Does connection with @realDonaldTrump affect stock prices?[*,**]

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Abstract

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Keywords: Twitter, US Election, stock market, investor sentiment, text classification, computational linguistics

JEL classification: D72, G12, G14, L86

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Abstract

This study investigates whether investors react to signals of an association between a firm and Donald Trump indicated by tweets containing both words ‘Trump’ (or ‘@realDonaldTrump’) and a S&P500 firm name. Our results reveal that a large number of such tweets ignite speculations about a political connection between a firm and the US’s President, thus affecting investors’ trading behaviors. In particular, a rise in these tweets induces significant increases in trading volatility and trading volume. However, we do not find such great impacts on stock returns, suggesting that the speculations are more likely to spread among small non-institutional investors. Further investigations show that sentiments embedded in these tweets have limited influence. There is evidence of a changing market behavior towards such tweets centered by the President’s inauguration.

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1. Introduction

Recent years have witnessed a significant rise of social media usages. Politicians use social media for a direct channel of communications to/from supporters (Tumasjan et al., 2010). Companies incorporate social media in investor relations and marketing strategies. Social media enables individuals to acquire information and to share their opinions at an incredible speed. These facts have gradually led investors to shift focuses from traditional news to internet-based media, such as online investment forums (e.g. Antweiler and Frank, 2004) and social media (e.g. Chen et al., 2014). Approximately 500 million messages are posted on Twitter universe every day on various topics, including stock markets. Prior literature shows that enormous numbers of Twitter messages convey valuable information for investors (e.g. Sprenger et al, 2014a,b; Bartov et al, 2017).

While several studies have investigated the link between Twitter features e.g. sentiments, volume and stock market features (e.g. Bollen et al., 2011; Zhang et al., 2011), an important dimension of information embedded in tweets has been largely ignored. A large number of tweets that mention two entities might indicate potential connectedness between them. This paper fills the gap in prior literature by examining stock market reactions to signals of associations between a company and political leaders. We use Twitter messages with both words 'Trump' (or '@realDonaldTrump') and a S&P500 company name as an ideal candidate as the joint mention could reflect close political ties (e.g. Tumasjan et al., 2010). Prior literature shows that political connections affect various corporate activities such as employment, financial gearing, taxation, and investment decisions which in turn would be incorporated into investors' expectations (e.g. Faccio, 2010; Wu et al., 2012).

However, given that not all information in social media are reliable, such tweets might also add considerable noises to public domains. The Efficient Market Hypothesis rules out the effects of noises since competitions between rational arbitrageurs would eliminate any irrationality and noise trading. In contrast, De Long et al. (1990) suggest that an asset's price could deviate far from its fair/fundamental value in the presence of noise traders. As a result, rational investors require a risk premium for such noises, ceteris paribus. Taken together, if investors are sensitive to the signals about political links, one would expect significant impacts of tweets on market features regardless of potential noises.

Our investigations are conducted before and after President Trump's inauguration in January 2016. In general, the empirical results are line with our expectation. There is evidence of market reactions to such tweets. Specifically, before the inauguration, positive tweets trigger positive expectations about the associated company, hence positive abnormal returns. After Trump's inauguration, association of a stock and a large volume of these tweets significantly reduces the stock's returns. In addition, increased numbers of such tweets consistently increase stock volatility and trading volume i.e. both before and after Trump's inauguration. The results suggest important implications for investors. Before Trump's inauguration, positive tweets with word 'Trump' ignite speculations and positive expectations over the related firm. After the inauguration, such tweets are likely to be treated as noise.

Our study connects three different strands of literature. Firstly, we contribute to the literature on the relationship between media and stock markets. Some studies suggest the predictive power of sentiment in forecasting stock returns. For example, Tetlock (2007) and Tetlock et al. (2008) argue that sentiments embedded in news are an important dimension of information forecasting individual stocks' future performances. Different forms of corporate disclosure induce heterogeneous effects on investors

(Hirshleifer and Teoh, 2003). Stock returns are closely related to media coverage. For instance, Barber and Odean (2008) point out that limited attention can affect investors' decisions and they are more likely to buy stocks that catch their attention. Mutual fund traders are also subject to limited attention from mass media coverage of stocks (Fang et al., 2014). Fang and Peress (2009) suggest a negative relationship between stock returns and media coverage. While Wall Street Journal columnists and Dow Jones Industrial Average daily returns are related (Dougal et al., 2012), trading volume of S&P 500 index firms can be predicted by local media coverage of earnings announcements (Engelberg and Parsons, 2011).

Secondly, we complement the existing literature on stock forecasts using online social media. Da et al. (2011) show that Search Volume Index can be used to capture investor attention and predict future stock returns. Chen et al. (2014) reveal a forecastability of stock prices using articles and commentaries on an online investor forum. Bollen et al. (2011) find a relationship between some collective mood states derived from Twitter and the value of the Dow Jones Industrial Average. Zhang et al. (2011) link levels of tweet emotionality to three U.S. stock market indexes: Dow Jones, NASDAQ, and S&P 500. Das and Chen (2007) argue that the relation between the information content embedded in social media and individual stock returns is weaker than stock index returns. While different types of stock-related news posted on Twitter can have different effects on companies (Sprenger et al., 2014a), there is a significant relationship between twitter message features, i.e. sentiment, volume and agreement, and market features, i.e. individual stock returns, liquidity and volatility (Sprenger et al. (2014b).

Finally, there is an extant strand of literature on changes in company behaviors as a result of political connections. Firms with political connections enjoy tax benefits and outperform those without (Wu et al., 2012). Faccio (2010) reveals that firm with political connections are associated with higher levels of leverage and larger market shares. Boubakri et al. (2012) show that politically connected companies enjoy better performance after the establishment of the political connections and that they can tap to finance and credit supplies easier. Political connections are also shown to affect corporate decisions such as employment levels, indebtedness and investment (e.g. Kuzman et al., 2017).

The remain of this paper is structured as follows. Section 2 describes the data of stock prices and tweets. Section 3 details the methodology. Section 4 presents the regression and the event study results. Section 5 summarizes the findings and draws conclusions.

2. Data

2.1 Data screening and cleaning

We use Twitter Streaming application programming interface (API) to collect the Twitter data in this study. API can be viewed as a messenger between users and Twitter servers system. When a user makes requests, the messenger passes them onto the system, then sends the responses back to the user. In this study, we send requests to collect tweet messages which contain keywords ‘Trump’ or ‘@realDonaldTrump’ and leave the connections open to collect as many tweets as possible during the harvest periods. Every tweet obtained contains information about the text of the tweet, user ID and name, and some other fields such as date, source, location, friend counts, follower counts, etc. We collect tweets with word “Trump” in its text from 3rd October 2016 to 16th October 2017 in order to cover a reasonable period both before and after the 2016 US Presidential Election. This array of tweets also contains ‘@realDonaldTrump’ (Official twitter account of Donald Trump) mentions and retweets. Next, we restricted our sample to contain S&P 500 constituent company names. Daily stock prices for S&P

500 composite firms are obtained from Compustat for the period between 2nd January 2015 and 16th October 2017.[1] We focus on 100 well-known companies which have a large number of tweet postings.[2]

Following Gorodnichenko et al. (2017), we screen and clean the collected tweets. Firstly, we delete special characters in tweets such as link tokens (starting with 'http', 'https', 'www'). Secondly, all tweets with only links or URLs are excluded. Lastly, all tweets not in English are eliminated. Our final sample has about 3.37 million tweets covering the period from 3rd October 2016 to 16th October 2017.

