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Trump's Effect on the Chinese Stock Market

Shijun Guo[a], Yang Jiao[b], Zhiwei Xu[c,*]

[a] Business School, The University of Queensland, Australia
[b] Department of Business and Public Policy, Young Harris College, United States
[c] Antai College of Economics and Management, Shanghai Jiao Tong University, China

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A B S T R A C T

U.S. President Donald J. Trump tweets frequently to communicate his thoughts to the public. We quantitatively evaluate the impact of Trump's China-related tweets on the Chinese stock market. We find that following Trump's inauguration, his tweets with a positive sentiment significantly increase abnormal returns for the manufacturing industry in the Chinese stock market. Furthermore, an increase in the absolute value of his positive sentiment increases both the trading volume and volatility of the market. The positive effect is more pronounced for those subindustries with high exposure to international trade and stronger business relations with the United States than for other subindustries. The results are robust for various sensitivity tests.

1. Introduction

Elected as the 45th president of the United States, Donald J. Trump actively uses Twitter to express his views on global affairs. With over 70 million followers on Twitter, President Trump has become the most followed world leader. Investors around the world are attentive to his tweets as indicators of his future policies. This may give Trump exclusive power to influence financial markets via a tweet of just 140 characters. A small but increasing number of studies have focused on the impact of Trump's tweets on the U.S. market (e.g., Colonescu, 2018; Ge, Kurov, & Wolfe, 2019); however, the effect of his tweets on the international market is understudied. The present paper fills that gap and quantitatively investigates the impact of Trump's China-related tweets on manufacturing stocks listed on the Chinese stock market.

The topic of our study is worth investigating for several reasons. First, as two of the most influential countries worldwide, the interactions between the U.S. and China generate a great deal of attention from politicians, business investors, and researchers. Second, the frequent use of social media by the current president offers us an ideal context to identify an influential politician's ability to impact the economy and markets, which are generally considered impervious to individual influence. A great deal of evidence shows that President Trump's tweets can bring more volatility to the stock market. One

* Corresponding author.
E-mail addresses: s.guo@business.uq.edu.au (S. Guo), yjiao0207@gmail.com (Y. Jiao), xuzhiwei09@gmail.com (Z. Xu).

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piece of anecdotal evidence from a CNBC news report was that "stocks rallied on Friday after President Donald Trump said China and the U.S. reached the first phase of a substantial trade deal that delays tariffs."[1] Moreover, previous studies have primarily focused on the U.S. domestic market, while we extend this focus investigates the social media impact on a foreign market, especially the spillover effect of social media on the Chinese stock market. Our study is the first to provide a systematic and quantitative analysis of the impact of President Trump's tweets on an international market.

The critical variable in our analysis is the quantification of President Trump's China-related tweets. We first employ a Python linguistic analysis to analyze the content of each tweet and construct sentiment indices for all these tweets. Based on the tweets' sentiment indices, we then compute a daily sentiment index by summing all China-related tweets posted on a trading day. By doing so, we account for the aggregate values of multiple tweets released within the same day. Following the literature, we use daily abnormal returns, daily abnormal volume, and daily volatility for the stock market variables. The estimation results suggest that a China-related tweet with positive sentiment posted by President Trump significantly increases market prices. An increase in the absolute value of tweet sentiment has a significantly positive impact on market trading volume and market volatility.

Our identification strategy relies on the assumption that the occurrence of President Trump's tweet postings is considered randomized events, which can be easily violated in reality, as the content and frequency of President Trump's tweets are closely related to current events. To circumvent the potential bias that our estimates may capture not only the tweet effect but also some policy effects, we include a couple of policy-related controls to mitigate the potential effect from other unobserved, specific events. We also perform a series of robustness checks, including propensity score matching (PSM) analysis and alternative measures for the sentiment of tweets and the stock market reaction. Our results are also robust to different empirical specifications.

We further examine the heterogeneity in the responses by listed firms to Trump's tweets. We find that the positive relationship between Trump's tweets and the Chinese stock market is stronger for Chinese firms with high exposure to the U.S. economy. Those firms usually have greater international trade with the U.S., receive a larger share of the revenue from the U.S., and have affiliations in the U.S. Our results suggest that the impact of Trump's China-related tweets on the Chinese stock market is largely amplified when firms have closer connections with the U.S. economy.

We also explore two possible mechanisms through which the effect of the tweets may operate. The first is the *information-revealing* channel, in which President Trump uses his tweets to express or underline important information. The second is the *emotional-expression* channel, in which Trump's China-related tweets only manifest his emotions. We argue that the first channel may serve as a signal about the prospective relation between the U.S. and China for investors. This is because, as one of the most powerful figures in the world (Ewalt, 2016; Gibbs, 2017), the president of the United States holds a unique position with broad powers to influence policy, such as the power to sign or veto legislation and command armed forces. For example, Ge et al. (2019) suggest that President Trump's company-specific tweets are understood by investors to include information relevant to further company fundamentals. If that were the case, we would expect the stock market effect to be long term without reverse. In contrast, if the tweets are mainly used to deliver President Trump's emotions about China, we would anticipate that the content of his tweets may evoke investors' emotions and attention, resulting in a temporary shock that drives a stock price away from the value predicted by its fundamentals. Therefore, the impact on the stock market would be expected to be contemporaneous and diminish rapidly due to market correction.[2]

To better identify these two channels, we first classify each tweet according to its content. A tweet stating some facts or policy stances is classified in the information-revealing category. In contrast, a tweet expressing strong personal feelings is classified in the emotion-expression category. To evaluate whether the tweet effect on the Chinese stock market is contemporaneous, we include different lags of the tweet sentiment index in the regression. The findings show that the effect of emotion-expression tweets on stock prices is contemporaneous and reverses over subsequent days, while the effect of information-revealing tweets persists, consistent with our hypothesis about these two channels.

Finally, we find that the positive relationship between Trump's tweets and stock market reaction is concentrated in the period after President Trump's inauguration. In addition, we analyze whether the impact of tweets varies with firms' ownership structure: state-owned enterprises (SOEs) versus non-SOEs. Our results suggest weak evidence that the influence of tweets is stronger for non-SOEs than SOEs.

Our paper contributes to two strands of the literature. First, it closely relates to the literature that studies the influence of social media on stock market activities. Existing studies find that social and traditional media (e.g., Twitter and newspapers, respectively) play a vital role in the determination of stock returns. It does so in many ways, including by acting as a corporate monitor or information communicator (e.g., Bartov, Faurel, & Mohanram, 2018; Chen, De, Hu, & Hwang, 2014; Kuhnen & Niessen, 2012; Lee, Hutton, & Shu, 2015; Liu & McConnell, 2013). Most of the research focuses on CEOs, traders, or individual analysts as participants. Our paper complements the literature by focusing on an influential politician and the U.S.-China nexus. Our findings confirm the conventional wisdom that investors in the financial market can be influenced by popular social media such as Twitter.

[1] The original article source: https://www.cnbc.com/2019/10/10/stock-futures-open-higher-after-optimistic-trump-comments-on-us-china-trade.html.

[2] The literature has documented the phenomenon that investors may initially mistakenly react to the message but correct their behavior shortly thereafter (Tetlock, 2007; Barber & Odean, 2008).

