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Presidential Attack Risk:
The Impact of Trump's Tweets on Financial Markets

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ABSTRACT

The prevalence of social media has inspired multiple researchers to investigate the value of information on various platforms. However, most studies focus on integrating individual views (the wisdom of the crowd), and few studies investigate just one person's effect. To close this gap, this article investigates the impact of Trump's tweets on stock markets. Based on intraday stock market data, this study uses an event study to test the immediate reaction of the stock markets in both the Chinese and U.S. markets. Next, with ordinary least squares (OLS) regression, this study testes the effect of tweets' content features on the returns and volatility of the Chinese and U.S. indices. The results show that Trump's tweets impacted the financial market, especially the returns of the U.S. stock market during the COVID-19 pandemic. With additional analyses based on industry indices and time frequencies, the researchers found that Trump's sentiment on Twitter affected the Chinese financial industry during the trade war and impacted the Chinese pharmaceutical industry during the pandemic.

KEYWORDS

COVID-19 Pandemic, Event Study, Stock Market, Trade War, Twitter

INTRODUCTION

"Make America Great Again," "MAGA2020," and "America First." These are just a few examples of popular slogans shared on Twitter. Due to the prevalence of social media, millions of people choose to express themselves via the virtual world. In addition, an increase in active mobile users means that more valuable information is being stored on social platforms.

A diverse group of users and a significant amount of information can be found on social media platforms. Therefore, many studies have investigated the real-world effect of social media content and information (table 1). For example, the integration of users' comments on social media has a positive impact on moviegoers (Cheng & Yang, 2022), serving to forecast box-office

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Table 1. Literature summary

Reference	Platforms	Information used for detection	Main research object
Azar & Lo, 2016	Twitter	Tweets' polarity score	Returns
Nofer & Hinz, 2014	European stock prediction communities	Stock recommendations	Returns
Chau, Lin, & Lin, 2020	Seeking Alpha	The negative sentiments	Returns
Da & Huang, 2020	Estimize.com	User information sets and user viewing activities	Corporate earnings forecasts
Yang, Mo, & Liu, 2015	Twitter	Sentiment of tweet messages	Returns
Y. Zhang, An, Feng, & Jin, 2017	Sina Weibo	Postings of celebrities and ordinaries	Returns
Coyne et al., 2017	StockTwits	Twits' sentiment	Stock prices prediction
Coelho et al., 2019	StockTwits	Twits' sentiment	Stock prices prediction
Sul, Dennis, & Yuan, 2017	Twitter	Sentiment of tweet messages	Returns
Colonescu, 2018	Twitter	Sentiment in Trump's tweets	Returns
Nicolau, Sharma, & Shin, 2020	Twitter	Sentiment in Trump's tweets	The tourism market value
Ge, Kurov, & Wolfe, 2019	Twitter	Company-specific Twitter feeds	Stock price, trading volume, volatility, and investor attention
Brans, Scholtens, & Bovet, 2020	Twitter	Company-specific Twitter feeds	Returns
Juma'h & Alnsour, 2018	Twitter	Tweets' content	Daily changes in major indexes and targeted companies share prices
Azar & Lo, 2016	Twitter	Tweets' polarity scores	Returns
Yang et al., 2015	Twitter	Sentiment of tweets	Returns
X. Zhang, Fuehres, & Gloor, 2011	Twitter	The mood of the masses on twitter	Stock market indices
Risius, Akolk, & Beck, 2015	Twitter	Sentiment of tweets	Stock price
Bollen, Mao, & Zeng, 2011	Twitter	Sentiment of tweets	Closing values
Machus et al., 2022	Twitter	Trump's tweets	Returns
Kinyua et al., 2021	Twitter	Sentiment in Trump's tweets	Stock market indices

revenues (Asur & Huberman, 2010). Microblogging content is a valid indicator of election results (Tumasjan et al., 2011). Additionally, media data from Twitter and Facebook can be used to predict a product's future demand and improve supply chain performance (Iftikhar & Khan, 2020). The most common research uses content to predict the performance of stock markets. In fact, in recent years, research has burgeoned surrounding social media platforms and stock markets (Chen et al., 2021; Jin et al., 2022).

While most studies have focused on the wisdom of the crowd (Bollen et al., 2011; Cheng & Yang, 2022), few have concentrated on individual perspectives (Ajjoub et al., 2020). There must be enough statements on social media to close the gap by examining one individual's perspective. Thus, former United States President Donald Trump is an ideal candidate to study the impact of an individual's continual postings on Twitter.

The slogans at the beginning of this section are, in fact, a common language used by Trump on Twitter. His words beyond the slogans also cause a stir around the world. In addition, after Trump won the U.S. presidential election in November 2016, the U.S. stock market underwent dramatic changes. In 2017, U.S. stock prices rose sharply while volatility hit historic lows. In 2018, U.S. stocks experienced severe turbulence and the country's economic environment underwent significant change. Trump tweeted: *The F-35 program and cost is out of control. Billions of dollars can and will be saved on military (and other) purchases after January 20th*. This seemingly ordinary tweet on December 12, 2016, however, caused a sharp drop in the Dow Jones Aerospace and Defense Index due to the peculiarity of the tweeter, Donald Trump. Jack Ablin, chief investment officer at BMO Private Bank, said: *This is a new type of risk that can be described as a Presidential Attack Risk*. A similar situation occurred on October 2, 2020, when Trump tweeted that he and first lady, Melania Trump, had started to quarantine after testing positive for the new coronavirus. This communication from the controversial politician caused U.S. stock index futures to fall sharply. Among them, Dow Jones futures fell more than 1.7%. The Nasdaq and Standard and Poor's also fell. This tweet also led to drops in European and Japanese stocks.

The posting in Figure 1, which declared an increase in tariffs, led the Asian and European stock markets to suffer heavy losses when they opened. Chinese Shanghai and Shenzhen markets both opened low. The Shanghai Composite Index fell below 3,000 points. At the close of the day, the Shanghai Composite Index fell 5.58%, the Shenzhen Component Index fell 7.56%, and the Growth Enterprise Index fell 7.94%. The Shanghai Composite Index fell 6.5% in the afternoon alone (more than 200 points). Nearly 900 stocks in the two markets fell by their limit. The Australian stock market fell 1.2% and the Nikkei 225 Index futures NKc1 tumbled 2.4% to 21,955 points. Taiwan's stock

Figure 1. Example of Trump's tweets

market also tumbled 1.8%, a three-week closing low. Hong Kong's Hang Seng Index fell 3.21%. E-mini S&P 500 index futures fell 1.7%[1].

JPMorgan quantified the impact of Trump's tweets on the bond market by designing an indicator, the Volfefe Index, to analyze how Trump's tweets affect the volatility of U.S. interest rates. In a research report, they pointed out: *We found strong evidence that (Trump's) tweets will immediately and increasingly affect the trend of the US interest rate market after it is published.* More interestingly, Bank of America Merrill Lynch reported that the days when Trump frequently commented on Twitter were often when the U.S. stock market returns were negative.

Several policies were proposed after Trump took office. For example, America First raised tariffs and launched a trade war between China and the U.S. This, in turn, undermined the economic development of both countries. Since 2020, due to the outbreak of COVID-19, the U.S. stock market has experienced a significant blow. During his presidency, Trump was a frequent tweeter, with content that always impacted the stock markets. To the best of the researchers' knowledge, existing analytical research on the content of Trump's tweets investigate the impact of those texts, which specifically mention the firms' names on the U.S. market (Kinyua et al., 2021). There is, however, limited work on the effects of Trump's opinions on global markets (Guo et al., 2021). In addition, there is no research on tweets that mention China or the U.S. Thus, the authors of this research analyze the impact of Trump's tweets on markets in China and the U.S. based on tweets that mention both countries.

This study first investigates the immediate reaction of stock markets to Trump's tweets. Second, it analyzes the effects of the tweets' content on stock markets. The researchers focus on the tweets posted by Trump that mention China or the U.S. and intraday data to analyze stock market performance. For the first objective, the researchers leverage an event study based on abnormal returns to test the instantaneous effects of tweets. For the second objective, the researchers calculate the sentiment expressed in the content and establish linear regression models to measure the performance of each feature of the tweets' content. The results of the event study indicate that Trump's tweets have an immediate positive impact on the U.S. stock markets and an immediate negative impact on the Chinese stock markets. Ten minutes later, only the Nasdaq Index showed a significantly negative reaction to the tweets. Twenty minutes later, two indices of the U.S. and two indices of the Chinese stock markets showed a significantly positive reaction to the tweets. The results of the OLS regression show that Trump's tweets impact the financial market, especially on the returns of the U.S. stock market during the pandemic.