There are in total 43,308,567 tweets containing 'Trump' and 1,233,318 tweets mentioning '@realDonaldTrump', and a S&P 500 constituent firm name. The daily means are 1,672 and 48 messages for tweets containing 'Trump' and tweets mentioning '@realDonaldTrump', respectively. The standard deviations of such tweets are 12,561 and 403 postings per day, respectively. The large numbers of tweets per firm per day imply a sound information content embedded in our dataset. The descriptive statistics of market and tweet features are shown in Table 1. Figure 1 plots the number of tweets with the word 'Trump' and a S&P 500 company name around 2016 US Presidential Election. The number increases from about 100 in the start of October to over 200,000 by the end of November.

2.2 Sentiments of Twitter messages

Since sentiments of news are important information, we separate between positive and

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[1] We use firms that are included in the S&P 500 as of 2nd January 2015. The reason for using stock data from 2015 is to estimate various measures of expected stock returns, volatility, trading volume.

[2] We could not obtain satisfactory Twitter data for some companies, e.g. Tiffany, as Trump has a daughter whose name is Tiffany. We have tried an alternative way using dollar sign followed by the ticker to collect Twitter information, but we end up with too much noise for some firms, e.g. Ford ('$F'). Full list of companies is reported in Appendix A.1

negative tweets. We employ a text-processing tool in Python, TextBlob, to obtain a polarity score for every Twitter message. TextBlob will give a polarity score between -1 and 1 for sentiment analysis: a negative score means negative sentiment, while a positive score suggests positive sentiment, and 0 score indicates neutral sentiment. We use both PatternAnalyzer and NaiveBayesAnalyzer in TextBlob to perform the sentiment analysis, and obtain the same sentiment score for every Twitter message, which adds the robustness of our analysis. Appendix A2 gives examples on how TextBlob calculates the polarity score in our sample.

3. Methodology

3.1 Aggregate daily Twitter messages

To investigate the relationship between all Twitter messages and stock price changes on a daily basis, we aggregate all daily tweets. We explore the relationship between market features (stock returns, trading volumes, and volatility) and tweet features (positiveness, message volume, and agreement). Following Antweiler and Frank (2004) and Sprenger et al. (2014b), we define positiveness as

$$Positiveness_t = \ln\left(\frac{1 + M_t^{positive}}{1 + M_t^{negative}}\right) \quad (1)$$

where $M_t^{positive}$ and $M_t^{negative}$ are the number of positive and negative tweets on day t, and this gives a measure of sentiment as the proportion of positive tweets.

We define Twitter message volume as the natural logarithm of the number of tweets on each day. Same as Antweiler and Frank (2004) and Sprenger et al. (2014b), we define agreement as

$$Agreement_t = 1 - \sqrt{1 - \left(\frac{M_t^{positive} - M_t^{negative}}{M_t^{positive} + M_t^{negative}}\right)^2} \quad (2)$$

The agreement measure is 1 if all messages are positive or negative.

Following Antweiler and Frank (2004) and Sprenger et al. (2014b), we define tweet message volume, positiveness and agreement as 0 during quiet periods i.e. when there is no tweet for a particular company on day t. Since the tweet and market features data are available for the majority of our dataset for all company and day combinations, the effects that quiet periods have on our results is negligible.

Lastly, in line with the opening time of NYSE and NASDAQ (9:30 am to 4:00 pm), we assign the tweet postings after the markets close at 4:00 pm to the next trading day. We separate Twitter messages posted after 4:00 pm because tweets posted after the markets close may only affect stock prices on the following day(s).

3.2 Stock market data

Although Sprenger et al. (2014b) use standard returns, we follow Antweiler and Frank (2004) to use log returns. We define abnormal returns as

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$

where $R_{i,t}$ is log-return for stock i on day t and $E(R_{i,t})$ is expected return. We employ two alternatives for the expected return. First, the mean return over the past 100 trading days from day -110 to day -10[3], hence

$$AR_{i,t} = R_{i,t} - \frac{1}{100}\sum_{k=10}^{110} R_{i,t-k}$$

However, this simple mean-adjusted return could not reflect the stock's idiosyncratic risk, hence we estimate the expected return using the market model estimated by an ordinary least squares (OLS) regression

[3] We also use alternative 1-year estimation period starting i.e. [-10,-260], and we obtain qualitatively similar results. These results are available upon request.

$$E(R_{i,t}) = \alpha_i + \beta_i(R_{m,t}) + \mu_i \ \ \forall\, t = 1, 2, \dots, T$$

where α_i is the intercept, β_i is the association between the stock and the market returns, μ_i is the error term and T is the number of periods in the estimation period. Following previous literature, we adopt a 100-day estimation period starting 10 days prior to the relevant date.[4]

We then define cumulative abnormal returns as

$$CAR_{i,t} = \sum (AR_{i,t})$$

and the average cumulative abnormal returns for *N* firms as

$$ACAR_t = \frac{\sum_{i=1}^{N} CAR_{i,t}}{N}$$

Following Parkinson (1980), we estimate daily volatility using intraday high and low stock prices $S_{t,high}$ and $S_{t,low}$, and the estimator is given as

$$Vol^{Park} = \frac{\ln(S_{t,high}/S_{t,low})}{2\sqrt{\ln 2}}$$

We use both the Parkingson volatility measure and abnormal changes in the volatility measure in order to obtain robust findings. An abnormal change in the volatility measure equals today volatility minus the average volatility in the past 100 trading days i.e. [-110, -10].

Trading volume is defined as the logarithm of numbers of shares traded in a given day. We also employ a similar measure of abnormal changes in trading volume as above.

3.3. Empirical specification

Our regression specifications are given as

$$y_t = \alpha + \beta_1 Positiveness_t + \beta_2 Message_t + \beta_3 Agreement_t + \delta R_t^{Market} + u_i + \varepsilon_t \quad (3)$$

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[4] Similarly, alternative 1-year estimation period yields qualitatively similar results (available upon request).

where y_t is a vector of dependent variables i.e. stock returns, volatility, trading volume.

To explore the effect of sentiment on stock market characteristics we construct $Positiveness_t$ variable using equation (1). It is noteworthy that we use tweets from 4:00pm, i.e. when the US market closes, in the previous trading day to mark to 3:59pm today to mitigate potential endogeineity. In line with prior literature (e.g. Sprenger et al., 2014b), we expect a positive (negative) coefficient of Positiveness in explaining returns (volatility, trading volume).

$Message_t$ is the natural logarithm of the number of tweets, from 4:00pm the previous trading day to 3:59pm today. We expect a positive coefficient of Message in explaining volatility and trading volume not returns (Antweiler and Frank, 2004; Sprenger et al., 2014b).