Our study also contributes to the literature on the impact of Trump's tweets. Prior studies find that President Trump frequently mentions U.S. corporate information in his tweets, that those tweets impact stock market returns, and that investors respond through trades in the U.S. market (e.g., Brans & Scholtens, 2020; Ge et al., 2019). Additionally, Burggraf, Fendel, and Huynh (2019) find that Trump's U.S.-China trade war tweets negatively predict S&P 500 returns and positively predict the VIX. Our study extends these studies by examining the impact of Trump's tweet on an international market and investigates how Trump's China-related tweets affect manufacturing stocks listed on the Chinese stock market.

The remainder of the paper is structured as follows. Section 2 describes our data and research methods. Section 3 discusses the empirical results on the relationship between Trump's China-related tweets and the Chinese stock market reaction. Section 4 considers some additional tests, and Section 5 contains our conclusions.

2. Data, variables and methodolgy

2.1. Data

We restrict our analysis to A-share firms in the manufacturing industry listed on the Shanghai and Shenzhen stock exchanges over the period from November 9, 2016, to March 23, 2018. The reason for concentrating on the manufacturing industry is that it represents the largest sector in the Chinese economy. According to the official statistics from the National Bureau of Statistics, for the period 2016–2018, the manufacturing industry accounted for approximately 35 % of China's aggregate GDP.[3] We acknowledge that the manufacturing industry, which involves supplying and producing more tradable goods, is more responsive to Trumps' tweets, especially the sentiments embedded in the messages. As pointed out by Bianconi, Esposito, and Sammon (2019), trade policy uncertainty is a systematic risk factor that affects asset prices. Based on the Chinese data, they find that an additional 6% per year on stock price is requested by the investors to compensate for the uncertainty about future trade policy. Moreover, the risk premium was larger in sectors more exposed to globalization. Trump's administrative policy agenda of international relations increases the trade uncertainty between the U.S. and China.[4] For this reason, we should cautiously interpret our results representing the upper bound estimates of market reaction to social media.

We also restrict our sample to the period immediately after Trump was elected as president of the United States and before he initiated the U.S.-China trade war. We exclude the trade war period to mitigate the policy endogeneity issue. The data on Chinese stock market activities come from the China Stock Market & Accounting Research (CSMAR) database, which is the most widely used database for Chinese financial market research. We compute the market variables described above based on financial information and variables for all listed manufacturing firms from the CSMAR.

2.2. Variable construction

2.2.1. Measure of sentiment on Twitter

All tweets come from the **@realDonaldTrump** and **@POTUS** Twitter accounts used by President Trump and include the keywords "China", "Chinese" or "President Xi". We construct a sentiment measure for the tweets, denoted as Sentiment, in three steps. First, we analyze each tweet with TextBlob, a text assessment package in Python. TextBlob returns a value based on the polarity and subjectivity of a sentence. The value of polarity lies between [-1,1], wherein -1 defines a negative sentiment and 1 defines a positive sentiment. A higher value indicates a more positive attitude/tone of the text. Negation words reverse the polarity. TextBlob has semantic labels that help with fine-grained analysis. More details regarding sentiment analysis and TextBlob are shown in Appendix A. Second, following the aging theory of news event detection (Mao & Chen, 2010), we compute the decay factor and rank each tweet based on its reinforcing factors (such as time awareness, content ingredients, and importance). Third, we weight the attitudinal value of each tweet from the first step by its decay factor computed in the second step to construct our sentiment indicator for each China-related tweet. Finally, we average the sentiment indices for all tweets that are posted on the same day to create a daily sentiment index for each trading day throughout the study.[5]

To illustrate the sentiment and distribution of Trump's Chinese related tweets, we draw a timeline as follows and present both the release date and sentiment for each tweet (Fig. 1). There are a lot of important events that occur within the sample period, we choose several of the events to illustrate the correlation between events and tweets. As expected, President Trump likes to use tweets to express his opinions or emotions about an ongoing event.

2.2.2. Stock market behavior

Regarding the behavior of the stock market, we mainly focus on daily abnormal returns, daily abnormal volume, and daily volatility.

[3] Data can be retrieved from http://www.stats.gov.cn/tjsj/ndsj/2019/indexch.htm.

[4] Source can be retrieved: https://assets.donaldjtrump.com/US-China-Trade-Reform.pdf.

[5] For those days with only one tweet related to China, the value of sentiment for the tweet represents the sentiment on that day. For those days with multiple China-related tweets, we compute the sentiment index for that day by taking the average of the sentiment indicator of each tweet.

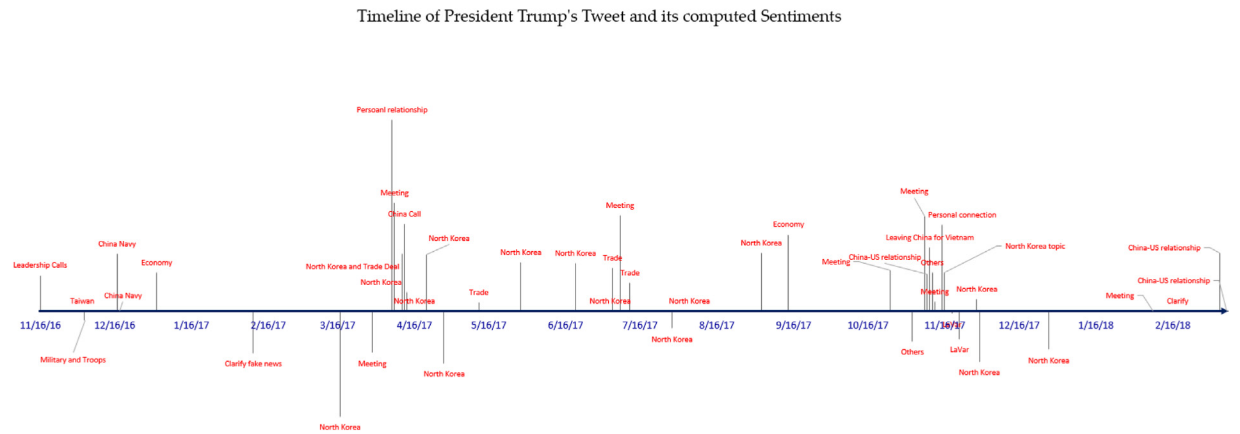

Fig. 1. Timeline of President Trump's Tweet and its computed Sentiments. This figure shows the distribution of each of Trump's Chinese related tweets in the timeline. A bar above the timeline indicates a positive sentiment, while a bar below the timeline represents a negative sentiment. The length of the bar indicates a magnitude of sentiment.

2.2.2.1. Daily abnormal return. To measure the impact on stock returns, we construct daily abnormal returns based on the Fama and French (1993) three-factor model. We first obtain the daily stock return, $R_{i,t}$, from the CSMAR database and compute the excess return as the return in excess of the risk-free return, RF_t, that is, $ER_{i,t}$=$R_{i,t}$-RF_t. The risk-free return is measured as the three-month fixed deposit base rate from The People's Bank of China. The three-factor model uses ordinary least squares (OLS) to regress the excess return on the stock market return, RM_t, minus RF_t, small-minus-big market capitalization, SMB_t, and high-minus-low book-to-market ratio, HML_t. The data for SMB and HML are calculated from the original data in the CSMAR database.

We then estimate the parameters of the following equation using a rolling window of 90 trading days (approximately three months)

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

As the prior literature suggests that the estimation and event windows should not overlap (e.g., MacKinlay, 1997), we use data up until day t-1 to estimate the Betas for day t. We then compute the abnormal return (AR) for each firm during our sample period as follows:

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

where $\hat{\beta}_\tau$ and $\tau = \{0,1,2,3\}$ are estimated coefficients from Eq. (1). The daily abnormal return for the manufacturing industry, AR_t, is calculated as the weighted average of each firm in the manufacturing industry based on its market value.