The contributions of this study are threefold. First, this study contributes to the research field of emotion extraction through a single person's comments and opinions. It advances the literature on social media by examining the context and content of messages posted by the highest-ranking government official in the largest economy in the world, Donald Trump. Second, this study confirms the existence of the presidential attack risk. This risk contributes to the theory that the statements of an influential politician have a relationship with stock markets. In fact, these statements can affect foreign financial markets. Finally, this study provides a new perspective for shareholders and relevant departments when making decisions related to investing or acting to diminish the shock.

The remainder of this article is structured as follows. In the next section, the authors present the literature review. Subsequently, the authors detail the data collection procedure and measurements, research design, results, and research findings from the analysis. Finally, the authors summarize the contributions and limitations before proposing avenues for future work.

LITERATURE REVIEW

Social networking platforms continue to gain momentum. Thus, the influence of social media has attracted significant attention from both academia and business (Nam & Kabutey, 2021; Qi et al., 2021). Many studies have focused on exploring the valuable information behind messages posted on social media.

Wisdom of the Crowd

A significant amount of work has been performed to exploit the influence of the wisdom of the crowd. This means that a diverse collection of independent decision makers is likely to make certain types of decisions and predictions better than individuals or experts. Surowiecki (2005) showed that the wisdom of the crowd does have an impact on stock markets, political elections, and quiz shows. Chen et al. (2014), after extracting investor opinions through Seeking Alpha, found that the information strongly predicts future stock returns and earnings surprises. Nofer (2015) collected recommendations from the largest European stock prediction communities, revealing that the crowd outperforms professional analysts on stock market prediction by comparing the forecast accuracy between the crowd and professional analysts. Azar and Lo (2016) focused on tweets from 2007 and 2014 that were related to the Federal Open Market Committee (FOMC). They found that tweet sentiment can be used to predict returns the following day. This impact intensified the day the FOMC meets. Furthermore, they confirmed that trading strategies based on tweet information outperformed the benchmark market on multiple dimensions. To examine whether collective wisdom plays a predictive role in a crisis, Chau et al. (2020) downloaded articles that described banks from Seeking Alpha. Their work found that the fraction of negative words contained in articles or comments in the pre-crisis period can predict the bank stock returns. However, some research shows that collective information can cause herding behavior due to dependent estimates by individuals. By tracking user activities on Estimize.com, an earning forecast website, Da and Huang (2020) found that individual opinions could be underweighted by viewing public information. When the platform initially blocks forecasts from other users, it can generate more accurate corporate earnings forecasts. This allows a better Estimize consensus.

Work that analyzes the wisdom of crowds tends to focus on social media. Although access to social platforms is widespread, the impact of collective wisdom varies among people of different identities. By analyzing tweet data during the Ukraine's conflict, Aldarbesti et al. (2020) showed that "elite" participants (e.g., journalists, professional associations, commercial organizations) attracted more retweets than non-commercial participants (e.g., religious networks, charities, volunteers). Yang et al. (2015) regressed the message sentiment from users (called critical nodes) that play a central role in the network to multiple market returns and VIX, respectively. Their study found that critical node behavior transforms the regression result, causing it to be more precise and accurate in explaining a financial asset's price movement. Zhang et al. (2017) divided the users of Sina Weibo into a celebrity group and an ordinary group. Their work concluded that the celebrity postings had a significant predictive power for stock returns. In contrast, postings by the ordinary group provided inefficient stock return predictions. This suggests that celebrity postings on social networks are informative. In fact, their posts can predict future stock returns, future public news, and current private information. Coyne et al. (2017) selected smart users from StockTwits, choosing posts that contained correct predictions. The messages from the smart users could be used to yield a more reliable indicator for the financial prediction. Similarly, Coelho et al. (2019) predicted stock prices with higher accuracy after selecting postings from smart users. However, Sul et al. (2017) found that the sentiment extracted from the tweets of users with fewer than 171 followers that were not retweeted had the most significant impact on future stock returns.

Sentiment Analysis in Social Media

The most common way to measure emotions expressed in social media postings is to divide them into a positive and negative. Furthermore, the existing literature provides multiple sentiment analysis techniques. Azar and Lo (2016) used a Pattern package in Python to calculate the polarity score of each tweet that cited the Federal Reserve. By regressing the scores, Fama French factors, and related variables to the excess daily return on the CRSP value-weighted market index, they concluded that the tweets contain predictive information of returns even after controlling for common market factors. Yang et al. (2015) used a comprehensive dictionary (SentiWordNet) with more than 8,000 sentimental words with positive and negative scores ranging from 0 to 1, respectively, to achieve the objective of computing the polarity sentiment score. Sul et al. (2017) used the Harvard-IV dictionary to classify words and investigated the sentiment polarity in tweets about individual firms. In addition, they explored the relationship to the stock returns of those matched companies. Their results indicate that tweets spread positive or negative sentiment about a stock through the market. It can also influence prices and, thus, the returns from trading those stocks.

However, classifying the sentiment in social media into positive and negative sentiment is not always a reliable predictor. To take a further step, some researchers propose more nuanced divisions of emotions. Zhang et al. (2011) extracted a randomized sub-sample of the full volume of Twitter feeds for six months and measured collective emotions (i.e., hope, happiness, fear, worry, nervousness, anxiety, and upset) each day. Then, they analyzed the correlation between these indices and stock market indicators. The finding indicated that the emotional tweet percentage was significantly negatively correlated with the Dow Jones, NASDAQ, and S&P 500. However, it displayed a significant positive correlation with the VIX. Risius et al. (2015) analyzed seven-dimensions emotions based on the validated scores provided by an open-source emotion-specific dictionary, SentiStrength 2. They examined the explanatory power of differentiated emotions expressed in tweets for company-specific stock prices. The emotion-specific analysis revealed that the differentiated emotions expressed in tweets have a more substantial relationship with company-specific stock price changes than the undifferentiated average sentiment. Negative emotions tend to have greater explanatory power. However, the positive emotionality strength is unrelated to stock price movements, which aligns with previous studies. Bollen et al. (2011) used OpinionFinder and Google Profile of Mood States to measure the polar sentiments and six-dimension mood of the content crawled from large-scale Twitter feeds. There was no evidence that a negative and positive mood affects stock market prediction. Still, the mood dimension of “Calm” as measured by GPOMS has a predictive power of future DJIA values. Accuracy can be improved when adding special moods like calm and happiness to the model for prediction.

Sentiment Analysis of Trump’s Tweets

The advantage of the rapid spread of information via social media has attracted many political figures. Trump is a prime example. Compared with other social media users, Trump prefers to use Twitter to communicate his thoughts with the public. As a controversial figure, he provided fruitful data to study an individual’s impact. Colonescu (2018) studied about 3,500 tweets by Trump, labeling each tweet as positive or negative. After aggregating the sentiment over a day via average score and extreme score methods, the researchers used time series to investigate the correlation between the sentiment and DJIA, exchange rate, or other economic variables of interest. Based on the results of the average sentiment method, the short-term effects of Trump’s tweet sentiment on the DJIA index for the first two-time intervals were statistically significant. However, they had no significance in the last interval. Machus et al. (2022) classified Trump’s tweets that mentioned individual firms into positive and negative. Their research performed event study to uncover the impact of tweets on stock markets. They found that Trump’s tweets could cause increased trading activity; however, they do not have lasting effects on stock prices. Similarly, Kinyua et al. (2021) performed event study to analyze the immediate impact of Trump’s tweets on two U.S. stock market indices using intra-day market data. The results showed that the 15-minute pre-trends and 15-minute post-trends for both the SPX and INDU had a significant negative reaction when Trump tweeted during open market hours.

In addition to analyzing the impact on the financial market, Nicolau et al. (2020) used Trump’s tweets to investigate whether the president’s performance on social media affected tourism. They found that messages that influence the national image can affect tourism’s market value. Other studies focus on Trump’s company-specific tweets. However, the results come to different conclusions. Ge et al. (2019) analyzed the effects of Trump’s tweets that contain the names of publicly traded companies on firm stock prices. The authors manually labeled each tweet with a negative or positive tag. Then, they used a combination of Google Cloud Natural API and two lexicons to infer the underlying sentiment. Based on the regression results, they concluded that the tweets had a significant impact on firm stock prices and trading volume, volatility, and institutional investor attention, especially because the impact was more substantial before the presidential inauguration. Brans and Scholtens (2020) analyzed the same question based on the dataset over a more extended period. Their finding indicates that the president's tweets that reveal strong negative sentiment are followed by a fall in the market value of the company mentioned. In contrast, supportive tweets do not render a significant effect. In contrast, Juma'h and Alnsour (2018) found that there is no significant impact of Trump's tweets on market indices or most of the targeted companies' share prices.