$Agreement_t$ captures the extent to which tweets agree to each other i.e. similar or very different numbers of positive versus negative tweets. The Agreement is estimated using equation (2). In line with prior literature (Sprenger et al., 2014b), we expect negative coefficients of Agreement in explaining returns, volatility, and trading volume. We also control for market return i.e. S&P 500 return, R_i^{Market}, and firm individual fixed effects since tweets volume are substantially different cross-sectionally.

4. Results

4.1 Relation between tweet and market features

Results for correlations between tweet and market features are shown in Table 2. There is a significant positive correlation between returns and the volume of tweets containing the word 'Trump'. Hence a change in the volume of tweets with the word 'Trump' can be linked to a change in stock returns. The relation between trading volume and the sentiment of tweets containing the word ‘Trump’ is also statistically significant. Although there are significant correlations between market and tweet features, we need to employ regressions to control for other features, and explore whether tweet features can help to explain stock market movements.

Table 3 reports fixed effects panel regressions of return as dependent variable and the three tweet features (positiveness, volume and agreement) for tweets containing ‘Trump’ or ‘@realDonaldTrump’ as independent variables. There is significant difference in market reaction patterns before versus after Trump’s inauguration. Positive sentiment in these tweets is significantly associated with higher (abnormal) stock returns before the inauguration but this association perishes after Trump became the President on 20th January 2017. In addition, the coefficient of tweets message volume becomes significantly negative in explaining (abnormal) returns after the inauguration. Our results imply that before the inauguration, investors do consider speculations of political connections between a firm and President-elect embedded in the tweets as an important information in making investment decisions. Particularly, positively sentimental ‘Trump’ tweets induce positive expectations over the associated company, hence, higher (abnormal) returns. However, since Trump officially became the President, hints about political links could be then found from official sources such as press releases. Thus, after the inauguration, such tweets are more likely to be treated as noises rather than reliable information sources. Consequently, the high number of such tweets leads to a reduction in (abnormal) returns as rational investors require a risk premium for the presence of noise trading (De long et al., 1990).

Next, we investigate whether volatility is affected by signals from social media. Table 4 shows contemporaneous fixed effects panel regressions. There is a statistically significant and positive relation between the volume of tweets containing 'Trump' and intraday volatility. Intraday volatility represents ex post disagreement among the market participants regarding the fair value of a stock on a given day. Enikolopov et. al (2016) suggest that tweets may have heterogeneous influence on market participants which amplify investors' heterogeneous beliefs. In particular, small non-institutional investors are more likely to expose to noisy signals such as Twitter messages. Our results continue to support De Long et al. (1990). Consistent with Sprenger et al. (2014b), we find no statistically significant relation between agreement of the tweets with the word 'Trump' or '@realDonaldTrump' and volatility.

Table 5 presents contemporaneous fixed effects panel regressions of volume as dependent variable and the three tweet features as independent variables. There is a statistically significant relationship between the volume of tweets containing the word 'Trump' or '@realDonaldTrump' and trading volume. This indicates that Twitter users post tweets about stocks that are traded more frequently. The coefficients can be interpreted as elasticities because volume is log transformed. Before Trump's inauguration, a 1% increase in the volume of tweets with the word 'Trump' is related to about 0.14% increase in the trading volume. Enikolopov et. al (2016) suggest that the reason for this is because institutional investors are unlikely to be distracted by the tweets, while non-institutional investors, who are more likely to be influenced by Twitter messages, can only affect trading volume but not returns. Moreover, there is a statistically significant and negative correlation between the agreement of the tweets containing the word 'Trump' and trading volume before Trump's inauguration. Lastly, we find a statistically significant and positive relation between the positiveness of the tweets with the word '@realDonaldTrump', and trading volume and volatility before Trump's inauguration. To sum up, we find that the relationships between message volume and trading volume, message volume and volatility, and positiveness and trading volume are the most significant.

4.2 Robustness check

We find some statistically significant relations between tweet and market features in our contemporaneous regressions. If tweet messages have information incorporated in stock prices, tweet features should predict changes in market features. We hence examine the lagged relationships between tweet and market features. We regress one day lag of every tweet feature on market features. Not surprisingly, we do not find a statistically significant relationship between lagged positiveness and stock returns. In contrast to Antweiler and Frank (2004), we do not find a statistically significant relationship between message volume and stock returns. This may suggest that investors are more cautious when assessing the information content of tweet postings compared to message boards. We also find a statistically significant relation between the volume of the tweet messages with the word ‘Trump’ one day ago and the trading volume, and volatility today. Overall, we find that some tweet features have significant casual relations with market features.

We then perform further robustness checks by separating the tweet messages into 2 groups based on the US trading hours: from 4:00 pm yesterday to 9:30am today as pre-trading, and between 9:30am and 4:00pm today as trading. We then repeat the same regressions and the lagged variables regressions by using the tweet features collected during the pre-trading periods, and the levels of significance are similar as before. All results for this section are reported in Appendix B.

4.3 Event study

We also employ event study to detect abnormal increases in tweets volume, and relate the volume and sentiment of these tweets to stock returns, volatility, and trading volume. We define an event i.e. an abnormal increase in tweets volume if the following three conditions are satisfied: 1) the absolute number of tweets is in the top 5% of the company's empirical distribution of daily tweets; 2) the relative increase in tweets volume is larger than 100%; 3) the absolute number of increase in tweets volume is greater than 100. Figure 2 shows the number of events around the 2016 US Presidential Election. The events seem to cluster close to the election day.

Table 6 presents the results from the event study before Trump's inauguration. An abnormal increase in the number of tweets with the word 'Trump' or '@realDonaldTrump' and a S&P 500 firm name will result in a 0.326% or 0.512% increase in returns on the following day of event. Although this relationship is statistically significant at the 1% significance level, the magnitude of the relation is not substantial. However, we find a statistically significant and economically meaningful relationship between an event and trading volume. An abnormal increase in the number of tweets containing the word 'Trump' and a S&P 500 company name will lead to about 16% increase in trading volume on the same day, and around 13% increase on the next day of event. Table 7 shows the results from the event study after Trump's inauguration and we find very little statistically significant relations.

5. Conclusions

The world has moved in a social media age where huge amount of information flows through rather unconventional channels such as Twitter, Facebook, Google plus, Yahoo. Prior literature shows that information in such channels induces significant impacts on stock performance (e.g. Antweiler and Frank, 2004; Chen et al., 2014; Sprenger et al., 2014a,b). This paper revisits the issue in a connection to another strand of literature on firms' political linkages (e.g. Faccio, 2010; Wu et al., 2012; Kuzman et al., 2017). We explore whether a stock market reacts to signals of associations between a firm and a political leader. Specifically, we employ tweets with both words 'Trump' (or '@realDonaldTrump') and a S&P500 company name as a proxy for such associations. Market reactions are measured by abnormal returns, trading volumes and volatility. Investigations before and after Trump's inauguration are carried out.