2.2.2.2. Daily Abnormal Vabnormal volume. To measure the impact on trading volume, we follow the literature (e.g., Ge et al., 2019; Joseph, Wintoki, & Zhang, 2011) and compute the abnormal trading volume, $AVolume_{i,t}$, as the difference between trading volume $V_{i,t}$ and the mean trading volume of the previous five days $\overline{V_t}$ divided by the mean trading volume of the previous five days: $AVolume_i = V_i - \frac{V_t}{\overline{V_t}}$, where $\overline{V_t} = \frac{1}{5}\sum_{j=1}^{5} V_{i,t-j}$. We then calculate the weighted average based on the market value of each _rm in the manufacturing industry to construct the abnormal trading volume of the manufacturing industry, $AVolume_t$.

2.2.2.3. Daily Market Vmarket volatility. We follow the literature (e.g., Ge et al., 2019; Rogers & Satchell, 1991) and construct the variance of each firm through the following equation:

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

where $O_{i,t}$, $C_{i,t}$, $H_{i,t}$, and $L_{i,t}$ are the opening, closing, high, and low prices, respectively, in a natural log for company i on day t. We take the square root of this estimated variance to calculate the volatility of each firm in the manufacturing industry. Again, the daily volatility of the manufacturing industry is the weighted mean of each firm based on its market value. The data on Chinese stock market activities come from the CSMAR database. We compute the market variables described above based on financial information and variables for all listed manufacturing firms from the CSMAR.

2.2.3. Control variables

To mitigate potential bias, we include the overall A-share stock market conditions, such as the daily stock return of the A-share market, total daily trading volume, daily transaction amount, daily turnover, and the number of trading firms in the manufacturing industry, as controls in the regression. Moreover, we control for other aggregate economic factors that may affect both the sentiment of tweets and stock market performance, such as Chinese economic policy uncertainty (EPU), aggregate output (GDP), exports and imports in China, and the confidence index of investors in the capital market. A full list of control variables and their descriptions are reported in Appendix B.

2.3. Empirical specification

To evaluate the sentiment impact of Trump's China-related tweets on the stock performance of the Chinese manufacturing industry, we estimate the following model:

$$Y_{t+2} = \alpha + \beta \cdot Sentiment_t + \gamma \cdot Controls_t + \tau_d + \varphi_t + \varepsilon_t, \tag{4}$$

where Y represents the stock market variables, including abnormal returns, abnormal trading volume, and volatility; α is a constant, and the subscript t indicates the day. While taking into account the time difference between China and the U.S. and the fact that the stock market takes time to absorb and react to the external newly released information fully, we consider the market outcome two days after a tweet was first posted, i.e., Y_{t+2}. β is the coefficient of variables of interest and shows the relationship between the sentiment of tweets and stock market outcomes. We use the raw value of sentiment for abnormal stock returns due to their potential conflicting impacts on stock returns. However, we take the absolute value of the sentiment indices when the dependent variable is abnormal trading volume or volatility because both stronger positive/negative sentiments manifested in the tweet context would increase the trading behavior of investors and thus make the stock price more volatile. To allow for daily variation in the stock market, we include a day-of-the-week dummy τ_d. By introducing the year fixed effect φ_t, the specification controls for the common shocks to all listed firms in the market, which varies by year.

3. Empirical results

3.1. Summary statistics

The descriptive statistics for the variables are reported in Panel A of Table 1. The mean value of Sentiment is 0.011, indicating that President Trump's tweets are on average neutral about China. All the stock market elements, including the means of abnormal returns, abnormal trading volume, and daily volatility, are positive. The means of abnormal returns, abnormal trading volume, and daily volatility are 0.001, 0.102, and 1.534, respectively, and all of them are positive. In addition, the means of all indicators in the whole A-share market are positive. Compared with the mean of Export and Import, we find that amount of exports is higher than that of imports in our sample period. The mean value of *Investors* is 0.539, suggesting that investors, in general, are not pessimistic about the stock market.

The Pearson correlation coefficients between the main variables used in the regressions are presented in Panel B, Table 1. The dependent variable, abnormal returns, and the key explanatory variable, Sentiment, are significantly and positively correlated. Abnormal trading volume and daily volatility are also positively associated with the absolute value of Sentiment. This gives preliminary support to our estimation that the sentiment of Trump's China-related tweets affects the Chinese stock market.

3.2. Baseline results

In Table 2, we evaluate the impact of the *Sentiment* of tweets on different stock market outcomes with Eq. (4). The results suggest that a one-point increase in the sentiment of Trump's China-related tweet improves the stock return for Chinese manufacturing firms by 1%, which equals a 50-percentage point increase in the mean value. A one-point increase in the absolute value of Sentiment increases trading volume by approximately 25.3 percentage points relative to the average trading volume from the previous five days and increases market volatility by 1.7%. Based on the estimated coefficients of Tweet’s Sentiment on the outcomes, one standard deviation increases in positive Sentiment associates with a 108% increase in abnormal return, 23% increase in abnormal volume, and 10% increase in volatility, respectively.[6] In sum, our estimates show that investor confidence, trading volume, and the total number of trading firms are also significant determinants.[7]

3.3. Sensitivity analysis and robustness checks

3.3.1. Unobserved specific events that occurred before the tweets

One may argue that our baseline results suffer from endogeneity issues caused by unobservable factors; for instance, some industry-specific events might have occurred immediately before the posting of the tweets. To circumvent such

[6] The standard deviation of the absolute value of Sentiment is 0.094.

[7] The results suggest a negative relationship among investor confidence, abnormal returns and abnormal volume. This pattern confirms the findings in Fisher and Statman (2000).

Table 1
Descriptive Statistics and Pearson Correlation Matrix.

Panel A. Descriptive Statistics

Variable	N	Mean	Median	SD	Max	Min
(1) *AR*	336	0.001	0	0.005	0.017	−0.019
(2) *AVolume*	336	0.102	0.068	0.178	0.895	−0.219
(3) *Volatility*	336	1.534	1.124	1.069	6.242	0.488
(4) *Sentiment*	336	0.011	0	0.098	1	−0.549
(5) *Volume*	336	23.210	23.210	0.199	23.740	22.570
(6) *Money*	336	25.750	25.760	0.196	26.270	25.090
(7) *Return*	336	<0.001	0.001	0.013	0.028	−0.061
(8) *Turnover*	336	0.006	0.006	0.001	0.011	0.003
(9) *EPU*	336	0.012	0.011	0.005	0.038	0.002
(10) *GPD*	336	99.690	99.720	0.110	99.820	99.480
(11) *Export*	336	0.140	0.145	0.022	0.171	0.074
(12) *Import*	336	0.137	0.133	0.014	0.174	0.117
(13) *Investor*	336	0.539	0.539	0.026	0.586	0.489
(14) *Num*	336	1.882	1.877	0.124	2.059	1.652