According to the literature review, the authors noticed that few works have been done on the effect of Trump's opinions on markets worldwide. In addition, no research has focused on tweets that mentioned China or the U.S. To close the gap of existing research, based on the tweets posted by the U.S. president that mentioned China or the U.S. and intraday stock market data, this study aims at investigating the immediate reaction of stock markets to the president's tweets and analyzing the effects of the tweets' content on stock markets.

DATA AND MEASUREMENTS

Collection of Tweet Data

"Trump Twitter Archive" provides all tweets from the @realDonaldTrump Twitter account, including those deleted shortly after posting. The authors extracted tweet data from the website from 9 p.m. on March 21, 2018, to 9 p.m. on June 30, 2020 (UTC). Then, because Chinese time precedes American time, the authors set 9 p.m. as the split point (the converted time of the closing trading time in American stock markets). Thus, the study can contain all tweets used for analyzing Chinese and U.S. stock markets.

During this period, 16,652 tweets were captured. Among them, 10,161 tweets were original (not retweeted). This study focuses on original tweets that mentioned target countries: China or the U.S. Considering various formats (full name, short name, or different spelling) of one country's name, the authors unified the different existing descriptions of the names of the two countries. That is, America, United States, US, USA, and U.S.A. are all unified and coded as America. In addition, tweets that explicitly mention two nations' affairs are important; therefore, the authors included representative words, such as American, Americans, Chinese, President Xi, and President Xi Jinping (and the capital forms of these words). Finally, 1,887 tweets mentioning the U.S. and 384 tweets mentioning China were collected.

During the data preprocessing stage, the authors removed all hyperlinks, usernames, and punctuation. They replaced abbreviations with full spellings. For example, *we're* was replaced by *we are.* Considering that words after the hashtag are not separated by blank space, the researchers manually added spaces between the words after a hashtag. The researchers kept the words after a hashtag for two reasons. First, the words following a hashtag are always associated with the tweet content and can be a necessary part of a sentence. For instance: ... *But #FakeNews likes to say we're in the 1930s. They are wrong. Some people think numbers could be in the 50's.* Second, the target words (nation names) may be contained in words after the hashtag. Additionally, stopwords can be essential structural elements in dependency analysis. Most stopwords have no emotional score in the dictionary. Thus, the researchers did not remove stopwords from these statements.

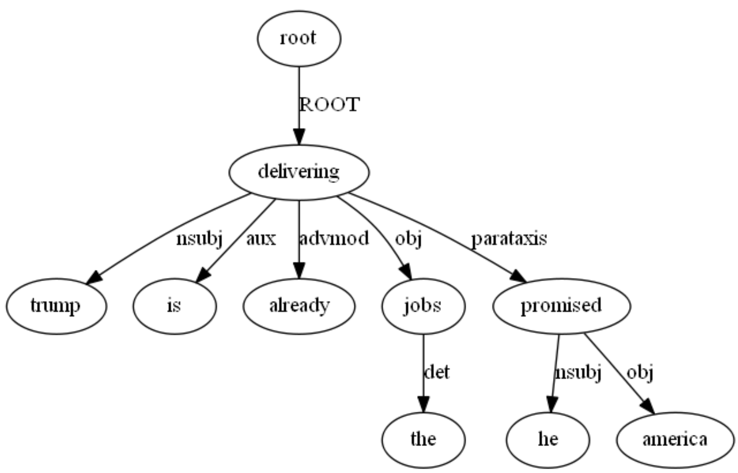
Target-Dependent Measurements of Sentiment

Before calculating the sentiment of each tweet, the authors used the package nltk to label each word based on the part of speech. This helps to calculate the sentiment value of each tweet more precisely. According to Boiy and Moens (2009), researchers use Stanford CoreNLP to weigh each word based on the distance between the word and national names in the dependency tree. Stanford CoreNLP is a tool developed by Stanford University for natural language processing, providing part-of-speech tagging, entity recognition, syntactic parsing, and other tasks required for the research. According to the dependency parsing provided by Stanford CoreNLP, the authors can obtain a dependency tree in which each node represents a word and each tweet has a tree. The researchers set the nation names as the target words, calculated the path distance from each word in the tree to the target word, and took the inverse of the distance as the weight of the word when calculating the emotional score.

Figure 2 shows the dependency tree of the tweet mentioned in the U.S. posted by Trump on January 3, 2017: *Trump is already delivering the jobs he promised America.* Based on this graph, the authors can count the path distance of each word in the sentence to 'america' separately. The distance between each word and 'america' in the sentence is three, three, three, two, four, three, two, one, and zero. Then, the researchers set the weight of the target word, 'america,' as zero. Thus, in Figure 2, the weight of these words in this tweet is the reciprocal of three, three, three, two, four, three, two, one, respectively, and the zero for the word 'america.' When a tweet mentions the target words more than once (for instance, there are two uses of 'america' in one tweet), the smaller path distance will be chosen to set as the weight of other words.

According to Sentiwordnet, the researchers can obtain a sentiment value for each word in the tweet. Sentiwordnet is a sentiment dictionary developed by Stanford University for research use, including 2,000k lexical entries and their positive and negative values (Kannan et al., 2016). Considering that a word can have multiple parts of speech and that each part of speech may have multiple meanings, researchers weighted all the scores of the word in the part of speech, which the researchers labeled previously, to obtain the final sentiment value of the word. In Sentiwordnet, the higher the order of the meaning within a part of speech of a word, the greater the meaning represents the meaning of the word. For instance, the first description of the word is always more common than the second description. Then, the authors took the reciprocal of the order number as the weight of the meaning. That is, the researchers give the first meaning weight of 1, the second a weight of 1/2, and so on. The score for each meaning is the positive score minus the negative score. The final sentiment value of each word is the sum of the score of each meaning multiplied by their weight. When the sentiment values of words are not included in the dictionary, the authors set the final sentiment value of words to zero. After calculating the sentiment score of each word, the researchers multiplied the emotional score of each word in a tweet by the weight of each word previously calculated according to the dependency tree. Then, they summed them to obtain a final sentiment score of each tweet message.

Figure 2. Dependency Tree



Collection of Intraday Stock Market Data

Regarding the stock market data, the authors chose 10-minute intraday stock market data. During the sample period, there were 573 trading days. For the Chinese stock market, the researchers downloaded three indices of China from the Ricequant database: (1) Shanghai Composite Index (SSEC); (2) Shanghai Shenzhen CSI 300 (CSI300); and (3) Shenzhen Component Index (SZI). For the U.S. stock market, the authors extracted three indices from the Bloomberg database: (1) Dow Jones Industrial Average Index (DJIA); (2) Standard & Poor's 500 (SPX); and (3) Nasdaq Index (NASDAQ). After that, the authors calculated three variables: (1) 10-minute return; (2) 30-day volatility; and (3) abnormal return.

The 10-minute return represents the result of dividing the closing price at time t by the closing price of the previous 10 minutes (t-10 m) and then taking the natural logarithm:

$$return_t = ln\left(\frac{price_t}{price_{t-1}}\right) \tag{1}$$

where $price_t$ means the closing price of the index at time t and $price_{t-1}$ means the closing price of the index at time t-10 m (which means 10 minutes before t).

Additionally, the 30-volatility represents the standard deviation of the return over the same period over the past 30 trading days. For instance, if the researchers want to calculate the volatility at 10:00 a.m. on April 20, 2018, the authors need the calculated return at 10:00 a.m. over past 30 trading days, which includes April 20, 2018. Then, the standard deviation of these returns will be the 30-volatility of April 20, 2018:

$$volatility_t = \sqrt{\frac{\sum_{i=t-29}^{t} return_i}{29}} \tag{2}$$

The abnormal return is the abnormal log return at time t. It is calculated as the difference between the return at time t and the average return from time t-35 to t-6 (a 5-hour period). There are 30 values:

$$AbReturn_t = return_t - \frac{\sum_{i=t-35}^{t-6} return_i}{30} \tag{3}$$

Since the frequency of the stock market data is 10 minutes, the researchers integrate the sentiment of tweets posted during the period [t-1, t) of trading time in the stock market, a period of 10 minutes. The researchers integrated tweets posted after the closing time of the stock market on trading Day d and before the opening time of the stock market on trading Day d+1. They considered that these tweets have the same impacts as the tweets posted during the first 10 minutes of trading time in the stock market on Day d+1.

Regarding the U.S. stock market, for example, the closing time of New York Stock Exchanges is 4 p.m. The authors integrated the tweets posted from 4 p.m. on trading Day d to 9:40 a.m. on trading Day d+1. They considered all of them as tweets posted during 9:30 a.m. to 9:40 a.m. on trading Day d. That is, when the authors counted the number of tweets posted between 9:30 a.m. to 9:40 a.m. on trading Day d, it equals the number of tweets posted from 4 p.m. on trading Day d to 9:40 a.m. on trading Day d+1.