Our findings show that sentiments of such tweets affect returns of S&P 500 stocks before Trump's inauguration. However, we cannot find any similar effect after the inauguration. Before the inauguration, positive 'Trump' tweets boost expectations over the associated firm, hence higher abnormal returns. After the inauguration, similar tweets are more likely to serve as noises and significantly reduces stock returns. Information posted on Twitter can ignite speculations over associations between a firm and the newly elected President. Our results support the argument in De Long et al. (1990), that rational investors require a risk premium for the presence of noise trading.

This study has limitations, and we suggest some areas for future research. We use daily stock prices, but the real-time nature of Twitter suggests research at an intraday level. Some tweet features such as positiveness are obtained based on all Twitter messages posted at different times in a given day. Consequently, sentiments of tweets could influence stock markets instantaneously or only at certain point(s) of times during the day. However, we assign Twitter messages posted after the market closes to the next day, hence there is a time lag before these tweet messages can affect the financial market on the next day.

Table 1
Summary statistics of market and tweet features. This table shows the summary statistics of market and tweet features. All daily statistics are reported on a per company basis. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Volume is the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. All returns and volatilities are reported as percentages. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump', while @realDonaldTrump is about all the Twitter messages with the word '@realDonaldTrump'. Sample size N=25,899 company trading days.

Variable	Mean	Std. Dev.
Market features		
Return	0.051	1.443
Mean-adjusted return	0.001	1.443
Market-model abnormal return	-0.009	1.350
Market return	0.066	0.479
Volume	6,818,184	12,204,487
Intraday volatility	1.184	0.716
Tweet features		
Message (Trump)	1,672.210	12,561.090
Positiveness (Trump)	0.374	1.047
Agreement (Trump)	0.119	0.171
Message (@realDonaldTrump)	47.620	402.835
Positiveness (@realDonaldTrump)	0.120	0.634
Agreement (@realDonaldTrump)	0.055	0.116

Table 2

Correlations between market and tweet features. This table displays correlations between market and tweet features. Returns are defined as log returns, market return is S&P 500 index return. Volume is the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump', while @realDonaldTrump is about all the Twitter messages with the word '@realDonaldTrump'. * denotes correlations that are significantly different from 0 at the 1% significance level.

	Return	Market return	Intraday volatility	Volume	Message (Trump)	Positiveness (Trump)	Agreement (Trump)	Message (@realDonaldTrump)	Positiveness (@realDonaldTrump)
Market return	0.342*								
Intraday volatility	-0.059*	-0.025*							
Volume	0.006	-0.002	0.136*						
Message (Trump)	0.010	0.030*	-0.005	0.129*					
Positiveness (Trump)	0.018*	0.008	-0.003	0.075*	0.186*				
Agreement (Trump)	0.016	0.014	-0.003	0.101*	0.235*	0.467*			
Message (@realDonaldTrump)	0.001	0.012	-0.017*	0.113*	0.819*	0.078*	0.001		
Positiveness (@realDonaldTrump)	0.005	0.007	0.011	0.042*	0.204*	0.183*	0.076*	0.245*	
Agreement (@realDonaldTrump)	0.009	0.008	0.001	0.013	0.397*	0.111*	0.105*	0.457*	0.414*

Table 3

Contemporaneous regressions of returns. This table shows the extent that 'Trump' and '@realDonaldTrump' tweet features can explain the changes in stock returns before and after Trump's inauguration. The first row displays market features as the dependent variables, tweet features are independent variables and market return is a control variable. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump', while @realDonaldTrump is about all the Twitter messages with the word '@realDonaldTrump'. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent Variable					
	Return		Mean-adjusted return		Market-model abnormal return	
	Before	After	Before	After	Before	After
Panel A: Trump						
Positiveness	0.028*	0.005	0.025	0.005	0.029*	0.006
	(2.19)	(0.60)	(1.95)	(0.55)	(2.08)	(0.63)
Message	-0.024	-0.040*	-0.034	-0.037*	-0.037	-0.035
	(-1.27)	(-2.19)	(-1.74)	(-2.01)	(-1.76)	(-1.80)
Agreement	-0.003	0.015	-0.002	0.012	-0.002	0.011
	(-0.24)	(1.65)	(-0.14)	(1.35)	(-0.13)	(1.13)
Adjusted R^2	0.133	0.109	0.131	0.104	-0.003	-0.003
Panel B: @realDonaldTrump						
Positiveness	0.001	-0.002	-0.000	-0.002	-0.001	0.001
	(0.06)	(-0.28)	(-0.01)	(-0.32)	(-0.07)	(0.11)
Message	-0.037	-0.011	-0.041	-0.008	-0.042	-0.011
	(-1.58)	(-0.66)	(-1.75)	(-0.51)	(-1.66)	(-0.66)
Agreement	0.007	0.009	0.007	0.011	0.007	0.012
	(0.43)	(1.20)	(0.40)	(1.39)	(0.41)	(1.50)
Adjusted R^2	0.133	0.108	0.130	0.104	-0.003	-0.003

Table 4
Contemporaneous regressions of volatility. This table shows the extent that ‘Trump’ and ‘@realDonaldTrump’ tweet features can explain the changes in volatility before and after Trump’s inauguration. The first row displays market features as the dependent variables in panel regressions with company fixed effects. Tweet features are independent variables and market return (S&P 500 index return) is a control variable. We calculate Parkinson (1980) intraday volatility using daily high and low prices. Abnormal volatility is the intraday volatility less the mean based on a 100-day estimation period starting 10 days prior to the relevant date. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word ‘Trump’, while @realDonaldTrump is about all the Twitter messages with the word ‘@realDonaldTrump’. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent variable			
	Intraday volatility		Abnormal volatility	
	Before	After	Before	After
Panel A: Trump				
Positiveness	0.017	-0.005	0.020	-0.012
	(1.41)	(-0.65)	(1.48)	(-1.42)
Message	0.067***	0.121***	0.080***	0.086***
	(4.06)	(6.03)	(4.31)	(3.73)
Agreement	-0.021	0.002	-0.026	0.004
	(-1.67)	(0.20)	(-1.80)	(0.42)
Market return	0.016	-0.053***	0.017	-0.060***
	(0.93)	(-7.99)	(0.89)	(-7.94)
Adjusted R^2	0.209	0.241	0.019	0.017
Panel B: @realDonaldTrump				
Positiveness	0.028**	0.009	0.033**	0.010
	(2.67)	(1.31)	(2.84)	(1.35)
Message	-0.019	0.032*	-0.016	0.063***
	(-1.14)	(2.19)	(-0.88)	(3.80)
Agreement	-0.012	-0.011	-0.015	-0.014
	(-0.98)	(-1.38)	(-1.11)	(-1.52)
Market return	0.020	-0.051***	0.021	-0.059***
	(1.15)	(-7.74)	(1.12)	(-7.83)
Adjusted R^2	0.207	0.238	0.018	0.016