Panel B. Pearson Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	1													
(2)	−0.005	1												
(3)	−0.016	0.975***	1											
(4)	**0.234*** **	**0.152*** **	**0.154*** **	1										
(5)	−0.013	0.099*	0.099*	0.146***	1									
(6)	0.010	0.079	0.083	0.148***	0.951***	1								
(7)	0.069	−0.142***	−0.137**	−0.026	−0.212***	−0.173***	1							
(8)	0.007	−0.031	−0.024	0.144***	0.963***	0.906***	−0.216***	1						
(9)	0.005	−0.247***	−0.212***	−0.017	−0.005	−0.009	0.004	0.094*	1					
(10)	−0.025	0.621***	0.580***	0.034	0.011	−0.020	−0.030	−0.203***	−0.433***	1				
(11)	−0.041	0.130**	0.117**	−0.144***	−0.014	−0.036	0.036	−0.100*	−0.220***	0.383***	1			
(12)	−0.015	−0.120**	−0.141***	−0.059	0.203***	0.188***	0.074	0.149***	−0.091*	0.153***	0.467***	1		
(13)	−0.052	−0.346***	−0.345***	−0.084	0.180***	0.200***	0.130**	0.216***	0.033	−0.154***	0.380***	0.545***	1	
(14)	−0.023	0.642***	0.610***	0.033	−0.013	−0.014	−0.039	−0.224***	−0.430***	0.979***	0.382***	0.107*	−0.158***	1

This table provides descriptive statistics and a Pearson correlation matrix for the data used in the analysis. The variables are defined in Appendix B. In column (1), the level of the sentiment index, Sentiment, is shown in row (4); In column (2)-(3), the absolute value of Sentiment is shown in row (4).

Table 2
Baseline Results.

	(1) Abnormal Return	(2) Abnormal Volume	(4) Volatility
Sentiment	0.011***	0.253***	1.700***
	(4.209)	(3.362)	(3.735)
Volume	−0.024**	0.097	0.456
	(-2.064)	(0.316)	(0.246)
Money	0.007	−0.142	−0.789
	(1.368)	(-0.986)	(-0.905)
Return	0.029	−0.766	−4.564
	(1.374)	(-1.390)	(-1.366)
Turnover	2.578*	16.499	101.229
	(1.916)	(0.466)	(0.472)
EPU	0.002	−0.175	1.116
	(0.041)	(-0.125)	(0.132)
GDP	0.010	0.036	−1.775
	(0.705)	(0.095)	(-0.775)
Export	0.005	−0.369	−2.105
	(0.283)	(-0.775)	(-0.729)
Import	0.021	−1.286**	−8.892**
	(0.860)	(-2.012)	(-2.296)
Investor	−0.025*	−0.875**	−3.651
	(-1.694)	(-2.263)	(-1.559)
Num	−0.003	1.004***	7.205***
	(-0.242)	(3.169)	(3.754)
Constant	−0.646	−3.274	177.940
	(-0.467)	(-0.090)	(0.809)
Day-of-week dummies	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	336	336	336
Adj.R^2	0.051	0.535	0.525

This table reports the estimation results for the sentiment effect of Trump's tweets on the stock market for the Chinese manufacturing industry. The model examines the relationship between sentiment and each of Abnormal Return, Abnormal Volume, and Volatility. The independent variable *Sentiment* in (1) is the level of the sentiment index. The independent variables in (2) and (3) are the absolute value of Sentiment. Further details about the data can be found in Appendix B. The levels of significance are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

endogeneity bias, we follow the approach adopted by Tetlock (2007) and Ge et al. (2019) and include five lags of abnormal returns, abnormal trading volume, and volatility in the specifications. This allows us to `account for the possibility that investors were responding to recent attention-grabbing events such as Trump's tweets. We report the estimated results in Panel A of Table 3, and the point estimates are quite similar to those in the baseline estimations.

3.3.2. Matched sample regression

Another concern that our results are biased arises when an omitted factor simultaneously increases the likelihood that President Trump will tweet about China and affect the Chinese stock market. For example, after meeting with President Xi in April 2017, President Trump posted five tweets within three days. Stock markets in both China and the U.S. were bullish after their meeting. To mitigate such bias, we apply the propensity score matching (PSM) approach to match the days with such tweets to days with no China-related tweets.[8] The same set of control variables is used in the PSM function. We then re-estimate our specifications with this matched sample. The results are reported in Panel B of Table 3 and are similar to those in the baseline estimations. Appendix C displays the means of the stock market outcome variables for unmatched and matched samples. According to t-tests, the differences between the matched sample are not statistically significant, suggesting that the matching method significantly improves the quality of observations and thus the accuracy of the estimation.

3.3.3. Firm-level evidence

In our baseline specification, the stock market activity variables are measured by the weighted average of all listed firms in the manufacturing industry based on their market values. One concern about the weights is that they may not be accurately assigned if the market values do not represent the firm's responsiveness to market shocks. To further verify the validity of the specification, we take advantage of the comprehensiveness of the CSMAR and conduct a firm-level analysis. In Panel C of Table 3, we evaluate firm-level daily observations (instead of the weighted market values) with Eq. (4). To control for the heterogeneous reactions from the firms and their unobserved characteristics, we include firm fixed effects in the regression. All the coefficients on *Sentiment* are positive and statistically significant, consistent with our baseline results.

[8] Over our sample period, President Trump posted 62 China-related tweets.

Table 3
Results of Sensitivity Analysis.

	(1) Abnormal Return	(2) Abnormal Volume	(4) Volatility
Panel A. *Unobserved events*			
Sentiment	0.012***	0.281***	1.922***
	(3.366)	(3.728)	(4.315)
Observations	336	336	336
Adj.R^2	0.087	0.571	0.582
Panel B. *Matched sample regression*			
Sentiment	0.016*	0.588***	4.004***
	(1.939)	(3.503)	(3.922)
Observations	62	62	62
Adj.R^2	0.023	0.484	0.499
Panel C. *Firm-level Regression*			
Sentiment	0.001**	0.139***	0.044***
	(1.983)	(13.266)	(12.986)
Observations	528217	528217	528217
Adj.R^2	0.007	0.017	0.027
Panel D. *Exclude event-related Tweets*			
Sentiment	0.006*	0.125*	0.736*
	(1.672)	(1.717)	(1.680)
Observations	306	306	306
Adj.R^2	0.019	0.570	0.549
Panel E. Alternative timing in the basic model			
Sentiment	0.009***	0.204***	1.326***
	(3.548)	(3.000)	(3.217)
Observations	336	336	336
Adj.R^2	0.037	0.532	0.520
Panel F. *Alternative timing in the basic model: off-hours twitter versus market-opened tweets*			
*Sentiment*Off*	0.009*	0.298**	1.968**
	(1.734)	(2.212)	(2.417)
*Sentiment*Open*	0.004	0.084	0.623
	(0.968)	(0.726)	(0.888)
Observations	336	336	336
Adj.R^2	0.047	0.544	0.537
Panel G. *Alternative Measurement of Sentiment*			
Sentiment	0.003***	0.099***	0.625***
	(2.793)	(3.070)	(3.187)
Observations	336	336	336
Adj.R^2	0.023	0.533	0.519
Panel H. *Alternative Measurement of Abnormal Returns/Volume*			
Sentiment	0.057**	0.237**	
	(2.185)	(2.505)	
Observations	336	336	
Adj.R^2	0.055	0.262	