In terms of the Chinese stock market, the closing time is 3 p.m. Thus, the researchers put the tweets posted from 3 p.m. on trading Day d to 9:40 a.m. on trading Day d+1. They considered all of them as tweets posted during 9:30 a.m. to 9:40 a.m. on trading Day d. Additionally, the Chinese stock market closes at noon. So, in a similar way, the tweets posted at noon will be put together with those tweets posted during the first 10 minutes of the opening in the afternoon.

Due to the time difference between China and the U.S. (and the daylight time of the U.S.), the authors adjusted all times to UTC time before integrating. After integrating tweets by trading time, the researchers calculated the average length of tweets and counted the number of tweets in each 10-minute period.

Summary Statistics

Table 2 summarizes all the variables and their measurements. Table 3 summarizes the statistics of the Twitter feeds data.

Table 3 shows that during the trade war, Trump tweeted more frequently than in other periods. However, the difference between the two periods is not as noticeable. Whatever the time phase, the

Table 2. Variables and measurements

Variables	Measurements
$return_t$	Log-return at t (10 minutes).
$return_{t-1}$	Log-return at t-1 (last 10 minutes).
$volatility_t$	The standard deviation of the return over the same time interval (10 minutes) over the past 30 days at t.
$volatility_{t-1}$	The standard deviation of the return over the same time interval (10 minutes) over the past 30 days at t-1.
$AbReturn_t$	The difference between the return at t and the average return from t-35 to t-6.
$sentiment_t$	The average sentiment score of tweets posted during an interval (10 minutes).
$NumberofTweets_t$	The total number of tweets posted during an interval (10 minutes).
$NumberofWords_t$	The average length of tweets during an interval (10 minutes).

Table 3. Statistics summary of tweets

	ALL				During the Trade War				During the COVID-19 pandemic			
Tweets mention	China		U.S.		China		U.S.		China		U.S.	
Tweets features	Number of Tweets	Number of Words	Number of Tweets	Number of Words	Number of Tweets	Number of Words	Number of Tweets	Number of Words	Number of Tweets	Number of Words	Number of Tweets	Number of Words
Median	1.00	43.58	3.00	36.46	1.00	43.67	3.00	37.50	2.00	42.67	3.00	33.58
Mean	2.20	40.86	3.73	35.24	2.24	40.81	3.78	35.76	2.07	41.02	3.50	33.10
Max	21.00	61.00	16.00	56.00	21.00	61.00	16.00	56.00	10.00	55.00	13.00	55.00
Min	1.00	6.00	1.00	3.50	1.00	6.00	1.00	3.50	1.00	16.00	1.00	5.00
Std	2.32	10.83	2.74	10.10	2.48	10.94	2.80	10.30	1.69	10.58	2.47	9.03

Twitter feeds mentioning China always contained more words than those mentioning the U.S. There are more tweets that mention America according to the mean. For instance, during the pandemic, Trump posted 2.07 tweets mentioning China on average. There were 3.50 Twitter feeds related to the U.S. on average during the same period. However, the average number of words in tweets including China was 41.02. Those tweets mentioning America have a smaller average number of words (33.10). Moreover, the table confirms that Trump is a frequent tweeter. For instance, in one day, he tweeted 21 posts that mentioned China.

RESEARCH DESIGN

Event Study

To examine the reaction of the financial stock markets to Trump's tweets, the authors considered leveraging an event study to investigate the shocks of the tweets. The authors regarded each tweet as an event. They considered a 30-period evaluation window and ±5 period event window. Several tweets could be posted within a short period of time; therefore, to avoid overlapping, the authors excluded tweets with an overlap event window. After that, 1,022 tweets mentioning the United States and 195 tweets mentioning China remained.

Due to the multiple events in the analysis, the authors ran the regression with dummy variables:

$$\begin{aligned} AbReturn_{it} &= \alpha + \beta_1 5t\min BeforeTW_{it} + \beta_2 4t\min BeforeTW_{it} + \beta_3 3t\min BeforeTW_{it} \\ &+\beta_4 2t\min BeforeTW_{it} + \beta_5 1t\min BeforeTW_{it} + \beta_6 TW_{it} + \beta_7 1t\min AfterTW_{it} \\ &+\beta_8 2t\min AfterTW_{it} + \beta_9 3t\min AfterTW_{it} + \beta_{10} 4t\min AfterTW_{it} + \beta_{11} 5t\min AfterTW_{it} \end{aligned}$$

where $AbReturn_{it}$ is an abnormal return at t for tweet i; $5tminBeforeTW_{it}$, $4tminBeforeTW_{it}$, $3tminBeforeTW_{it}$, $2tminBeforeTW_{it}$, and $1tminBeforeTW_{it}$ are dummy variables equal to 1, separately, if time t falls in period five, period four, period three, period two, or period one before tweet i posted; TW_{it} is a dummy variable equal to 1 if tweet i posted at t; and $1tminAfterTW_{it}$, $2tminAfterTW_{it}$, $3tminAfterTW_{it}$, $4tminAfterTW_{it}$, and $5tminAfterTW_{it}$ are dummy variables for whether time t falls in period one, period two, period three, period four, or period five after tweet i posted.

Tweet Content Features

To examine the impact of the emotion expressed by Trump's Twitter feeds on the stock market more accurately, the authors divided the whole time into two parts with one point—January 15, 2020 (UTC), the day China and the U.S. signed the first phase of the trade war agreement. One part is March 22, 2018, to January 15, 2020, which represents the outbreak of the trade war declared by Trump. The other part, ending June 30, 2020, represents the outbreak period of the pandemic.

In view of the frequency of the data, Trump does not tweet every time. Therefore, the number of tweets posted by Trump is zero in many intervals after integrating the stock data and tweet data. The authors chose the OLS regression model to evaluate the effect of the sentiment extracted from tweets on the stock market. Furthermore, the researchers deleted the data of time intervals in which no Twitter messages were posted by Trump. They retained research data of those time intervals in which at least one tweet was posted and inserted them into the regression model. To have a better explanation of the return, the authors added the return of the last period to the explanatory variables. The regression model is as follows:

$$return_t = \alpha + \beta_1 sentiment_t + \beta_2 return_{t-1} + \beta_3 NumberofTweets_t + \beta_4 NumberofWords_t \quad (5)$$

$$volatility_t = \alpha + \beta_1 sentiment_t + \beta_2 volatility_{t-1} + \beta_3 NumberofTweets_t + \beta_4 NumberofWords_t \quad (6)$$

RESULTS

Event Study

Tweets That Mention the U.S.

Table 4 collects the results of the event study based on the abnormal returns of the U.S. indices. The results show that the U.S. stock market had an immediately positive reaction to Trump's tweets that mention the U.S. In addition, Twitter's rapid spread of information allowed more people to process the information. Thus, stakeholders could make quick decisions based on the tweets. Within 10 minutes, only the Nasdaq Index showed a significantly negative reaction to the tweets. Within 20 minutes, the Nasdaq Index and SPX500 Index showed a significantly positive reaction to the tweets.

Tweets That Mention China

Table 5 shows the results of the event study based on the abnormal returns of the Chinese indices. Like the U.S. stock market, the results show that the Chinese stock market had an immediate reaction

Table 4. Results of event study (U.S.)

	Abnormal Return		
	DJIA	NASDAQ	SPX
α	-5.11E-06	-9.56E-06	-7.69E-06
	(-0.267)	(-0.512)	(-0.424)
5tminBeforeTW	6.38E-05	7.71E-06	5.05E-05
	(0.64)	(0.08)	(0.54)
4tminBeforeTW	5.70E-05	1.43E-05	2.58E-05
	(0.57)	(0.15)	(0.27)
3tminBeforeTW	-0.0001	-0.0001	-9.60E-05
	(-1.113)	(-1.059)	(-1.022)
2tminBeforeTW	-0.0001	-0.0002*	-0.0001
	(-1.43)	(-1.825)	(-1.471)
1tminBeforeTW	-1.80E-05	-1.76E-05	-2.22E-05
	(-0.181)	(-0.181)	(-0.236)
TW	0.0002*	0.0004***	0.0003***
	(1.83)	(4.47)	(2.99)
1tminAfterTW	-7.11E-05	-0.0002**	-0.0001
	(-0.716)	(-2.35)	(-1.465)
2tminAfterTW	0.0001	0.0002**	0.0002*
	(1.42)	(2.19)	(1.88)
3tminAfterTW	-9.13E-05	-2.95E-05	-5.07E-05
	(-0.919)	(-0.304)	(-0.54)
4tminAfterTW	4.53E-05	6.91E-05	4.68E-05
	(0.46)	(0.71)	(0.50)
5tminAfterTW	0.0001	0.0002*	0.0002
	(1.45)	(1.77)	(1.64)

