclusive. For example, Wang (2016) reports that the Lockheed Martin stock price dropped after President Trump tweeted about the company on December 22, 2016: "Based on the tremendous cost and cost overruns of the Lockheed Martin F-35, I have asked Boeing to price-out a comparable F-18 Super Hornet!", and numerous sources, for example, Peltz (2017), describe attempts at creating algorithms for trading around President Trump's tweets, but Kaissar (2017) cautions that the impact of the presidential tweets on stock prices may not be predictable.

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

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

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

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

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

Our paper contributes to the growing literature on the role of social media in the stock market. Previous research has extensively studied the role of traditional media in the stock market; recent papers examine the role of newspaper coverage (Fang & Peress, 2009), local newspapers (Engelberg & Parsons, 2011), and writing by speci c 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 a ected by the number of messages in social media (for example, posts by nance industry professionals and regular users of China's social network Sina Weibo in Zhang, An, Feng, & Jin, 2017)[3] or investor sentiment that is derived using textual analysis of a large number of messages in online investment forums (for example, Chen, De, Hu, & Hwang, 2014), Facebook posts (for example, Karabulut, 2013 and Siganos, Vagenas-Nanos, & Verwijmeren, 2014), and Twitter feeds (for example, Azar & Lo, 2016, Bartov, Faurel, & Mohanram, 2017, Bollen, Mao, & Zeng, 2011, and Sprenger, Sandner, Tumasjan, & Welpe, 2014). Our study advances this social media literature by carefully examining the context and content of messages posted by one user { the highest-ranking government o cial in the largest economy in the world. The stock market impact of comments

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

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

II The Data

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

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

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

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

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

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

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

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

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

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

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

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

We analyze the content of each tweet in the context of previous statements that President Trump repeatedly made during the election campaign about the topics of the tweets: keeping jobs and manufacturing in the United States and bringing them back from other countries, 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 toward the company. If the tweet notes that a company may reduce the government's costs, we classify the tone as positive toward the company (for example, a tweet about Boeing on December 22, 2016). Again, the rationale for this classi cation is based on threats to punish companies by measures, such as canceling government orders (for example, a tweet about Boeing on December 6, 2016).

To determine the tone of the tweets related to the A ordable Care Act (tweet events #29, 34, and 41), we base the classi cation on the election campaign against this legislation as stated in, for example, the third presidential candidate debate in Nevada: "And one thing we have to do: Repeal and replace the disaster known as Obamacare."

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

III Empirical Strategy and Results

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

A Stock Market Reaction to President Trump's Tweets

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

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

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

[13] The company stock data are from Bloomberg.

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

$$ER_{i;t} = \beta_0 + \beta_1(RM_t - RF_t) + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_{i;t}: \qquad (1)$$

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

$$AR_{i;t} = ER_{i;t} - [\hat{\beta}_0 + \hat{\beta}_1(RM_t - RF_t) + \hat{\beta}_2 SMB_t + \hat{\beta}_3 HML_t]: \qquad (2)$$

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

To measure the impact on trading volume, we compute the abnormal trading volume, $AV_{i;t}$, as the difference between the trading volume $V_{i;t}$ and the mean trading volume of the previous five days divided by the mean trading volume of the previous five days to control for intra-week volume pattern similar to Joseph, Wintoki, and Zhang (2011). $AV_{i;t} = \frac{V_{i;t} - V_{Avrg;t}}{V_{Avrg;t}}$ where $V_{Avrg;t} = \frac{\sum_{1}^{J} V_{i;t-j}}{J}$ and $J = 5$.[16]

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

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

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

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

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

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

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

To measure investor attention, we use the Bloomberg institutional investor attention measure described in Ben-Rephael, Da, and Israelsen (2017).[17] Bloomberg tracks how many times Bloomberg users read articles and search for information about each company using the company ticker. Bloomberg records hourly counts, compares the counts in the recent eight hours to those in the previous 30 days and assigns a score of 0, 1, 2, 3, and 4 if the average of the last eight hours is less than 80%, between 80% and 90%, between 90% and 94%, between 94% and 96%, or higher than 96% of the hourly counts in the previous number of panel observations is 7,749. As described in Section II, the Twitter variable represents the positive (negative) tone expressed by President Trump toward the company. If President Trump's tweets affect the company stock price, we expect β_1 to be positive because positive (negative) information about the company will increase (decrease) the stock price.