This table reports the estimated results from various robustness checks. Panel A reports the results in the estimation with five lags of the dependent variables. Panel B reports the results for the PSM approach. Panel C presents the results of daily firm observations. Panel D reports the coefficients for an alternative measurement of sentiment that is based on human rating indices. Panel E chooses different windows when calculating abnormal returns and abnormal volumes. For each panel, the independent variable Sentiment in (1) is the level of the sentiment index. The independent variables in (2) and (3) are the absolute value of Sentiment. All specifications control for the daily stock return of the A-share market, total daily trading volume, daily transaction amount, the daily turnover of the A-share market, the number of trading firms, Chinese economic policy uncertainty (EPU), aggregate output (GDP), exports from and imports to China, the confidence index of investors in the capital market, day-of-week dummies and year fixed effects. In the firm regression, we also control for firm fixed effects. Robust t-statistics are reported in parentheses. The levels of significance are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

3.3.4. Exclude event-related twitter

As twitters in our sample are not exogenous and random, one concern is that our results may be driven by the certain events associated with tweets, rather than the influence of twitters. Although finding twitters fully exogenous is difficult, we try to exclude these tweets which are explicitly associated with events that may impact the stock market and do a further robust check. We classify each tweet to the following classifications based on its contents, including the political topic, China-US relationship topic, economic topic, military topic, energy sources topic, personal connection with China, and others cannot be defined. Considering its relation to a specific event, tweets included in the last classification are expected to have a weaker impact while the event-driven tweets have a much stronger impact on the stock price. We acknowledge that it is difficult to completely disentangle whether the fluctuation in the stock market is driven by a tweet or the specific event it relates to. However, the classification mentioned above provides a good experiment for us to perform so. We first remove all events related tweets and preserve tweets belonging to “others” (a total of 11 tweets in 10 different days) and then combine days without tweets to run a robustness check. The results are reported in Panel D of Table 3. We still find a positive association between the sentiments of tweets and reaction from the stock market, although the standard error increases largely due to a small sample.

3.3.5. Alternative timing in the basic model

Our basic model considers market outcomes from two days after a tweet was first posted. One concern here is that events during the two-period lag may impact the market outcome.[9] Thus, the market outcome in a narrow window of each of Trump's tweets can further corroborate our base findings. We execute two approaches. First, we revise the timing in our basic model (4). For each tweet, we identify the positing time in Chinese time standards and match the market outcomes from the stock market in the following trading day. Similarly, we include all days without tweets in our sample and estimate model (4) again. The results are shown in Panel E of Table 3. We continuously find the results show a robust outcome, as *Sentiment* is still significantly and positively correlated. In the second approach, we cautiously identify the posting time of each tweet based on the US Eastern Time Zone,[10] and then covert the US Eastern time into the time standards in China. Such conversion allows us to identify whether a tweet is posted during regular trading hours or posted after the closure of the Chinese Stock Market. We find a total of twelve tweets are posted during normal trading hours but fifty tweets are posted off-hours. Tweets posted when the market opens are matched to the stock market of the same day, whereas tweets posted when the market closes match to the stock market of the following trading day. Following this classification, we divide president Trump's tweets into off-market (*Off*) tweets and open market (*Open*) tweets, which both are dummy variables that return the value of 1 if tweets fall into the category and 0 otherwise. We further include the interaction term of *Sentiment* and *Off* and the interaction term of *Sentiment* and *Open* in our specification. The results presented in Panel F of Table 3 shows that, relative to the tweets posted on the same trading days of the Chinese stock market, after-hours tweets have a larger impact on the stock market in the following day. Results indicate that a time lag in the reactions of the market to the media information and the market may not respond swiftly to additional information.

3.3.6. Alternative measurement of sentiment

Another concern arises from measurement errors, especially in our variable of interest, the sentiment index, which is based on a computational methodology in Python. Following the approach used by You, Zhang, and Zhang (2018), we construct an alternative measurement by analyzing all tweets and classifying (assigning value) them as positive (one), neutral (zero), and negative (negative one) tones based on their context.[11] The correlation coefficient between our baseline and the alternative measurement is 0.6. The results are reported in Panel G of Table 3. Although the magnitude of the coefficients is smaller than that in the baseline results, we still find that positive tweets are associated with a higher stock price, greater trading volume, and higher trading volatility.

3.3.7. Alternative time window

In our last robustness check, we consider different lengths of rolling windows when calculating abnormal returns and trading volume. In our baseline specification, we use 90 trading days for abnormal returns and the mean trading volume of the past five trading days for the abnormal trading volume. Alternatively, we apply a shorter window: 60 trading days and the previous three days. The results presented in Panel H of Table 3 change little and are highly consistent with those reported in Table 2.

3.4. Heterogeneity Effects

Our findings thus far suggest a positive association between President Trump's China-related tweets and the stock market reaction in the Chinese manufacturing industry. In this section, we examine the extent of the firm's engagement in international business with the U.S. and examine the heterogeneous effect of business interaction at both the industry and firm levels.

3.4.1. International relations with the United States

Social media may have different impacts on firms with different international contacts. President Trump's tweets may serve as a stronger signal and hence have a greater effect on firms more closely tied to the U.S. economy. To achieve a better understanding of the impact of Trump's China-related tweets on the Chinese stock market, we explore how the effect varies with firms' international relations with the U.S. and their dependence on the U.S. economy. We first partition firms based on their exposure to international trade with the U.S. and evaluate the heterogeneous effects by firm type. Firms engaged in producing metal products, automobiles, electrical machinery and equipment, and computers, communications, and other

[9] We thank an anonymous referee for this helpful suggestion.

[10] The United States uses nine standard time zones. From east to west they are Atlantic Standard Time (AST), Eastern Standard Time (EST), Central Standard Time (CST), Mountain Standard Time (MST), Pacific Standard Time (PST), Alaskan Standard Time (AKST), Hawaii-Aleutian Standard Time (HST), Samoa standard time (UTC-11) and Chamorro Standard Time (UTC+10). As a result, the time varies by location and the geographic information of tweets are not reported and traced in the data source. Therefore, we assume that all tweets are posted in the White House, which follows the Easter Time Zone.

[11] In addition to the authors, three professional individuals with finance-related backgrounds were asked to evaluate the context of the tweets. If all reviewers agreed with the sentiment of the context, we assigned the tweet that value; otherwise, we assigned to the tweet the majority sentiment value.

Table 4
Results of Heterogeneous Effect.

	(1) Abnormal Return	(2)	(3) Abnormal Volume	(4)	(7) Volatility	(8)
Panel A: High versus Low Exposure to Trade						
	High	Low	High	Low	High	Low
Sentiment	0.007***	0.001	0.382***	−0.057	2.042***	0.201
	(2.633)	(0.341)	(3.629)	(-0.596)	(12.642)	(0.365)
Difference (High-Low)	**0.006**		**0.439**		**1.841**	
Chi-square	**4.29****		**3.96****		**3.20***	
Observations	336	336	336	336	336	336
Adj.R^2	0.016	0.024	0.331	0.287	0.471	0.535
Panel B: US Income versus. non-US Income						
	Yes	No	Yes	No	Yes	No
Sentiment	0.038***	0.005**	0.400***	0.024	0.559***	0.235***
	(10.404)	(2.415)	(3.914)	(0.273)	(14.439)	(5.788)
Difference (Yes-No)	**0.033**		**0.376**		**0.324**	
Chi-square	**4.39****		**4.78****		**3.26***	
Observations	336	336	336	336	336	336
Adj.R^2	0.298	0.051	0.317	0.321	0.531	0.276
Panel C: US Affiliated firm. non- US Affiliated firm						
	Yes	No	Yes	No	Yes	No
Sentiment	0.022***	0.005**	0.437***	0.101	0.494***	0.253***
	(7.830)	(2.439)	(4.514)	(1.214)	(12.465)	(6.705)
Difference (Yes-No)	**0.017**		**0.336**		**0.241**	
Chi-square	**4.23****		**2.72***		**2.82***	
Observations	336	336	336	336	336	336
Adj.R^2	0.191	0.051	0.290	0.296	0.501	0.323