Table 5. Results of event study (China)

	Abnormal Return		
	SSEC	CSI300	SZI
α	6.01E-07	-1.70E-06	-1.31E-05
	(0.03)	(-0.071)	(-0.492)
5tminBeforeTW	3.11E-06	1.95E-05	-3.60E-06
	(0.02)	(0.09)	(-0.015)
4tminBeforeTW	0.0001	0.0001	0.0003
	(0.52)	(0.53)	(1.04)
3tminBeforeTW	-0.0002	-0.0003	-0.0004
	(-1.157)	(-1.24)	(-1.586)
2tminBeforeTW	0.0001	0.0001	8.01E-05
	(0.53)	(0.63)	(0.33)
1tminBeforeTW	0.0005**	0.0004*	0.0003
	(2.34)	(1.92)	(1.41)
TW	-0.001***	-0.0007***	-0.0002
	(-5.223)	(-3.251)	(-0.657)
1tminAfterTW	0.0001	0.0002	0.0004
	(0.60)	(0.75)	(1.49)
2tminAfterTW	0.0003*	0.0003	0.0006**
	(1.79)	(1.47)	(2.49)
3tminAfterTW	4.41E-05	-3.55E-05	0.0001
	(0.23)	(-0.163)	(0.55)
4tminAfterTW	0.0001	0.0001	0.0001
	(0.52)	(0.47)	(0.46)
5tminAfterTW	-1.66E-05	-1.70E-06	3.83E-05
	(-0.085)	(-0.008)	(0.16)

to the president's tweets that mention China. Specifically, the reaction is negative. Twenty minutes later, there was a directional change in the reaction. Two indices showed a significantly positive reaction to the tweets. The president often posted tweets after an announcement of a policy, min1b, which represents the abnormal return of the Chinese stock market 10 minutes before the tweet was posted. This shows a positive significance. That is, Trumps' tweets changed the reaction direction of the stock markets.

Tweets' Content Features

Tweets That Mention the U.S.

To obtain a more detailed view of the effect of the tweets' content features, the authors established a regression model. First, the researchers considered the effect of tweets mentioning the U.S. on U.S. stock markets. With the average sentiment score, the return of the last period, the $NumberofTweets$, and $NumberofWords$, researchers perform the regression.

Table 6 presents the results of the regression for two intervals and the whole period based on the returns of the U.S. indices. For the sentiment score, there was no significance for the whole period and first period. However, for the second phase, during the pandemic, the effects of sentiment on U.S. stock market are statistically significant. The last interval shows the period after the outbreak of COVID-19. During that time, the U.S. stock market suffered a significant blow. The sentiment expressed by Trump on Twitter had an impact on the stock markets. In addition, during the pandemic, the number of tweets shows a significant impact on stock returns. More specifically, Trump's sentiment on Twitter had a negative impact on the U.S. stock markets during the pandemic. The number of his posts negatively influenced the return of the U.S. stock markets.

The regression results of the volatility of the U.S. stock indices based on Trump's tweets that mention the U.S. are shown in Table 7. Per the results, over the whole period, the sentiment extracted

Table 6. Regression results of tweets mentioning the U.S.-return

	ALL			During the Trade War			During the COVID-19 pandemic		
	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ
α	0.0015	0.0013	0.0013	0.0005	0.0003	0.0002	0.0093**	0.0085**	0.0084**
	(1.64)	(1.55)	(1.55)	(0.89)	(0.72)	(0.35)	(2.21)	(2.18)	(2.39)
sentiment	-0.0009	-0.0008	-0.0008	-3.29E-05	-3.75E-05	-5.44E-05	-0.0079**	-0.007**	-0.0065**
	(-1.545)	(-1.534)	(-1.462)	(-0.101)	(-0.125)	(-0.146)	(-2.334)	(-2.275)	(-2.303)
$return_{t-1}$	0.2818*	0.3036*	0.2537	0.0056	-0.0007	-0.0238	0.3759	0.4116	0.4172
	(1.73)	(1.82)	(1.62)	(0.04)	(-0.005)	(-0.153)	(1.00)	(1.04)	(1.13)
Number of Tweets	-0.0002	-0.0002	-0.0001	-3.53E-05	-1.93E-06	-6.07E-06	-0.0014**	-0.0013**	-0.0011*
	(-1.625)	(-1.425)	(-1.193)	(-0.47)	(-0.028)	(-0.07)	(-2.042)	(-2.035)	(-1.818)
Number of Words	-1.94E-05	-1.46E-05	-1.16E-05	-3.52E-06	-6.66E-07	6.48E-06	-0.0002	-0.0001	-0.0001
	(-0.847)	(-0.691)	(-0.558)	(-0.272)	(-0.056)	(0.44)	(-1.442)	(-1.374)	(-1.552)

Table 7. Regression results of tweets mentioning the U.S.-volatility

	ALL			During the Trade War			During the COVID-19 pandemic		
	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ
α	0.0043***	0.0038***	0.0036***	0.0027***	0.0024***	0.0028***	0.0092***	0.008***	0.0063***
	(6.72)	(6.44)	(6.74)	(10.39)	(10.15)	(9.38)	(3.38)	(3.17)	(2.81)
sentiment	-0.0008*	-0.0007*	-0.0007*	-0.0002	-0.0002	-0.0002	-0.0031	-0.0027	-0.002
	(-1.848)	(-1.852)	(-1.914)	(-1.185)	(-1.255)	(-1.342)	(-1.44)	(-1.361)	(-1.155)
$volatility_{t-1}$	-0.5041***	-0.3877***	-0.2329**	-0.9219***	-0.8574***	-0.8032***	-1.2629***	-1.0431***	-0.4479
	(-3.337)	(-2.763)	(-2.07)	(-9.91)	(-9.959)	(-9.087)	(-3.491)	(-3.109)	(-1.624)
Number of Tweets	0.0005***	0.0005***	0.0006***	0.0004***	0.0004***	0.0005***	0.0009*	0.0008*	0.001**
	(4.90)	(5.10)	(7.18)	(9.94)	(10.31)	(10.79)	(1.84)	(1.93)	(2.56)
Number of Words	-1.51E-06	5.82E-07	7.11E-06	0.000012*	0.000012**	0.000016**	4.32E-05	4.73E-05	4.24E-05
	(-0.096)	(0.04)	(0.54)	(1.85)	(2.12)	(2.23)	(0.64)	(0.76)	(0.76)

from the Twitter account show that the president had a significant impact on the volatility of stock indices. In particular, the polarity of Trump's emotions had a negative impact on market volatility, as the coefficient of the sentiment score is negative. Moreover, the volatility of the last interval was significant in the regression results of the three time phases (except for the NASDAQ during the pandemic). In addition, the number of tweets had a significant impact on volatility both during the trade war and during the pandemic. This influence was positive. That is, the more tweets Trump posted, the more the stock market fluctuated.

Tweets That Mention China

To investigate the impact of the tweets mentioning China on Chinese stock markets, the authors performed the same regression on three indices of China: SCI, CSI, and SZSE.

Table 8 shows the results of the regression. The sentiment extracted from those tweets does not show a prominent effect on the return over either the two phases or the total period. In contrast, the number of tweets shows a more noticeable influence on the return of Chinese markets during the whole period and during the pandemic. Moreover, the coefficients of the number of tweets of the two phases are both negative. This means that the more frequently Trump tweets, the lower the returns of Chinese stock indices.

Table 8. Regression results of tweets mentioning China-return

	ALL			During the Trade War			During the COVID-19 pandemic		
	SSEC	CSI300	SZI	SSEC	CSI300	SZI	SSEC	CSI300	SZI
α	-0.0011	-0.002	-0.0004	0.0017	0.0015	0.0022	-0.0065	-0.0091	-0.0055
	(-0.392)	(-0.645)	(-0.122)	(0.73)	(0.54)	(0.76)	(-0.746)	(-0.959)	(-0.558)
sentiment	-0.0003	0.0003	-0.0001	0.0018	0.0025	0.0022	-0.0069	-0.0067	-0.0081
	(-0.185)	(0.19)	(-0.077)	(1.33)	(1.62)	(1.32)	(-1.583)	(-1.405)	(-1.614)
$return_{t-1}$	0.3438	0.4251	0.1436	0.0767	0.0856	-0.0156	0.249	0.5534	-0.1973
	(0.94)	(1.18)	(0.38)	(0.24)	(0.26)	(-0.041)	(0.23)	(0.52)	(-0.209)
Number of Tweets	-0.0006**	-0.0007**	-0.0007*	-0.0003	-0.0004	-0.0004	-0.0026**	-0.0027*	-0.003**
	(-2.074)	(-2.033)	(-1.94)	(-1.502)	(-1.522)	(-1.2)	(-2.046)	(-1.966)	(-2.079)
Number of Words	3.35E-05	6.22E-05	4.04E-05	-4.16E-05	-2.56E-05	-3.95E-05	0.0002	0.0003	0.0003
	(0.54)	(0.90)	(0.54)	(-0.793)	(-0.416)	(-0.591)	(1.26)	(1.46)	(1.21)

In addition, the researchers performed the same regression based on the volatility of Chinese stock indices. Table 9 shows that the number of tweets is statistically significant over the whole time and during the trade war other than for SCI over the whole time. Additionally, the positive coefficients mean that the more tweets Trump posts, the more volatile were the Chinese stock markets.