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

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

$$AV_{i;t} = \beta_0 + \beta_1 |T_{i;t}| + \alpha_i + \delta_d + \varepsilon_{i;t}; \qquad (5)$$

where α_i and δ_d account for the company-specific, and day-of-week fixed effects, respectively. We use the absolute value of the Twitter variable because we expect the tweets to increase the trading volume regardless of whether their tone is positive or negative. This means that we expect β_1 to be positive. Column (2) reports the results. We find that the tweets on average increase trading volume by approximately 39 percentage points compared to the average trading volume on the previous five days.

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

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

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

$$AR_{i;t} = {}_0 + {}_1 T_{i;t} + {}_2 L5(AR_{i;t}) + {}_3 L5(AV_{i;t}) + {}_4 L5(\hat{}_{it}) + {}_5 L5(AIIA_{i;t}) + {}_i + {}_d + {}_{i;t}; \quad (6)$$

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

Table 4 reports results from these full speci cations. We nd that for all four dependent variables the results are similar to those reported in Table 3. This suggests that the results in Table 3 are not driven by investors systematically responding to attention-grabbing events that took place on trading days prior to the presidential tweets. We come back to this point

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

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

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

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

C Do Tweets Have a Permanent Effect on Stock Returns

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

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

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

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

IV Robustness Checks

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

A Outlier Robust Regression

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

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

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

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

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

B Asymmetry between Positive and Negative Tweets

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

We repeat the analysis of Section III.A while including a term interacting the Twitter variable with an indicator variable equal to 1 if the tweet is negative and 0 otherwise. Table 8 reports the results. Although the response appears to be larger in positive tweets (an increase of 0.93% in returns) than negative tweets (a decrease of 0.37% in returns computed as the sum of the Twitter variable and interaction term coefficients), the difference (measured by the interaction term) is not statistically significant. With the caveat of a small sample size

day following the tweet.[26]

While 18 of our presidential tweet events do not have preceding related news events, we day of the tweet is reversed by price moves on the following days. These findings raise the policy question of whether it is optimal for high-ranking government officials to communicate industrial policy by making statements about specific companies since such statements can potentially instantly create or wipe out hundreds of millions of dollars in shareholder value.

This topic lends itself to further research when a larger population of presidential tweets becomes available. Future research could investigate whether certain industry or firm-level attributes make the tweets particularly influential. For example, some industries may be more influenced by the tweets due to their dependence on government contracts (such as the defense industry) or bailouts (such as the automobile industry). Likewise, the size of the targeted company could play a role in explaining the stock market reaction. Also, if more tweets occur during the stock market trading hours, a comprehensive analysis of intraday

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Tbl1: LsbfTw

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 con dence in me!	1	Jobs	1
Carrier[a] (UTX)	11/24/16	10:11	I am working hard, even on Thanksgiving, trying to get Carrier A.C. Company to stay in the U.S. (Indiana). MAKING PROGRESS - Will know soon!	2	Jobs	1
Carrier[a] (UTX)	11/29/16	22:40	I will be going to Indiana on Thursday to make a major announcement concerning Carrier A.C. staying in Indianapolis. Great deal for workers!	3	Jobs	1
Carrier[a] (UTX)	11/29/16	22:50	Big day on Thursday for Indiana and the great workers of that wonderful state.We will keep our companies and jobs in the U.S. Thanks Carrier	3	Jobs	1
Carrier[a] (UTX) [b]	11/30/16	14:51	RT @DanScavino Great interview on foxandfriends by SteveDoocy w/ Carrier employee- who has a message for #PEOTUS realDonaldTrump & #VPEOTUS mike _pence.	3	Jobs	1
Carrier[a] (UTX) [b]	11/30/16	15:00	Its not uncommon for a Republican to be pro-business. But President-elect Donald Trump showed Tuesday night hes pro-worker, too, by saving 1,000 jobs at the Carrier plant in Indiana.	3	Jobs	1