This table reports the estimated coefficients of the sentiment effect of Trump's tweets on the stock market indicators for the Chinese manufacturing industry. The model examines the relationship of sentiment with each of Abnormal Return, Abnormal Volume, and Volatility. Panel A examines the influence of foreign trade with the U.S. on the association between China-related tweets and the stock market indicators for the manufacturing industry. An observation is classified as "High" if it belongs to four high-foreign-trade types of manufacturing industry and "Low" otherwise. Panel B examines the impact of income from the U.S. on the association between China-related tweets and the stock market indicators for the manufacturing industry. An observation is classified if these firms have income from the U.S. and "No" otherwise. Panel C test the influence of U.S. affiliated firms on the association between China-related tweets and the stock market indicators for the manufacturing industry. An observation is classified if these firms have affiliated firms in the U.S. and "No" otherwise. The seemingly unrelated regression estimation is used to examine the difference between the two groups, and the Chi-square result is reported in the table. For each panel, the independent variable *Sentiment* in (1)-(2) is the level of the sentiment index. The independent variables in (3)-(8) are the absolute value of Sentiment. All specifications control for the daily stock return of the A-share market, total daily trading volume, daily transaction amount, the daily turnover of the A-share market, the number of trading firms, Chinese economic policy uncertainty (EPU), aggregate output (GDP), exports from and imports to China, the confidence index of investors in the capital market, day-of-week dummies and year fixed effects. Robust t-statistics are reported in parentheses. The levels of significance are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

electronic equipment are classified in the high-exposure group.[12] The firms in the remaining sub manufacturing industries are assigned to the low-exposure group. Panel A in Table 4 shows that the effects of tweets are stronger for firms with high exposure to international trade with the U.S. The differences between high- and low-exposure firms are statistically significant for all three stock market indicators.

3.4.2. Business revenue from the United States

Since China's acceptance into the WTO in 2001, Chinese firms have become more globalized and now actively participate in international trade and economic activities. For instance, the Chinese government encourages and promotes firms to operate abroad and export their products or services to various countries (Boisot & Meyer, 2008). Income in foreign countries, i.e., those outside of China, is an important component of business income for Chinese listed firms. As President Trump's China-related tweets may raise the level of uncertainty regarding trade between China and the U.S., we would expect that President Trump's tweet effect is stronger for firms that have closer international connections with and receive more business revenue from the U.S. than it is for other firms.

To examine how a tweet's effect varies by the firm's international business relationship, we partition firms into two groups according to whether or not they receive revenue from the U.S. We obtain the overseas income data of each firm from the CSMAR dataset and identify the source of the revenue. The regressions are operated at the market level for both groups.

[12] According to bilateral trade data, these four types of Chinese listed firms in the manufacturing industry have the highest volume of goods exported to the U.S. economy. Data source: http://www.customs.gov.cn/customs.

Panel B of Table 4 presents the results. In the first two columns, the coefficients of Sentiment are both positive and statistically significant. It is worth noting that, as expected, the magnitude of Sentiment is much larger for firms doing business with the U.S. The chi-square statistic, based on seemingly unrelated estimation, suggests that the difference is significant at the 5% level. Regarding abnormal trading volume, the coefficients of Sentiment reported in the next two columns are both positive. However, these coefficients are statistically significant only for firms receiving revenue from the U.S. Moreover, the impact of tweets on daily volatility is stronger for firms with income from the U.S. than for other firms. In sum, we find that the effects of tweets are more noticeable for firms reporting overseas revenue from the U.S., confirming that firms with closer connections with the U.S. are more likely than other firms to be influenced by Trump's China-related tweets.

3.4.3. Affiliations in the United States

Another way firms can form a relationship with the foreign market is by establishing an affiliated firm overseas. Affiliated firms include subsidiaries, associated companies, and joint ventures. To explore firms with affiliations in the U.S., we collect affiliate data from the CSMAR and identify the location of the affiliations. Firms with U.S. affiliations may be more attentive and affected by President Trump's tweets than firms without such affiliations; hence, a tweet is more relevant for firms with U.S. affiliations. We divide our sample into two groups based on whether the firms have affiliated firms in the U.S. and then run the regressions.

Panel C of Table 4 reports the results. As anticipated, we find that the sentiment of Trump’s tweets has a stronger impact on abnormal stock returns, abnormal trading volume, and daily volatility for firms with affiliations in the U.S. than for firms without such affiliations. The chi-square statistics for comparing the coefficient differences, based on the seemingly unrelated estimation, imply that the difference between the two groups is statistically significant for all three stock market outcome variables. The empirical results suggest that the positive effect of tweets on market reaction is consistent with our expectation that Trump’s tweets have a stronger effect on firms with stronger connections with the U.S. than on other firms.

4. Further Ddiscussion

4.1. Test of Cchannels

Our initial results confirm that the tweets of an influential politician, the U.S. president, in particular, could have an international spillover effect on a foreign stock market. To further understand how tweets may affect stock market performance (e.g., the abnormal return), we explore two possible mechanisms by which tweets may operate: an information-revealing effect and an emotional-expression effect.

Regarding the first channel, the stock market may consider tweets to be a source of information relevant to future political or economic fundamentals. As one of the most influential persons in the world (Ewalt, 2016; Gibbs, 2017), the president of the United States holds a unique position to influence policy. If the message in a tweet by President Trump states some facts or policy stances and reinforces that information, we would expect the message to have a lasting effect. Regarding the second channel, if the tweet involves emotional expression, investors may initially mistakenly react to the message but correct their behavior shortly thereafter (Barber & Odean, 2008; Tetlock, 2007). In that case, the impact on the stock market would be expected to be contemporaneous and diminish rapidly due to market correction.

To support and separate these two channels, we partition all tweets into two categories: information-revealing tweets and emotional-expression tweets. We analyze and manually classify each tweet based on its content. Appendix D illustrates some examples of the tweets in both categories. To evaluate whether the effect is contemporaneous, we focus on abnormal returns and include lags of the tweet sentiment index in the regressions.

Table 5 presents the estimated results for the above two types of tweets. Columns (1) and (2) show that both types of tweets have significant contemporaneous effects on abnormal returns. As expected, we find some evidence of a reversal effect for emotional-expression tweets. The F-test statistics of the sum of coefficients on the contemporaneous and lagged terms is not significant, suggesting that the initial impact on the day of an emotional-expression tweet is reversed over the subsequent days. For the information-revealing tweets, the sum of coefficients on the contemporaneous and lagged terms is significantly higher than zero, implying that the impact of this type of tweet is relatively persistent.

4.2. Pre- and post-inauguration

Our sample comprises two distinct periods: from the election to the inauguration (November 9, 2016, to January 18, 2017) and from the inauguration to the end of our sample period (January 20, 2017, to March 23, 2018). If the impact of tweets on the Chinese stock market is based on the political influence of the Twitter account owner (as a policymaker), we would expect the effect of the tweets to be more pronounced after Trump's inauguration. To test this argument, we run the regressions separately for two periods.