ADDITIONAL ANALYSES

To investigate the impact of the statements posted on Twitter by the influential political figure more precisely, the researchers considered analyses by employing industry index data and changing the frequency of the index data.

Industry Analysis

First, the researchers used the industry indices to examine whether those tweets affect the return of sector indices through the sentiment they expressed. For the U.S. stock market, the authors chose the sector indices of S&P. In all, there were 11 industry indices. The regression results are presented in Table 10 in the Appendix. Per the results, Trump's tweets during the pandemic impacted the return of several industries, including S5BANKX, S5COND, S5CONS, S5FINL, S5HLTH, S5INDU, S5INFT,

Table 9. Regression results of tweets mentioning China-volatility

	ALL			During the Trade War			During the COVID-19 pandemic		
	SSEC	CSI300	SZI	SSEC	CSI300	SZI	SSEC	CSI300	SZI
α	0.0047***	0.006***	0.0066***	0.0041***	0.0048***	0.0056***	0.0068*	0.009**	0.0095**
	(4.70)	(5.61)	(5.65)	(5.15)	(5.38)	(5.73)	(1.96)	(2.59)	(2.52)
sentiment	-0.0003	-0.0005	-0.0003	-0.0005	-0.0005	-0.0005	0.0006	0.0006	0.0015
	(-0.655)	(-0.912)	(-0.476)	(-1.091)	(-1.071)	(-0.91)	(0.32)	(0.34)	(0.75)
$volatility_{t-1}$	-0.064	-0.2676	-0.4193	0.0009	0.0385	-0.2085	-0.2877	-1.0338	-1.2219
	(-0.176)	(-0.77)	(-1.234)	(0.00)	(0.13)	(-0.686)	(-0.227)	(-0.907)	(-1.3)
Number of Tweets	0.0002	0.0002*	0.0002*	0.0002**	0.0002***	0.0002**	0.0001	0.0002	0.0001
	(1.65)	(1.86)	(1.67)	(2.55)	(2.68)	(2.54)	(0.26)	(0.42)	(0.20)
Number of Words	2.77E-05	2.50E-05	2.66E-05	0.000032*	0.000032*	3.10E-05	9.00E-06	4.91E-06	1.58E-05
	(1.32)	(0.04)	(1.09)	(1.95)	(1.76)	(1.58)	(0.12)	(0.07)	(0.20)

and S5UITL. The number of words within the tweet had a noticeable effect on the returns of S5HLTH and S5UITL during the pandemic. Regarding S5ENRS, the return of the previous period influenced the return significantly. During the trade war, the number of tweets showed an obvious impact on its return. The results of the regression of volatility show that the sentiment calculated based on Trump's Twitter feeds had a significant influence on the index, S5HLTH, over the whole period. Moreover, the volatility of all the indices in the last interval affected their volatility significantly during the trade war. Additionally, for all the indices of the U.S. stock market, the number of tweets played an important role in affecting the indices' volatility during the trade war and the pandemic. In addition, during the period of the trade war, the number of Trump tweets had a noticeable effect on the volatility of several sector indices, including S5BANK, S5COND, S5CONS, S5HLTH, S5INDU, S5INFT and S5UTIL. Table 10 in the Appendix presents the regression results.

Regarding the Chinese stock markets, the researchers chose a total of 10 industry indices. The results show that during the trade war, the sentiment expressed in Trump's tweets significantly affected the returns of the Shanghai Financial Index. Surprisingly, the coefficient of the sentiment was positive. This means that the sentiment of those tweets had a positive impact on the financial market during the trade war. Additionally, the emotion extracted from those Twitter texts showed a significant effect on the return of the Shanghai Pharmaceutical Index during the pandemic. It is worth noting that over the whole period, the number of tweets posted by Trump on Twitter had a noticeable impact on the return of several sector indices, such as Shanghai Composite Industry, Shanghai Industrial Index, and Shanghai Optional Index. In addition, the number of tweets played an essential role in affecting several industry indices' returns during the pandemic (for instance, the Shanghai Consumer Staples Index). In addition to the regression of index returns, the researchers performed a similar regression based on the volatility of indices. For all three periods, sentiment extracted from Trump's Twitter texts showed no significant impact on volatility. However, the number of tweets played an important role in influencing Chinese sector indices over different time periods. Moreover, during the trade war, the mean number of words in the tweets had a noticeable effect on volatility. The regression results are presented in Table 11 in the Appendix.

Change in Time Frequency

In addition, the authors exploited the impact of tweets more precisely by using stock data with different frequencies. First, the authors changed the frequency of the intraday stock data to one hour. The regression results of returns show that for the Chinese stock market, the sentiment score calculated based on Trump's Twitter messages posted during the trade war and pandemic affected returns. However, for the U.S. stock markets, the sentiment expressed by Trump's tweets did not show a significant effect on the returns. For U.S. stock markets, $return_{t-1}$ had a significant impact on the return of the three indices in the whole period and during the pandemic. By analyzing the results of volatility over the whole period and during the pandemic, $volatility_{t-1}$ and the quantity of Twitter feeds impacted the U.S. stock indices' volatility. Then, during the trade war, both the Chinese stock market and U.S. stock market, $volatility_{t-1}$ and the number of Trump's tweets affected volatility.

In addition, the researchers performed the regression based on the daily stock data (see Table 13 in the Appendix). It was found that the president's emotion significantly affected the returns of U.S. stock markets over the whole period and during the pandemic. Meanwhile, $return_{t-1}$ showed a noticeable impact on the returns of the DJI Index, SP500, and Nasdaq Index of U.S. stock markets during the pandemic and the entire observation period. Additionally, for the whole period, the number of tweets played a necessary role in affecting the returns. In terms of the regression results of volatility, it is worth noting that only for DJI does the sentiment expressed by Trump on Twitter show a significant impact on volatility during the pandemic. That is, there is no noticeable influence of tweets' sentiment on either Chinese indices or U.S. indices. However, $volatility_{t-1}$ affected the volatility of all the indices in both the Chinese stock market and U.S. stock market during the different time phases. More detailed results can be seen in Table 12 in the Appendix.

RESEARCH FINDINGS

The convenience and prevalence of social platforms have changed the way people communicate (Liu, 2020). This includes many political figures. Trump may be the most active politician on the social media platform. In fact, he has been at the center of public opinion since he took office. His sharp words attract attention, inciting both enthusiasm and criticism.

This article concentrates on intraday stock data, focusing on tweets that mention China or the U.S. posted by Trump on Twitter. It finds that these tweets have an influence on the stock markets of both China and the U.S. From the results of the event study, there is a significant immediate effect of the president's tweets on the stock market in both countries. The effect is positive for the U.S. market; it is negative for the Chinese market. That is, the rapid spread of the social network provides immediate information for investors, allowing them to make decision in short time.

Regarding the content of the tweets, for the U.S. stock market, the emotion expressed by Trump shows an obvious impact on the market returns during the pandemic. Then, p values of the sentiment in the regression for the three indices are 0.026, 0.06, and 0.031 (coefficients -0.0076, -0.0067, and -0.0061, respectively). That is, the sentiment expressed in those tweets had a negative impact on the return of the U.S. stock market. In terms of the stock market in China, the main results based on the composite indices do not have perfect performance. However, the number of tweets shows a significant impact on the return of indices during the pandemic, with p values of 0.045, 0.053, and 0.037 (significant at the 5%, 10%, and 5% levels, respectively). Simultaneously, the coefficients are -0.0026, -0.0028, and -0.0031, respectively. This means that the number of tweets posted by Trump on Twitter had a negative effect on the index return. From the regression results, the number of tweets posted by Trump greatly affected the stock market. This is even more significant than the influence of sentiment. That is, investors pay more attention to Trump than to the sentiment expressed in his Twitter texts. Thus, investors could pay more attention to Trump's posting behavior instead of the message content.