SoftBank (SFTBY) [b,c]	12/06/16	14:09	Masa (SoftBank) of Japan has agreed to invest $50 billion in the U.S. toward businesses and 50,000 new jobs....	7	Jobs	1
SoftBank (SFTBY) [b,c]	12/06/16	14:10	Masa said he would never do this had we (Trump) not won the election!	7	Jobs	1
ExxonMobil (XOM)	12/11/16	10:29	Whether I choose him or not for \State"- Rex Tillerson, the Chairman & CEO of ExxonMobil, is a world class player and dealmaker. Stay tuned!	8	CEOs	1
ExxonMobil (XOM)	12/13/16	6:43	I have chosen one of the truly great business leaders of the world, Rex Tillerson, Chairman and CEO of ExxonMobil, to be Secretary of State.	9	CEOs	1
Boeing (BA)	12/22/16	17:26	Based on the tremendous cost and cost overruns of the Lockheed Martin F-35, I have asked Boeing to price-out a comparable F-18 Super Hornet!	10	Cost control	1
Lockheed Martin (LMT)	12/22/16	17:26	Same as above.	11	Cost control	-1
General Motors (GM)	01/03/17	7:30	General Motors is sending Mexican made model of Chevy Cruze to U.S. car dealers-tax free across border. Make in U.S.A.or pay big border tax!	12	Jobs	-1
Ford (F) [b]	01/03/17	11:44	\@DanScavino: Ford to scrap Mexico plant, invest in Michigan due to Trump policies"	13	Jobs	1
Ford (F)	01/04/17	8:19	Thank you to Ford for scrapping a new plant in Mexico and creating 700 new jobs in the U.S. This is just the beginning - much more to follow	14	Jobs	1
Toyota (TM) [b,c]	01/05/17	13:14	Toyota Motor said will build a new plant in Baja, Mexico, to build Corolla cars for U.S. NO WAY! Build plant in U.S. or pay big border tax.	15	Jobs	-1
Fiat Chrysler (FCAU)	01/09/17	9:14	It's nally happening - Fiat Chrysler just announced plans to invest $1BILLION in Michigan and Ohio plants, adding 2000 jobs. This after...	16	Jobs	1
Fiat Chrysler (FCAU)	01/09/17	9:16	Ford said last week that it will expand in Michigan and U.S. instead of building a BILLION dollar plant in Mexico. Thank you Ford & Fiat C!	16	Jobs	1
Ford (F)	01/09/17	9:16	Same as above.	17	Jobs	1

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

ExxonMobil (XOM)	03/06/17	22:49	Buy American & hire American are the principles at the core of my agenda, which is: JOBS, JOBS, JOBS! Thank you @exxonmobil.	31	Jobs	1
ExxonMobil (XOM)	03/06/17	22:50	Thank you to @exxonmobil for your $20 billion investment that is creating more than 45,000 manufacturing & construction jobs in the USA!	31	Jobs	1
Charter Communications (CHTR) [b]						

Amazon (AMZN)	08/16/17	6:12	Amazon is doing great damage to tax paying retailers. Towns, cities and states throughout the U.S. are being hurt - many jobs being lost!	44	Jobs	-1
Andeavor (ANDV)	09/06/17 [e]	19:20	Wonderful to be in North Dakota with the incredible hardworking men & women @ the Andeavor Re nery. Full remarks: http://45.wh.gov/POTUSNorthDakota	45	Jobs	1
Broadcom (AVGO) [b,e]						

Table 2: Summary Statistics

	Return	Absolute Value Return	Abnormal Return	Absolute Value Abnormal Return	Abnormal Trading Volume	Volatility	Abnormal Institutional Investor Attention
Median	0:076	0.640	0:027	0.577	0:077	0:825	0.000
Mean	0:091	0.913	0:006	0.836	0:055	0:973	0.234
Minimum	10:842	0.000	11:545	0.000	0:962	0:000	0.000
Maximum	13:216	13216	11:365	11.545	16:437	14:587	1.000
Std Dev	1:343	0.989	1:249	0.928	0:677	0:640	0.423
Observations	7,749	7,749	7,749	7,749	7,749	7,749	7,749

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

Tbe4: IpofPdTtw FLSpbLgCbVia
be

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	0:800***	0:380***	0:239***	0:358***
	(0:168)	(0:086)	(0:073)	(0:059)
Lagged controls	Y	Y	Y	Y
Company xed e ects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.006	0.080	0.317	0.115
Observations	7,749	7,749	7,749	7,749

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i;t} = (V_{i;t} \quad V_{Avrg;t})=V_{Avrg;t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. Lagged