The results are presented in Table 6. We find that the coefficients of Sentiment are all positive and significant after the inauguration. However, the coefficients of Sentiment are negative and not significant before the inauguration. Based on the

Table 5
Results of Channel Test.

	(1) Emotion-Expression Tweet	(2) Information-Revealing Tweet
Contemporaneous	0.014***	0.010***
	(4.353)	(2.752)
Lag1	−0.001	0.004
	(-0.438)	(1.429)
Lag2	−0.006*	−0.003
	(-1.931)	(-0.875)
Lag3	0.001	0.002
	(0.304)	(0.485)
F-Test (Contemporaneous>0)	18.95***	7.58***
F Test (Contemporaneous + lag1−3 > 0)	2.57	5.68**
Observations	323	324
Adj.R^2	0.079	0.047

This table examines the effect of emotional-expression tweets and information-revealing tweets on stock returns. The dependent variable is the Abnormal Return. The observations in column (1) include days with emotional-expression tweets and days without a tweet. The observations in column (2) include days with information-revealing tweets and days without a tweet. All specifications control for the daily stock return of the A-share market, total daily trading volume, daily transaction amount, the daily turnover of the A-share market, the number of trading firms, Chinese economic policy uncertainty (EPU), aggregate output (GDP), exports from and imports to China, the confidence index of investors in the capital market, day-of-week dummies and year fixed effects. Robust t-statistics are reported in parentheses. The levels of significance are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6
Results of Pre- and Post- Inauguration.

	(1) Abnormal Return	(2)	(3) Abnormal Volume	(4)	(7) Volatility	(8)
	Pre	Post	Pre	Post	Pre	Post
Sentiment	−0.004	0.012***	−0.354	0.258***	−0.813	1.701***
	(-0.187)	(4.079)	(-0.637)	(3.244)	(-0.451)	(3.422)
Difference (Pre-Post)	**0.016**		**0.612**		**2.514**	
Chi-square	**3.93****		**4.67****		**5.01****	
Observations	51	285	51	285	51	285
Adj.R^2	0.048	0.071	0.045	0.509	0.008	0.495

The table compares the results before and after Trump's inauguration. An observation is classified as "Pre" if it is in the pre-inauguration sample period (November 9, 2016, to January 18, 2017) and "Post" if it is in the post-inauguration sample period (January 20, 2017, to March 23, 2018). The seemingly unrelated regression estimation is used to examine the difference between the two groups, and the Chi-square result is reported in the table. For each panel, the independent variable *Sentiment* in (1)-(2) is the level of the sentiment index. The independent variables in (3)-(8) are the absolute value of Sentiment. All specifications control for the daily stock return of the A-share market, total daily trading volume, daily transaction amount, the daily turnover of the A-share market, the number of trading firms, Chinese economic policy uncertainty (EPU), aggregate output (GDP), exports from and imports to China, the confidence index of investors in the capital market, day-of-week dummies and year fixed effects. Robust t-statistics are reported in parentheses. The levels of significance are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

seemingly unrelated estimation, the difference between pre-inauguration and post-inauguration is significant, suggesting that the impact of Trump's tweets on the Chinese stock market is focused on after Trump was elected president of the United States.[13]

4.3. SOEs versus non-SOEs

Compared with non-SOEs, the Chinese government has more intervention in SOEs, and these enterprises must follow strict government guidelines in their operation (Cheung, Rau, & Stouraitis, 2010). Therefore, government policies and regulatory measures can easily distort investor sentiment in China (Chong, Liu, & Zhu, 2017) and attenuate the impact of sentiment on the stock market. The prior literature suggests that compared to SOEs, non-SOEs are more autonomous and more sensitive to the market and have a stronger market response to various events (e.g., He, Wan, & Zhou, 2014; Wang, Chen, Chin, & Zheng, 2017). To analyze the impact of ownership structure on the association between Trump's tweets and stock market reaction, we divide the firms into SOEs and non-SOEs based on their ownership structures. A listed firm is

[13] One concern is that the inauguration period is too short to compare with post-inauguration. To address this concern, we extend our sample period to June 2015, when Trump started his presidential campaign, and find that the results remain robust.

Table 7
Results of SOEs versus. non-SOEs.

	(1) Abnormal Return	(2)	(3) Abnormal Volume	(4)	(7) Volatility	(8)
	SOE	Non-SOE	SOE	Non-SOE	SOE	Non-SOE
Sentiment	0.017***	0.011***	0.217**	0.215**	0.228***	0.247***
	(4.972)	(5.262)	(2.243)	(2.455)	(5.381)	(6.464)
Difference (SOE – non-SOE)	**0.006**		**−0.002**		**−0.019**	
Chi-square	**0.21**		**0.01**		**0.01**	
Observations	336	336	336	336	336	336
Adj.R^2	0.128	0.114	0.354	0.302	0.300	0.297

The table compares the results in SOES and non-SOEs. An observation is classified as "SOE" if these firms are state-owned enterprises, and "non-SOE" otherwise. The seemingly unrelated regression estimation is used to examine the difference between the two groups, and the Chi-square result is reported in the table. For each panel, the independent variable *Sentiment* in (1)-(2) is the level of the sentiment index. The independent variables in (3)-(8) are the absolute value of Sentiment. All specifications control for the daily stock return of the A-share market, total daily trading volume, daily transaction amount, the daily turnover of the A-share market, the number of trading firms, Chinese economic policy uncertainty (EPU), aggregate output (GDP), exports from and imports to China, the confidence index of investors in the capital market, day-of-week dummies and year fixed effects. Robust t-statistics are reported in parentheses. The levels of significance are denoted as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

defined as an SOE when the government is its ultimate controlling shareholder (e.g., Bradshaw, Liao, & Ma, 2019). We then run separate regressions for SOEs and non-SOEs by Eq. (4) to detect whether our baseline findings vary with the firm's ownership structure.

Table 7 reports the main results. Although the estimated results show a positive relationship between President Trump's China-related tweets and stock market reaction for both SOEs and non-SOEs, the seemingly unrelated regression estimation provides weak evidence that this positive association is stronger in non-SOEs than in SOEs.

5. Conclusion

We examine the impact of President Trump's China-related tweets on the stocks of firms in the Chinese manufacturing industry. We find that positive tweets increase stock prices, abnormal trading volume, and market volatility. These results are robust to a battery of checks. We further document that the positive association between tweets and stock market reaction is more significant for manufacturing firms in subindustries with high exposure to international trade with the U.S. economy, firms with revenue from the U.S. and firms with U.S.-affiliated companies than for firms without these characteristics. These results imply that Trump's tweets have a stronger influence on firms with a closer connection with the U.S. than on other firms. Moreover, we investigate how tweets could affect market performance through information-revealing or emotional-expression channels. The effect of emotional-expression tweets on stock prices is contemporaneous and reverses over subsequent days, but the effect due to information-revealing tweets persists. Finally, we find that the impact of Trump's tweets on the Chinese stock market is concentrated in the period after his presidential inauguration. Additionally, the effect of tweets works for both SOEs and non-SOEs.

In summary, our findings suggest that the content of social media impacts stock market characteristics and highlights the importance of behavioral finance for stock markets around the world. Our topic lends itself to further research when a larger dataset of presidential tweets or another influential person's tweets becomes available.