From the additional analysis, tweets that mention China had a remarkable impact on the returns of the pharmaceutical industry index during the pandemic and the return of the financial industry index during the China-U.S. trade war period (p values of 0.054 and 0.036, respectively). Moreover, the number of tweets impacted the returns of several indices within Chinese industries. During the pandemic, the number of tweets had a significantly negative impact on the Shanghai Composite Consumption index, with a coefficient and p value of -0.0038 and 0.009, respectively. Regarding the U.S. stock market, the impact of Trump's tweets was significant in many sector indices during the pandemic. For instance, the regression results note that the coefficients of S&P500 Information Technology, S&P500 Industrials, S&P500 Consumers Staples, and S&P500 Consumer Discretionary were -0.0069, -0.0072, -0.0044 and -0.0063, respectively (with p values of 0.021, 0.035, 0.03 and 0.019, respectively). An interesting phenomenon is that the coefficients are negative, which means that Trump's emotion expressed on Twitter had a negative impact on the returns of most of the U.S. industries. It is obvious that a frequency change to one hour does not have a significant effect on the returns of either the Chinese or U.S. stock market related to the sentiment extracted from Trump's tweets. When the researchers used daily data to do the regression, there is not a pronounced impact of the tweets' sentiment on the Chinese stock market. However, the sentiment of Trump's tweet feeds noticeably affected the U.S. stock market during the pandemic, with p-values of 0.035, 0.05, and 0.053 for the three U.S. indices, separately.

CONTRIBUTIONS

Theoretical Contributions

This study connects several strands of literature. First, this study contributes to the literature that focuses on the impact of information stored on social media platforms. To the best of the researchers' knowledge, existing studies focus on the wisdom of the crowd (Azar & Lo, 2016; Chau et al., 2020; Nofer, 2015), paying attention to messages posted by a large number of people on social media. It does not, however, concentrate on an individual's statements on social platforms or investigate the social impact generated by one person. There is both the wisdom of the crowd and the wisdom of one individual.

An individual can produce social influence that is not less than that of the masses. For instance, due to the pandemic, live streaming is now booming in China. Online celebrities like Li Jiaqi affect the development of the industry. Ordinary products can sell through their promotion. The publicity effect is even better than that of ubiquitous advertisements. Thus, it is important to explore the impact of social behavior and comments of an influential celebrity. In fact, it could enrich the strand of research on social media.

While there is no shortage of analytical studies of politicians' statements (Brans & Scholtens, 2020; Colonescu, 2018), prior studies are aimed at connecting views related to a political figure with policies or using them to predict election results (Choy et al., 2012; Tumasjan et al., 2011). Few investigate the relationship between politicians' opinions and the stock market (Ajjoub et al., 2020; Kinyua et al., 2021), particularly foreign stock markets (Guo et al., 2021). They tend to focus on the tweets that mention specific firms (Machus et al., 2022). No studies paid attention to the tweets that mention the name of a nation. Therefore, this article contributes to this strand of the literature by studying whether the view of the unique president is related to stock markets. In addition, it examines whether Trump's tweets associated with China have an impact on Chinese stock markets.

Furthermore, by analyzing the impact of Trump's tweets on the Chinese stock market, this article confirms that a world-class political celebrity can influence politics and global financial markets. The result is consistent with prior studies (Guo et al., 2021). Thus, this study confirms the global influence of the social behavior of a political celebrity, enriching the research on the link between politics and the stock market (Wisniewski, 2016) by examining politicians' opinions on social platforms.

Practical Contributions

This article has implications for financial markets and a political analysis. First, most existing predictions of stock prices focus on machine learning algorithms (Chang et al., 2021). JPMorgan proposed the Volfefe Index to quantify the impact of Trump's tweets on the bond market, linking Trump's shocking online comments with changes in the securities capital market. Considering this study's results, investors can make a brief prediction about the stock price and choose what to invest in based on tweets posted by influential political figures. For instance, when Trump shows negative emotion on his social platforms, investors may see a benefit by investing in the industrial sector. Second, from a political perspective, Trump's tweets have had an evident impact on Chinese financial markets during the trade war. Thus, the relevant departments of each country can take measures to relieve the influence of politicians' statements posted on social media that target a country.

LIMITATIONS AND FUTURE WORK

This article is subject to limitations and, therefore, creates opportunities for research. First, this study analyzes the effect of one political figure's opinions. Future studies could consider social media statements from several politicians. Comparing their impacts can contribute to the universality of the results. Second, the volume of the data is limited, especially the dataset of tweets that mention China, which only contains 384 tweets. Future studies could collect data from various channels like social platforms, public speeches, and interview recordings. Third, the analysis of the content of tweets only considers the counts and sentiment. Future work could focus on identifying the relevant topics and analyzing sentiment from multiple dimensions. Another potentially fruitful avenue of research may be the inclusion of punctuation and emojis in sentiment evaluation as it considers the overall sentiment expressed in those tweets. Furthermore, future work may use machine learning algorithms to uncover the relevant topics within tweets.

REFERENCES

Ajjoub, C., Walker, T., & Zhao, Y. (2020). Social media posts and stock returns: The Trump factor. *International Journal of Managerial Finance*, *17*(2), 185–213. doi:10.1108/IJMF-02-2020-0068

Aldarbesti, H., Deng, H., Sutanto, J., & Wei, C. (2020). Who are more active and influential on Twitter? An investigation of the Ukraine's conflict episode. [JGIM]. *Journal of Global Information Management*, *28*(2), 225–246. doi:10.4018/JGIM.2020040110

Asur, S., & Huberman, B. A. (2010). Predicting the future with social media. *2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology.* IEEE. doi:10.1109/WI-IAT.2010.63

Azar, P. D., & Lo, A. W. (2016). The wisdom of Twitter crowds: Predicting stock market reactions to FOMC meetings via Twitter feeds. *Journal of Portfolio Management*, *42*(5), 123–134. doi:10.3905/jpm.2016.42.5.123

Boiy, E., & Moens, M.-F. (2009). A machine learning approach to sentiment analysis in multilingual Web texts. *Information Retrieval*, *12*(5), 526–558. doi:10.1007/s10791-008-9070-z

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. doi:10.1016/j.jocs.2010.12.007

Brans, H., & Scholtens, B. (2020). Under his thumb the effect of President Donald Trump's Twitter messages on the US stock market. *PLoS One*, *15*(3), e0229931. doi:10.1371/journal.pone.0229931 PMID:32160241

Chang, T.-H., Wang, N., & Chuang, W.-B. (2021). Stock price prediction based on data mining combination model. *Journal of Global Information Management*, *30*(7), 1–19. doi:10.4018/JGIM.296707

Chau, M., Lin, C.-Y., & Lin, T.-C. (2020). Wisdom of crowds before the 2007–2009 global financial crisis. *Journal of Financial Stability*, *48*, 100741. doi:10.1016/j.jfs.2020.100741

Chen, H., De, P., Hu, Y. J., & Hwang, B.-H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies*, *27*(5), 1367–1403. doi:10.1093/rfs/hhu001

Chen, Y., Hu, C., Zhang, W., & Li, Q. (2021). CEO exposure, media influence, and stock returns. *Journal of Global Information Management*, *29*(6), 1–19. doi:10.4018/JGIM.20211101.oa43

Cheng, L.-C., & Yang, Y. (2022). The effect of online reviews on movie box office sales: An integration of aspect-based sentiment analysis and economic modeling. *Journal of Global Information Management*, *30*(1), 1–16. doi:10.4018/JGIM.298652

Choy, M., Cheong, M., Laik, M. N., & Shung, K. P. (2012). US presidential election 2012 prediction using census corrected Twitter model. *arXiv preprint arXiv:1211.0938*.

Coelho, J., D'almeida, D., Coyne, S., Gilkerson, N., Mills, K., & Madiraju, P. (2019). Social media and forecasting stock price change. *2019 IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC).* IEEE.

Colonescu, C. (2018). The effects of Donald Trump's tweets on US financial and foreign exchange markets. *Athens Journals.*

Coyne, S., Madiraju, P., & Coelho, J. (2017). Forecasting stock prices using social media analysis. 2017 *IEEE 15th International Conference on Dependable, Autonomic and Secure Computing.* IEEE.