Tbe5: Ipt of Pst Tw Pe d Pslg

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Twitter variable	1:211***	0:474***	0:336***	0:452***
	(0:235)	(0:135)	(0:104)	(0:094)
Post-inauguration	0:694**	0:167	0:197	0:143
interaction term	(0:331)	(0:175)	(0:144)	(0:121)
Coe cient sum	0:517**	0:306***	0:139	0:309***
	(0:233)	(0:112)	(0:100)	(0:076)
Post-inauguration	0:043	0:016	0:067**	0:009
indicator variable	(0:040)	(0:035)	(0:027)	(0:014)
Lagged controls	Y	Y	Y	Y
Company xed e ects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.007	0.081	0.318	0.115
Observations	7,749	7,749	7,749	7,749

Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i;t} = (V_{i;t} \quad V_{Avrg;t})=V_{Avrg;t}$, volatility is computed as the square root of variance from equation (3) multiplied by 100, and abnormal institutional investor attention (AIIA) is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger than 94% of the hourly counts in the previous 30 days and 0 otherwise. The post-inauguration indicator variable equals 1 if the event falls into the post-inauguration period and 0 otherwise. The post-inauguration interaction term multiplies the Twitter variable and the post-inauguration indicator variable. Coe cient sum reports the sum of the coe cients on the Twitter variable and the post-inauguration interaction term and shows the impact in the post-inauguration period. Lagged control variables include ve lags of abnormal returns, abnormal trading volume, volatility, and abnormal institutional investor attention. Panel-corrected standard errors accounting for cross-correlation across stocks are shown in parentheses. *, **, and *** indicate statistical signi cance at 10%, 5%, and 1% levels, respectively. Pseudo-R^2 is reported for the AIIA. The sample period is from November 9, 2016 to December 31, 2017. There are 287 days and 27 companies. The total n evenriable.

Tb7: IpfoPlsTtw OtbRbsRig

	(1) Abnormal Return	(2) ATV	(3) Volatility
Full Sample			
Twitter variable	0:765***	0:273***	0:202***
	(0:141)	(0:049)	(0:049)
Lagged controls	Y	Y	Y
Company xed e ects	Y	Y	Y
Day of week dummies	Y	Y	Y
R^2	0.006	0.096	0.311
Observations	7,749	7,749	7,749
Pre- and Post- Inauguration			
Twitter variable	1:142***	0:395***	0:344***
	(0:219)	(0:076)	(0:077)
Post-inauguration interaction term	0:597**	0:214**	0:284***
	(0:286)	(0:100)	(0:100)
Coe cient sum	0:545***	0:181***	0:060
	(0:184)	(0:064)	(0:064)
Post-inauguration indicator variable	0:026	0:017	0:055***
	(0:032)	(0:011)	(0:011)
Lagged controls	Y	Y	Y
Company xed e ects	Y	Y	Y
Day of week dummies	Y	Y	Y
R^2	0.006	0.096	0.313
Observations	7,749	7,749	7,749

This table reports the Huber (1973) outlier robust regression (M-estimation). Abnormal return is computed using equation (2) and stated in percentage, abnormal trading volume (ATV) is computed as $AV_{i;t} = (V_{i;t} \quad V_{Avrg;t})=V_{Avrg;t}$, and volatility is computed as the square root of variance from equation (3) multiplied by 100. The post-inauguration indicator variable equals 1 if the event falls into the post-inauguration period and 0 otherwise. The post-inauguration interaction term multiplies the Twitter variable and the post-inauguration indicator variable. Coe cient sum in the bottom panel reports the sum of the coe cients on the Twitter variable and the post-inauguration interaction term. Lagged control variables include ve lags of abnormal returns, ATV, volatility, and abnormal institutional investor attention (AIIA), which is an indicator variable equal to 1 if the average hourly count of Bloomberg users reading articles and searching for information about a company during the last eight hours is larger

Tble 8: Tsf A yE tf NgdPbTw

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

Table 9: Split Based on Whether Tweets are Preceded by Related News

	(1) Abnormal Return	(2) ATV	(3) Volatility	(4) AIIA
Tweets not preceded by related news				
Twitter variable	0.756***	0.361**	0.385***	0.471***
	(0.243)	(0.146)	(0.108)	(0.105)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.015	0.140	0.281	0.140
Observations	2,870	2,870	2,870	2,870
Tweets preceded by related news				
Twitter variable	0.806***	0.408***	0.161*	0.309***
	(0.226)	(0.106)	(0.094)	(0.072)
Lagged controls	Y	Y	Y	Y
Company fixed effects	Y	Y	Y	Y
Day of week dummies	Y	Y	Y	Y
R^2	0.006	0.095	0.327	0.102
Observations	6,314	6,314	6,314	6,314