Table 5
Contemporaneous regressions of volume. This table shows the extent that 'Trump' and '@realDonaldTrump' tweet features can explain the changes in volume before and after Trump's inauguration. The first row displays market features as the dependent variables in panel regressions with company fixed effects. Tweet features are independent variables and market return (S&P 500 index return) is a control variable. Log volume is the natural logarithm of the number of shares traded. Abnormal log volume is the log volume less the mean based on a 100-day estimation period starting 10 days prior to the relevant date. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump', while @realDonaldTrump is about all the Twitter messages with the word '@realDonaldTrump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent Variable			
	Log(volume)		Abnormal log(volume)	
	Before	After	Before	After
Panel A: Trump				
Positiveness	0.012^{*}	0.001	0.033^{*}	-0.004
	(2.30)	(0.26)	(2.27)	(-0.54)
Message	0.046^{***}	0.052^{***}	0.140^{***}	0.123^{***}
	(6.71)	(7.51)	(7.34)	(5.66)
Agreement	-0.018^{**}	0.003	-0.054^{***}	0.005
	(-3.22)	(1.12)	(-3.43)	(0.60)
Market return	0.014^{***}	-0.006^{**}	0.041^{***}	-0.016^{*}
	(3.51)	(-2.60)	(3.55)	(-2.23)
Adjusted R^2	0.882	0.899	0.073	0.043
Panel B: @realDonaldTrump				
Positiveness	0.015^{**}	0.000	0.043^{**}	0.000
	(3.21)	(0.12)	(3.27)	(0.02)
Message	0.019^{**}	-0.003	0.062^{**}	-0.007
	(2.70)	(-0.48)	(3.10)	(-0.44)
Agreement	-0.008	0.002	-0.024	0.006
	(-1.52)	(0.68)	(-1.58)	(0.65)
Market return	0.016^{***}	-0.005^{*}	0.046^{***}	-0.014
	(3.94)	(-2.24)	(4.01)	(-1.95)
Adjusted R^2	0.882	0.898	0.069	0.040

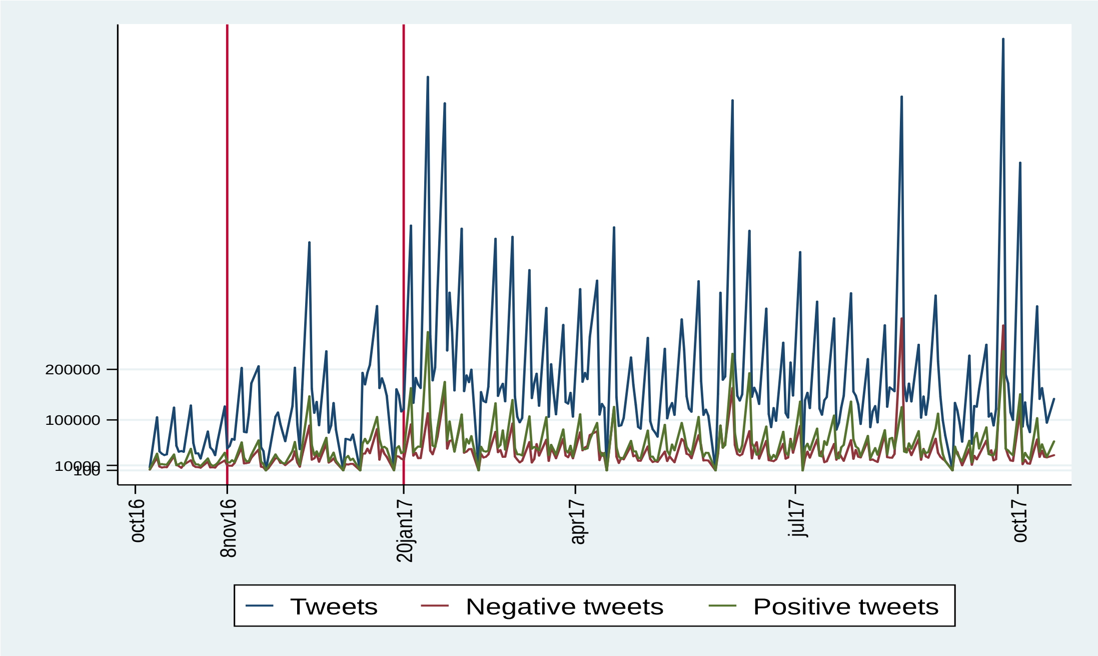
Table 6
Effects of event on market features. This table shows the changes in return, trading volume and volatility after abnormal increases in tweets volume on the event day (0), the following day (1), and the next 4 days (2, 5) before Trump's inauguration. Tweets are grouped into positive and negative based on discussions in section 2.2. All reactions are reported in percentage points. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Log volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Trump is about all the tweets containing the word 'Trump', while @realDonaldTrump is about all the Twitter messages with the word '@realDonaldTrump'. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively.

	Trump			@realDonaldTrump		
	All tweets	Negative tweets	Positive tweets	All tweets	Negative tweets	Positive tweets
Panel A: Return						
[0]	0.075	0.056	-0.003	0.057	-0.118	0.281
[1]	0.326**	0.472*	0.582***	0.512**	0.462	0.442
[2,5]	0.059	0.037	0.013	-0.094	-0.139	0.072
Panel B: Mean-adjusted return						
[0]	0.013	-0.001	-0.073	-0.023	-0.171	0.241
[1]	0.264*	0.412*	0.518***	0.430*	0.405	0.403
[2,5]	-0.001	-0.019	-0.056	-0.17	-0.203	0.027
Panel C: Market-model abnormal return						
[0]	-0.082	-0.159	-0.157	-0.051	-0.394	0.005
[1]	0.107	0.267	0.430***	0.417*	0.311	0.232
[2,5]	-0.067	-0.065	-0.101*	-0.217	-0.169	-0.038
Panel D: Intraday volatility						
[0]	0.232***	0.110*	0.069	-0.033	0.053	0.002
[1]	0.236***	0.223***	0.173**	0.1	0.087	0.201*
[2,5]	0.070*	0.082*	0.075*	0.137*	0.024	0.124
Panel E: Log (volume)						
[0]	15.913***	9.233*	9.436**	8.718	10.855	16.581**
[1]	13.456***	14.522***	12.457***	7.937	14.231*	16.070*
[2,5]	2.702	-0.615	2.12	7.174	6.675	9.022

Table 7
Effects of event on market features. This table shows the changes in return, trading volume and volatility after abnormal increases in tweets volume on the event day (0), the following day (1), and the next 4 days (2, 5) after Trump's inauguration. Tweets are grouped into positive and negative based on discussions in section 2.2. All reactions are reported in percentage points. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Log volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Trump is about all the tweets containing the word 'Trump', while @realDonaldTrump is about all the Twitter messages with the word '@realDonaldTrump'. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively.