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Appendix A. Description of Sentiment Analyst and TextBlob

Sentiment analysis is a process of analyzing data and helps researchers decipher the mood and emotions of the general public and gather insightful information regarding the context. Processed by the analysis, these sentiments can thus be used for a better understanding of various events and the impact caused by it. In this study, we adopt the methodology and algorithm of TextBlob, a python library for Natural Language Processing (NLP). To achieve its tasks, TextBlob actively used Natural Language ToolKit (NLTK), which is a library that gives easy access to a lot of lexical resources and allows users to work with categorization and classification. Therefore, TextBlob offers the function of a word library which supports complex analysis and operations on textual data.

TextBlob returns a value based on the polarity and subjectivity of a sentence. The value of polarity lies between [-1,1], wherein -1 defines a negative sentiment and 1 defines a positive sentiment. Negation words reverse the polarity. TextBlob has semantic labels that help with fine-grained analysis. On the other hand, subjectivity quantifies the amount of personal opinion and factual information contained in the text. Subjectivity takes any values between [0,1] and the higher subjectivity means that the text contains personal opinion rather than factual information. For example, we would like to calculate both the polarity and subjectivity for the sentence "I do not like this example at all, it is too boring". TextBlob will return the value of -1 for polarity and 1 for subjectivity 1, which seems fairly accurate to capture both of the content's subjectivity and sentiments. Our analysis is solely based on sentiment value but not subjectivity estimated by TextBlob. On the timeline of the Tweets, we also add the value of sentiments for each text. The direction of the bar indicates whether a specific tweet exhibits a positive or negative attitude and the height of the bar shows the intensity of the sentiment.

The massive development of broadband technology makes digitized textual materials more accessible to readers across the world. However, people can't absorb all pertinent information on the Internet promptly. People are likely to be exposed to the "hot" topic, such as the "presidential campaign" in 2020. The "hotness" of a topic depends on a couple of factors: how often "hot" terms appear in a document, the number of documents that contain those terms, and the timeline since the topic first appears. In this study, we focus on the last elements in determining the hotness of a topic and adopt an augmented aging theory method by Mao and Chen (2010), who introduce a virtual graph model to describe the properties of news. In our setting, a news event becomes popular with a burst of news reports, and it fades away with time. Based on their model, a ranking algorithm can fully exploit the reinforcement between news sources, topics, and articles. Following their approach, we can compute the decay factor and rank each tweet based on its reinforcing factors (such as time awareness, content ingredients, and importance).

In particular, our decay factor is determined by both the time eclipse and hotness intensity of the topic.

$$\mathrm{Decay}_i(\mathrm{V}, \mathrm{t}) = e^{-V_i t}$$

where V denotes the hotness intensity and is calculated by $1 - \frac{Number\ of\ Retweet\ for\ Tweet\ i}{Total\ Number\ of\ all\ Retweets}$, t measures the time. The value of Decay_i for a specific tweet (i) decreases more as time eclipse given by the same intensity of topic hotness or deteriorates faster for less "hot" topic conditional on the same period.

Appendix B. Definition of Variables

This table provides the descriptions for each variable we use in the estimation. All the data series, except for GDP and the economic policy uncertainty (EPU) index, are directly downloaded from the China Stock Market & Accounting Research (CSMAR) database. The GDP variable we use is the ratio-to-trend index for China's gross domestic product constructed by OECD, downloaded from the Main Economic Indicators-complete database. The series is an index that reflects the fluctuations in aggregate output and does not contain a long-run trend. The EPU index is from Huang and Luk (2020), download link: https://economicpolicyuncertaintyinchina.weebly.com/.[a]

Variable	Acronym	Definition
A. Independent variable		
The sentiment of Trump's Twitter	*Sentiment*	The sentiment of Trump's Twitter.
	ABSentiment	The absolute value of Sentiment.
B. Dependent Variable		
Abnormal return	*AR*	The abnormal return of the manufacturing industry
Abnormal Volume	*Avolume*	The abnormal trading volume of the manufacturing industry
Volatility	*Volatility*	The volatility of the manufacturing industry
C. The control Variables		
Market Return	*Return*	The stock return of the A-share market each day.
Market Volume	*Volume*	Log of the trading volume of the A-share market each day.
Market Transaction Amount	*Money*	Log of the trading money of the A-share market each day.
Market Turnover	*Turnover*	The turnover of the A-share market each day equals the total trading volume divided by the total shares in the market.
EPU	*EPU*	Daily China Economic Policy Uncertainty Index divided by 10,000.
GDP	*GDP*	Ratio-to-trend index for China's GDP, monthly data.
Export	*Export*	Log of total exports (in dollars) from China divided by 100, monthly data.
Import	*Import*	Log of total imports (in dollars) to China divided by 100, monthly data.
Investor	*Investor*	The confidence index of investors in the capital market from China Economic Monitoring Center divided by 100, monthly data.
Number of firms	Num	The number of firms in our sample to calculate the weighted average in the manufacturing industry is divided by 1000.

[a]Regarding the EPU index, we choose the one from Huang and Luk (2020) instead of the index constructed by Baker, Bloom, and Davis (2016), because the former is the daily frequency that fits our stock market data better.

Appendix C. Balance Test of Propensity Score Matching

Variable	Unmatched(U) /Matched (M)	Mean		%bias	%reduct |bias|	t-test
		Treat	Control			
Return	U	−0.001%	−0.0001	1.2		0.05
	M	−0.001%	−0.001	5.4	−356.8	0.14
Volume	U	23.241	23.202	20.4		0.99
	M	23.241	23.259	−9.6	53.1	−0.35
Money	U	25.808	25.750	30.5		1.52
	M	25.808	25.813	−2.4	92.2	−0.09
Turnover	U	0.006	0.006	16.1		0.83
	M	0.006	0.007	−16.1	0.4	−0.56
Investor	U	0.527	0.540	−51.5		−2.45
	M	0.527	0.526	6.4	87.6	0.26

Appendix D. Examples of Tweet Category

This table lists several examples of Trump's China-related tweets. Columns of Sentiment (Textblob) and Sentiment (manually) correspond to the scores constructed by the Python package, Textblob, and by the authors' judgment based on their reading. The manually constructed sentiment index takes three values: -1 for negative, 0 for neutral, and 1 for positive. Each China-related tweet is partitioned into the emotion and information categories.

Date	Text of Tweets	Sentiment (Python Textblob)	Sentiment (Manually)	Category
2017-01-02	*China has been taking out massive amounts of money & wealth from the U.S. in totally one-sided trade, but won't help with North Korea. Nice!*	0.2	−1	Information
2017-05-12	*China just agreed that the U.S. will be allowed to sell beef, and other major products, into China once again. This is REAL news!*	0.046	1	Information
2017-07-04	*. . . .and Japan will put up with this much longer. Perhaps China will put a heavy move on North Korea and end this nonsense once and for all!*	0	0	Information
2017-08-05	*The United Nations Security Council just voted 15-0 to sanction North Korea. China and Russia voted with us. Very big financial impact!*	0	1	Information
2017-11-08	*Looking forward to a full day of meetings with President Xi and our delegations tomorrow. THANK YOU for the beautiful welcome China! @FLOTUS Melania and I will never forget it!* https://t.co/sQoUWIGAiQ	0.667	1	Emotion
2017-11-15	*The failing @nytimes hates the fact that I have developed a great relationship with World leaders like Xi Jinping, President of China . . . ..*	0.450	1	Emotion
2017-12-28	*Caught RED HANDED - very disappointed that China is allowing oil to go into North Korea. There will never be a friendly solution to the North Korea problem if this continues to happen!*	−0.200	−1	Emotion

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