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

Appendix A. Alternative Tweet Tone Classification Methods

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

The textual analyses employed in previous studies that examine social media messages are mostly based on matching the exact wording with established words lists, such as the lexicon compiled by Loughran and McDonald (2011) (LM hereafter) and the NRC Sentiment and Emotion Lexicons compiled by the National Research Council Canada (NRC hereafter). Since these lexicons may not be adapted to non-standard language usage, such as President Trump's tweets that have been documented in numerous sources (for example, Begley, 2017), NRC lexicons and Google API classi cation in 49 of the 59 tweets (83%) in the sample. This comparison provides strong support for the applicability and accuracy of our classi cation method.

Our context-based classi cation gains further support once we take into account the context and content of the ten tweets for which the standard textual analysis di ers from our classi cation. 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 classi es the tweet as exhibiting negative sentiment because of the two negations \never" and \not" contained in the tweet. However, if we take the context and content of the tweet into account, this tweet clearly exhibits a positive tone by the President toward SoftBank because it follows a tweet posted one minute earlier where President Trump commends the company for bringing jobs to the United States: \Masa (SoftBank) of Japan has agreed to invest $50 billion in the U.S. toward businesses and 50,000 new jobs...." This demonstrates the importance of considering the context and content of the social media messages, especially those with nonstandard language usage. The limitations of the standard textual analysis algorithms are also evident when analyzing tweets that are positive about one company and negative about another company, such as a tweet about Lockheed Martin (negative) and Boeing (positive) on December 22, 2016: \Based on the tremendous cost and cost overruns of the Lockheed Martin F-35, I have asked Boeing to price-out a comparable F-18 Super Hornet!" A detailed discussion of the tone classi cation for all ten mismatched tweets is provided in Table A1.

TbA1: AbTwTeChbMd

Tweet Event #	Our Classi cation	LM/NRC/Google API Classi cations	Tweet Content & Explanation
#7	1	0/0/-0.1	\ Masa said he would never do this had we (Trump) not won the election!" Negations such as \never" and \not" may trigger a negative classi cation from Google API. However, given the context of the tweet, this tweet exhibits a positive tone by the President toward SoftBank because it follows a tweet posted one minute earlier where President Trump commends the company for bringing jobs to the United States: \Masa (SoftBank) of Japan has agreed to invest $50 billion in the U.S. toward businesses and 50,000 new jobs"...
#10,#11	-1	0/0/0.2	\ Based on the tremendous cost and cost overruns of the Lockheed Martin F-35, I have asked Boeing to price-out a comparable F-18 Super Hornet!" Google API classi es this tweet with positive sentiment possibly due to positive words such as \tremendous." However, since this tweet pertains to controlling govern-

TbeA1: AltTwTeCsbMb(Cp)

Tweet Event #	Our Classification	LM/NRC/Google API Classifications	Tweet Content and Explanation
#31	1	0/0/0	“‘President Trump Congratulates Exxon Mobil for Job-Creating Investment Program’” All three alternative classification methods assign a neutral sentiment to this tweet. However, this tweet shows the President Trump's positive tone toward Exxon Mobil because its investment program aligns with the President's campaign promises of keeping and creating jobs and manufacturing in the United States.
#36,37,38	1	0/0/0	“Billions of dollars in investments & thousands of new jobs in America! An initiative via Corning, Merck & Pfizer: 45.wh.gov/jKxBRE” All three alternative classification methods assign a neutral sentiment to this tweet. However, this tweet shows the President's positive tone toward Corning, Merck and Pfizer because their investments align with the President's campaign promises of keeping and creating jobs and manufacturing in the United States.
#41	1	0/0/-0.3	“RT @foxandfriends: Anthem announces it will withdraw from ObamaCare Exchange in Nevada https://t.co/d0CxeHQKwz” Google API classifies this tweet with negative sentiment possibly due to negative words such as “withdraw.” However, since this tweet relates to Anthem's exit from the Affordable Care Act health exchange, it suggests President Trump's positive tone toward Anthem because President Trump considers the Affordable Care Act as negative.

This table lists the tweet events where our tone classification described in Section II does not match the alternative tone classifications discussed in this Appendix. The LM and NRC scores are based on the difference between the number of positive and negative words that are matched with the lexicons from Loughran and McDonald (2011)