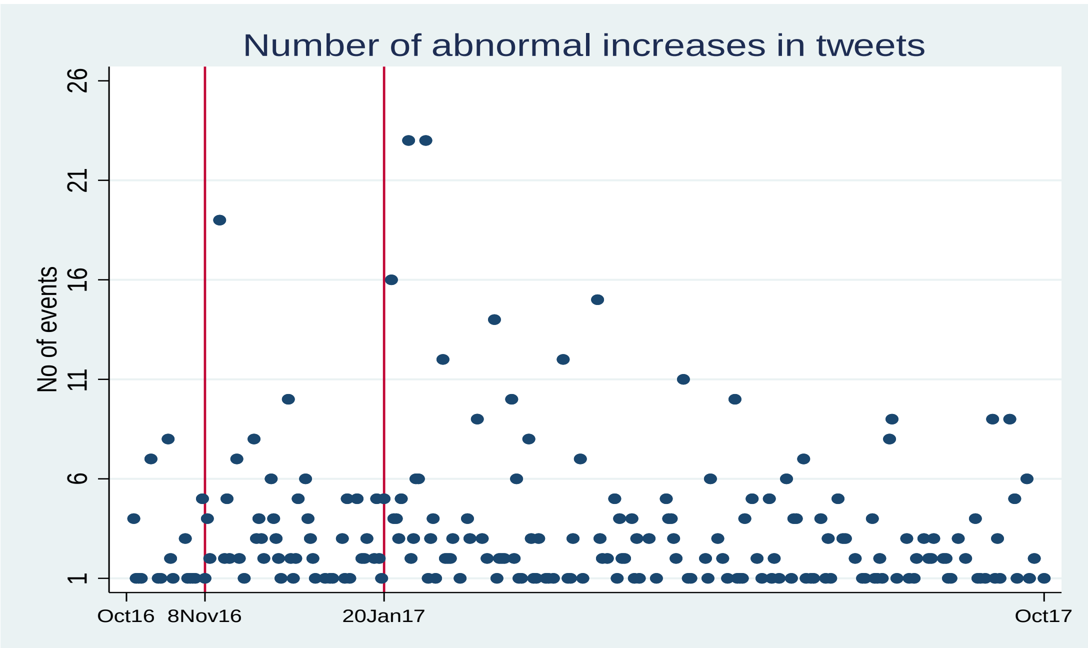
	Trump			@realDonaldTrump		
	All tweets	Negative tweets	Positive tweets	All tweets	Negative tweets	Positive tweets
Panel A: Return						
[0]	0.074	0.085	0.017	0.238**	0.107	0.304**
[1]	0.054	-0.035	0.003	0.056	-0.161	0.017
[2,5]	0.026	-0.018	0.041	0.084	0.094	-0.005
Panel B: Mean-adjusted return						
[0]	0.022	0.035	-0.027	0.205**	0.083	0.290**
[1]	0.004	-0.083	-0.036	0.023	-0.199	0
[2,5]	-0.026	-0.065	-0.003	0.052	0.071	-0.022
Panel C: Market-model abnormal return						
[0]	-0.007	0.011	-0.023	0.154*	0.006	0.278**
[1]	0.032	-0.065	-0.02	0.073	-0.176	0.025
[2,5]	-0.029	-0.055	-0.005	0.058	0.048	-0.049
Panel D: Abnormal intraday volatility						
[0]	-0.062*	-0.005	-0.027	-0.05	-0.03	-0.04
[1]	-0.062*	-0.03	-0.039	-0.013	-0.009	-0.064
[2,5]	-0.054**	0.016	-0.014	-0.015	-0.051	-0.001
Panel E: Abnormal trading volume						
[0]	-0.677	0.122	2.931	-9.327***	-9.068*	-11.407***
[1]	-0.077	2.236	2.435	-2.753	-4.541	0.001
[2,5]	0.12	4.123*	2.762	-0.809	-5.636	-1.284

Figure 1. Number of tweets containing the word 'Trump' and a S&P 500 firm name.



This figure shows the evolution of the number of tweets containing the word Trump and a S&P 500 firm name during the sampled period with the reference (red) lines represent the election day and the inauguration day, respectively.

Figure 2. Number of events (abnormal increases in tweets volume).



This figure shows numbers of events in the event study i.e. numbers of abnormal increases in tweets during the sampled period.

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Appendix A

Table A.1: Sampled companies

	Company		Company		Company
1	AES Corp	35	Expedia Inc	68	Netapp Inc
2	Aetna Inc	36	Exxon Mobil	69	Netflix Inc
3	Allergan Plc	37	Facebook Inc	70	Newell Brands Inc
4	American Airlines Group	38	Fluor Corp	71	Nike Inc
5	American Express	39	Ford Motor	72	Nordstrom Inc
6	Anthem Inc	40	Foxconn	73	Oracle Corp
7	Aon Plc	41	Gap Inc	74	Paypal Holdings Inc
8	Arconic Inc	42	General Electric	75	Pepsico Inc
9	AT&T Inc	43	General Motors	76	PG&E Corp
10	Bank Of America Corp	44	Goldman Sachs	77	Phillips 66
11	Bayer AG	45	HCP Inc	78	Progressive Corp-Ohio
12	Boeing Co	46	Hershey Co	79	Raytheon Co
13	Campbell Soup Co	47	Hologic Inc	80	Red Hat Inc
14	Carnival Corp/Plc	48	Home Depot Inc	81	Scana Corp
15	Caterpillar Inc	49	HP Inc	82	Snap-On Inc
16	CBRE Group Inc	50	Humana Inc	83	Softbank Group
17	CBS Corp	51	Illumina Inc	84	Southern Co
18	Charter Communications	52	Intel Corp	85	Staples Inc
19	Chevron Corp	53	Intl Paper Co	86	Starbucks Corp
20	Citigroup Inc	54	Intuit Inc	87	Stryker Corp
21	CME Group Inc	55	Kellogg Co	88	Target Corp
22	Coach Inc	56	Kohl's Corp	89	Time Warner Inc
23	Coca-Cola Co	57	Lockheed Martin Corp	90	TJX Companies Inc
24	Comcast Corp	58	Loews Corp	91	Toyota Motors
25	Corning Inc	59	Lowe's Companies Inc	92	UDR Inc
26	Delta Air Lines Inc	60	Macy's Inc	93	United Technologies
27	Devon Energy Corp	61	Masco Corp	94	Ventas Inc
28	Disney (Walt) Co	62	Mcdonald's Corp	95	VF Corp
29	Dover Corp	63	Merck & Co	96	Visa Inc
30	E Trade Financial	64	Microsoft Corp	97	Vulcan Materials Co
31	Ebay Inc	65	Morgan Stanley	98	Wells Fargo & Co
32	Edison International	66	Mosaic Co	99	Whirlpool Corp
33	Equifax Inc	67	Nasdaq Inc	100	Zimmer Biomet
34	Equity Residential				

This table reports the full list of companies from S&P 500 as of 2nd January 2015. We could not obtain satisfactory Twitter data for all S&P 500 companies, e.g. Tiffany, as Trump has a daughter whose name is Tiffany. We have tried an alternative way using dollar sign followed by the ticker to collect Twitter information, but we end up with too much noise for some firms, e.g. Ford (‘$F’).

Table A.2: Examples of sentiments score from Tweets

This table gives examples of polarity score of tweet messages calculated by TextBlob.

Text	Sentiment score
Trump	
Trump campaign using targeted Facebook posts to discourage Black Americans from voting	-1
@CNN @NBC @CBS we are counting on you to address #Trumpcorruption	0
@CBSnews normalizing Trump pitiful hope you're happy when he shuts down in favor of Pravda I mean Breitbart	1
@realDonaldTrump	
@realDonaldTrump wow Twitter Google and Facebook are burying the FBI criminal investigation of Clinton media	-1
@realDonaldTrump he's distracting you he's filling his administration with Goldman Sachs people here's another	0
So excited I will be in Hershey Friday to see @realDonaldTrump	1

Appendix B

Table B1

Regressions of returns. This table shows the extent that 1 day lagged 'Trump' tweet features can explain the changes in stock returns. The first row displays market features as the dependent variables. 1 day lagged tweet features are independent variables and market return is a control variable. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,498 (18,591) company trading days before (after) inauguration.

	Dependent variable					
	Return Before	Return After	Mean-adjusted return Before	Mean-adjusted return After	Market-model abnormal return Before	Market-model abnormal return After
Lagged Positiveness (Trump)	0.013	0.013	0.010	0.012	0.007	0.012
	(0.96)	(1.73)	(0.75)	(1.68)	(0.50)	(1.57)
Lagged Message (Trump)	0.000	-0.027	-0.010	-0.023	-0.010	-0.024
	(0.00)	(-1.53)	(-0.49)	(-1.32)	(-0.49)	(-1.30)
Lagged Agreement (Trump)	-0.011	-0.001	-0.010	-0.004	-0.010	-0.005
	(-0.72)	(-0.17)	(-0.64)	(-0.50)	(-0.58)	(-0.53)
Lagged Market return	0.368***	0.328***	0.366***	0.327***	-0.002	-0.015
	(32.00)	(44.20)	(31.87)	(44.04)	(-0.17)	(-1.93)
Adjusted R^2	0.132	0.109	0.130	0.104	-0.004	-0.003

Table B2

Regressions of volatility and volume. This table shows the extent that 1 day lagged 'Trump' tweet features can explain the changes in volatility and volume. The first row displays market features as the dependent variables. 1 day lagged tweet features are independent variables and market return (S&P 500 index return) is a control variable. Log volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Abnormal volatility (log volume) is the volatility (log volume) less the mean based on a 100-day estimation period starting 10 days prior to the relevant date. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,498 (18,591) company trading days before (after) inauguration.

	Dependent variable							
	Intraday volatility Before	Intraday volatility After	Abnormal volatility Before	Abnormal volatility After	Log(volume) Before	Log(volume) After	Abnormal log(volume) Before	Abnormal log(volume) After
Lagged Positiveness (Trump)	0.005	-0.007	0.007	-0.014	0.007	0.002	0.019	-0.001
	(0.42)	(-0.94)	(0.48)	(-1.69)	(1.41)	(0.68)	(1.33)	(-0.10)
Lagged Message (Trump)	0.051**	0.106***	0.060**	0.066**	0.036***	0.052***	0.113***	0.121***
	(3.02)	(5.28)	(3.23)	(2.89)	(5.34)	(7.56)	(6.04)	(5.60)
Lagged Agreement (Trump)	-0.009	-0.008	-0.012	-0.007	-0.014*	0.003	-0.041**	0.004
	(-0.69)	(-1.01)	(-0.81)	(-0.73)	(-2.38)	(1.00)	(-2.60)	(0.48)
Lagged Market return	0.016	-0.051***	0.017	-0.058***	0.015***	-0.005*	0.043***	-0.013
	(0.94)	(-7.60)	(0.92)	(-7.69)	(3.70)	(-2.11)	(3.75)	(-1.85)
Adjusted R^2	0.206	0.240	0.018	0.016	0.881	0.899	0.071	0.043

Table B3

Regressions of returns. This table shows the extent that 'Trump' tweet features during pre-trading hours can explain the changes in stock returns. The first row displays market features as the dependent variables. Tweet features during pre-trading hours are independent variables and market return is a control variable. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent variable					
	Return Before	Return After	Mean-adjusted return Before	Mean-adjusted return After	Market-model abnormal return Before	Market-model abnormal return After
Positiveness (Trump)	0.022	0.006	0.019	0.006	0.024	0.006
	(1.73)	(0.76)	(1.49)	(0.68)	(1.74)	(0.70)
Message (Trump)	-0.026	-0.040*	-0.034	-0.037*	-0.036	-0.033
	(-1.31)	(-2.26)	(-1.72)	(-2.04)	(-1.70)	(-1.75)
Agreement (Trump)	0.010	0.006	0.011	0.004	0.010	0.003
	(0.78)	(0.72)	(0.86)	(0.50)	(0.70)	(0.36)
Market return	0.369***	0.329***	0.367***	0.328***	-0.001	-0.014
	(32.20)	(44.26)	(32.08)	(44.08)	(-0.11)	(-1.82)
Adjusted R^2	0.133	0.109	0.131	0.104	-0.003	-0.003

Table B4

Regressions of volatility and volume. This table shows the extent that 'Trump' tweet features during pre-trading hours can explain the changes in volatility and volume. The first row displays market features as the dependent variables. Tweet features during pre-trading hours are independent variables and market return (S&P 500 index return) is a control variable. Log volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Abnormal volatility (log volume) is the volatility (log volume) less the mean based on a 100-day estimation period starting 10 days prior to the relevant date. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. Trump is about all the tweets containing the word 'Trump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent variable							
	Intraday volatility Before	Intraday volatility After	Abnormal volatility Before	Abnormal volatility After	Log(volume) Before	Log(volume) After	Abnormal log(volume) Before	Abnormal log(volume) After
Positiveness (Trump)	-0.001	-0.007	0.000	-0.015	0.006	-0.000	0.018	-0.007
	(-0.06)	(-0.90)	(0.04)	(-1.69)	(1.29)	(-0.12)	(1.31)	(-0.89)
Message (Trump)	0.054**	0.088***	0.067***	0.053*	0.044***	0.038***	0.137***	0.082***
	(3.19)	(4.70)	(3.50)	(2.49)	(6.41)	(5.83)	(7.06)	(4.06)
Agreement (Trump)	-0.014	0.004	-0.018	0.008	-0.018***	0.004	-0.054***	0.008
	(-1.11)	(0.50)	(-1.28)	(0.88)	(-3.34)	(1.22)	(-3.62)	(0.90)
Market return	0.017	-0.053***	0.018	-0.059***	0.014***	-0.006**	0.041***	-0.015*
	(0.97)	(-7.97)	(0.93)	(-7.90)	(3.51)	(-2.58)	(3.54)	(-2.19)
Adjusted R^2	0.208	0.240	0.019	0.016	0.882	0.898	0.073	0.042

Table B5

Regressions of returns. This table shows the extent that 1 day lagged '@realDonaldTrump' tweet features can explain the changes in stock returns. The first row displays market features as the dependent variables. 1 day lagged tweet features are independent variables and market return is a control variable. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. @realDonaldTrump is about all the tweets containing the word '@realDonaldTrump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,498 (18,591) company trading days before (after) inauguration.

	Dependent variable					
	Return Before	Return After	Mean-adjusted return Before	Mean-adjusted return After	Market-model abnormal return Before	Market-model abnormal return After
Lagged Positiveness (@realDonaldTrump)	0.004	0.004	0.003	0.003	0.002	0.004
	(0.33)	(0.51)	(0.27)	(0.46)	(0.18)	(0.51)
Lagged Message (@realDonaldTrump)	-0.002	-0.018	-0.006	-0.016	-0.006	-0.020
	(-0.11)	(-1.11)	(-0.30)	(-0.93)	(-0.31)	(-1.13)
Lagged Agreement (@realDonaldTrump)	-0.009	0.011	-0.010	0.013	-0.006	0.014
	(-0.64)	(1.34)	(-0.68)	(1.54)	(-0.43)	(1.62)
Lagged Market return	0.368***	0.328***	0.366***	0.328***	-0.002	-0.014
	(32.08)	(44.37)	(31.93)	(44.21)	(-0.19)	(-1.90)
Adjusted R^2	0.132	0.109	0.130	0.104	-0.005	-0.003

Table B6

Regressions of volatility and volume. This table shows the extent that 1 day lagged '@realDonaldTrump' tweet features can explain the changes in volatility and volume. The first row displays market features as the dependent variables. 1 day lagged tweet features are independent variables and market return (S&P 500 index return) is a control variable. Log volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Abnormal volatility (log volume) is the volatility (log volume) less the mean based on a 100-day estimation period starting 10 days prior to the relevant date. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. @realDonaldTrump is about all the tweets containing the word '@realDonaldTrump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,498 (18,591) company trading days before (after) inauguration.

	Dependent variable							
	Intraday volatility	Intraday volatility	Abnormal volatility	Abnormal volatility	Log(volume)	Log(volume)	Abnormal log(volume)	Abnormal log(volume)
	Before	After	Before	After	Before	After	Before	After
Lagged Positiveness (@realDonaldTrump)	0.004	0.001	0.006	0.002	0.007	0.000	0.022	0.001
	(0.31)	(0.21)	(0.49)	(0.31)	(1.56)	(0.18)	(1.69)	(0.10)
Lagged Message (@realDonaldTrump)	-0.017	0.024	-0.014	0.053**	0.014*	0.003	0.049**	0.008
	(-1.08)	(1.65)	(-0.80)	(3.22)	(2.12)	(0.47)	(2.60)	(0.46)
Lagged Agreement (@realDonaldTrump)	-0.006	0.002	-0.009	0.001	-0.006	0.006*	-0.019	0.018*
	(-0.44)	(0.19)	(-0.62)	(0.06)	(-1.23)	(2.14)	(-1.30)	(2.09)
Lagged Market return	0.018	-0.051***	0.019	-0.058***	0.016***	-0.005*	0.045***	-0.014
	(1.02)	(-7.68)	(1.00)	(-7.72)	(3.86)	(-2.22)	(3.93)	(-1.94)
Adjusted R^2	0.206	0.238	0.017	0.016	0.881	0.898	0.068	0.040

Table B7

Regressions of returns. This table shows the extent that '@realDonaldTrump' tweet features during pre-trading hours can explain the changes in stock returns. The first row displays market features as the dependent variables. Tweet features during pre-trading hours are independent variables and market return is a control variable. Returns are defined as log returns, mean-adjusted return is based on a 100-day estimation period starting 10 days prior to the relevant date, market-model abnormal return is calculated using a version based on market model that reflects stock's idiosyncratic risk, market return is S&P 500 index return. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. @realDonaldTrump is about all the tweets containing the word '@realDonaldTrump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent variable					
	Return	Return	Mean-adjusted return	Mean-adjusted return	Market-model abnormal return	Market-model abnormal return
	Before	After	Before	After	Before	After
Positiveness (@realDonaldTrump)	0.001	-0.004	0.001	-0.005	-0.001	-0.003
	(0.08)	(-0.68)	(0.04)	(-0.71)	(-0.07)	(-0.44)
Message (@realDonaldTrump)	-0.035	-0.015	-0.038	-0.014	-0.039	-0.016
	(-1.61)	(-1.07)	(-1.76)	(-0.94)	(-1.68)	(-1.03)
Agreement (@realDonaldTrump)	0.005	0.015^{*}	0.004	0.017^{*}	0.004	0.019^{*}
	(0.34)	(1.96)	(0.25)	(2.21)	(0.24)	(2.34)
Market return	0.368^{***}	0.328^{***}	0.367^{***}	0.328^{***}	-0.002	-0.014
	(32.12)	(44.16)	(31.96)	(43.99)	(-0.15)	(-1.86)
Adjusted R^2	0.133	0.109	0.130	0.104	-0.003	-0.003

Table B8

Regressions of volatility and volume. This table shows the extent that '@realDonaldTrump' tweet features during pre-trading hours can explain the changes in volatility and volume. The first row displays market features as the dependent variables. Tweet features during pre-trading hours are independent variables and market return (S&P 500 index return) is a control variable. Log volume is the natural logarithm of the number of shares traded, and we calculate Parkinson (1980) intraday volatility using daily high and low prices. Abnormal volatility (log volume) is the volatility (log volume) less the mean based on a 100-day estimation period starting 10 days prior to the relevant date. Message is the natural logarithm of the volume of daily tweets per company, positiveness refers to the sentiment of a tweet message, and agreement is the concurrence of messages for a company regarding the sentiment. @realDonaldTrump is about all the tweets containing the word '@realDonaldTrump'. Huber-White robust standard errors are employed. *, **, *** denote significance at the 5%, 1% and 0.1% levels respectively. T-statistics are reported in parenthesis below coefficients. Sample size N=7,598 (18,591) company trading days before (after) inauguration.

	Dependent variable							
	Intraday volatility Before	Intraday volatility After	Abnormal volatility Before	Abnormal volatility After	Log(volume) Before	Log(volume) After	Abnormal log(volume) Before	Abnormal log(volume) After
Positiveness (@realDonaldTrump)	0.024*	0.007	0.029*	0.008	0.011*	-0.001	0.032*	-0.003
	(2.09)	(0.98)	(2.30)	(1.04)	(2.43)	(-0.26)	(2.45)	(-0.33)
Message (@realDonaldTrump)	-0.024	0.019	-0.022	0.045**	0.018**	-0.006	0.058**	-0.019
	(-1.51)	(1.44)	(-1.23)	(2.94)	(2.64)	(-1.08)	(3.01)	(-1.22)
Agreement (@realDonaldTrump)	-0.013	-0.011	-0.016	-0.014	-0.007	0.002	-0.019	0.006
	(-1.08)	(-1.45)	(-1.17)	(-1.63)	(-1.29)	(0.56)	(-1.32)	(0.69)
Market return	0.020	-0.051***	0.022	-0.059***	0.016***	-0.005*	0.046***	-0.014
	(1.17)	(-7.74)	(1.14)	(-7.84)	(3.93)	(-2.22)	(4.00)	(-1.93)
Adjusted R^2	0.207	0.238	0.018	0.016	0.882	0.898	0.068	0.040