Da, Z., & Huang, X. (2020). Harnessing the wisdom of crowds. *Management Science*, *66*(5), 1847–1867. doi:10.1287/mnsc.2019.3294

Ge, Q., Kurov, A., & Wolfe, M. H. (2019). Do investors care about presidential company-specific tweets? *Journal of Financial Research*, *42*(2), 213–242. doi:10.1111/jfir.12177

Guo, S., Jiao, Y., & Xu, Z. (2021). Trump's effect on the Chinese stock market. *Journal of Asian Economics*, *72*, 101267. doi:10.1016/j.asieco.2020.101267

Iftikhar, R., & Khan, M. S. (2020). Social media big data analytics for demand forecasting: Development and case implementation of an innovative framework. *Journal of Global Information Management*, *28*(1), 103–120. doi:10.4018/JGIM.2020010106

Jin, X., Wang, J., Tan, J., & Li, Q. (2022). Media platforms and stock performance: Evidence from Internet news. *Journal of Global Information Management*, *30*(1), 1–25. doi:10.4018/JGIM.315611

Juma'h, A., & Alnsour, Y. (2018). Using social media analytics: The effect of President Trump's tweets on companies' performance. *Journal of Accounting and Management Information Systems*, *17*(1), 100–121. doi:10.24818/jamis.2018.01005

Kannan, A., Mohanty, G., & Mamidi, R. (2016). Towards building a SentiWordNet for Tamil. *Proceedings of the 13th International Conference on Natural Language Processing.*

Kinyua, J. D., Mutigwe, C., Cushing, D. J., & Poggi, M. (2021). An analysis of the impact of President Trump's tweets on the DJIA and S&P 500 using machine learning and sentiment analysis. *Journal of Behavioral and Experimental Finance*, *29*, 100447. doi:10.1016/j.jbef.2020.100447

Liu, Y. (2020). Manipulating temporal cues and message concreteness for deal communication: A study on microblogging site. *Journal of Global Information Management*, *28*(2), 111–130. doi:10.4018/JGIM.2020040106

Machus, T., Mestel, R., & Theissen, E. (2022). Heroes, just for one day: The impact of Donald Trump's tweets on stock prices. *Journal of Behavioral and Experimental Finance*, *33*, 100594. doi:10.1016/j.jbef.2021.100594

Nam, T., & Kabutey, R. (2021). How does social media use influence the relationship between emotional labor and burnout? The case of public employees in Ghana. *Journal of Global Information Management*, *29*(4), 32–52. doi:10.4018/JGIM.20210701.oa2

Nicolau, J. L., Sharma, A., & Shin, S. (2020). The tourism effect of President Trump's participation on Twitter. *Tourism Management*, *81*, 104133. doi:10.1016/j.tourman.2020.104133

Nofer, M. (2015). Are crowds on the Internet wiser than experts? The case of a stock prediction community. In *The value of social media for predicting stock returns* (pp. 27–61). Springer. doi:10.1007/978-3-658-09508-6_3

Qi, G., Hou, L., Chen, J., Liang, Y., & Zhang, Q. (2021). How does user social network improve innovation outcomes on a virtual innovation platform? Evidence from LEGO ideas platform. *Journal of Global Information Management*, *29*(3), 188–211. doi:10.4018/JGIM.2021050108

Risius, M., Akolk, F., & Beck, R. (2015). *Differential emotions and the stock market-the case of company-specific trading*.

Sul, H. K., Dennis, A. R., & Yuan, L. (2017). Trading on twitter: Using social media sentiment to predict stock returns. *Decision Sciences*, *48*(3), 454–488. doi:10.1111/deci.12229

Surowiecki, J. (2005). *The wisdom of crowds*. Anchor.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., & Welpe, I. M. (2011). Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social Science Computer Review*, *29*(4), 402–418. doi:10.1177/0894439310386557

Wisniewski, T. P. (2016). Is there a link between politics and stock returns? A literature survey. *International Review of Financial Analysis*, *47*, 15–23. doi:10.1016/j.irfa.2016.06.015

Yang, S. Y., Mo, S. Y. K., & Liu, A. (2015). Twitter financial community sentiment and its predictive relationship to stock market movement. *Quantitative Finance*, *15*(10), 1637–1656. doi:10.1080/14697688.2015.1071078

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through twitter "I hope it is not as bad as I fear.". *Procedia: Social and Behavioral Sciences*, *26*, 55–62. doi:10.1016/j.sbspro.2011.10.562

Zhang, Y., An, Y., Feng, X., & Jin, X. (2017). Celebrities and ordinaries in social networks: Who knows more information? *Finance Research Letters*, *20*, 153–161. doi:10.1016/j.frl.2016.09.021

ENDNOTES

[1] https://p.dw.com/p/3HzsE

APPENDIX

Table 10a. Regression results of tweets mentioning U.S.: industry analysis (return)

	ALL										
	BankX	COND	CONS	ENRS	FINL	HLTH	INDU	INFT	MATR	TELS	UTIL
α	0.0018	0.0012	0.0009	-0.0001	0.0015	0.0013**	0.001	0.0013	0.001	0.0011	0.0017**
	(1.41)	(1.51)	(1.55)	(-0.087)	(1.51)	(1.99)	(1.10)	(1.44)	(1.12)	(1.36)	(2.33)
sentiment	-0.0013	-0.0007	-0.0005	-0.0003	-0.001	-0.0005	-0.0008	-0.001*	-0.0004	-0.0006	-0.0007
	(-1.58)	(-1.251)	(-1.393)	(-0.321)	(-1.537)	(-1.19)	(-1.322)	(-1.654)	(-0.739)	(-1.129)	(-1.316)
$return_{t-1}$	0.1081	0.1744	0.2064	0.3913**	0.1123	0.1596	0.254	0.1143	0.1985	0.1745	0.073
	(0.68)	(1.21)	(1.60)	(2.50)	(0.74)	(1.24)	(1.62)	(0.76)	(1.22)	(1.22)	(0.51)
Number of	3.97E-05	-1.65E-05	1.27E-05	0.0002	5.77E-06	-2.05E-05	-1.16E-05	-0.0001	-5.16E-05	-0.0001	-2.15E-05
Tweets	(0.21)	(-0.137)	(0.15)	(1.30)	(0.04)	(-0.209)	(-0.082)	(-1.018)	(-0.392)	(-1.103)	(-0.19)
Number of	-3.51E-05	-1.77E-05	-1.71E-05	-1.71E-05	-2.91E-05	-0.000028*	-1.84E-05	-8.65E-06	-1.75E-05	-1.46E-05	-0.000047**
Words	(-1.104)	(-0.878)	(-1.174)	(-0.539)	(-1.16)	(-1.686)	(-0.77)	(-0.375)	(-0.788)	(-0.734)	(-2.476)

	During the Trade War										
	BankX	COND	CONS	ENRS	FINL	HLTH	INDU	INFT	MATR	TELS	UTIL
α	0.0013*	0.0003	0.0002	-0.0002	0.0009	0.0003	0.0002	4.42E-05	9.43E-05	0.0006	0.0008*
	(1.72)	(0.45)	(0.62)	(-0.276)	(1.53)	(0.71)	(0.28)	(0.06)	(0.16)	(0.93)	(1.92)
sentiment	-0.0003	9.50E-05	7.69E-06	0.0003	-0.0002	-1.22E-06	-1.44E-05	-0.0002	2.18E-05	-0.0001	7.96E-06
	(-0.596)	(0.25)	(0.03)	(0.61)	(-0.503)	(-0.004)	(-0.037)	(-0.393)	(0.06)	(-0.338)	(0.03)
$return_{t-1}$	0.0238	-0.0362	0.0073	0.0369	0.0403	0.1388	0.063	-0.0253	0.0984	-0.0363	0.1515
	(0.16)	(-0.244)	(0.05)	(0.21)	(0.28)	(1.07)	(0.39)	(-0.148)	(0.60)	(-0.236)	(1.26)
Number of	-1.04E-06	1.98E-05	3.76E-05	0.0003**	-2.04E-06	-2.50E-05	-8.45E-05	-5.41E-06	-8.41E-05	-4.13E-05	-7.82E-05
Tweets	(-0.009)	(0.23)	(0.64)	(2.32)	(-0.023)	(-0.38)	(-0.934)	(-0.052)	(-0.937)	(-0.46)	(-1.326)
Number of	-2.04E-05	1.46E-06	-4.26E-06	-6.76E-06	-1.39E-05	-3.35E-06	5.80E-06	1.44E-05	7.02E-06	-4.00E-06	-0.000021**
Words	(-1.084)	(0.10)	(-0.425)	(-0.341)	(-0.902)	(-0.297)	(0.37)	(0.80)	(0.46)	(-0.259)	(-2.056)

	During the COVID-19 pandemic										
	BankX	COND	CONS	ENRS	FINL	HLTH	INDU	INFT	MATR	TELS	UTIL
α	0.0061	0.0069**	0.0049*	0.0032	0.006	0.0067**	0.006	0.0094**	0.0059	0.0054*	0.0071*
	(1.04)	(2.07)	(1.93)	(0.56)	(1.31)	(2.35)	(1.42)	(2.52)	(1.52)	(1.68)	(1.96)
sentiment	-0.0098**	-0.0066**	-0.0047**	-0.0055	-0.0077**	-0.0047**	-0.0075**	-0.0073**	-0.0043	-0.0044*	-0.0061**
	(-2.096)	(-2.459)	(-2.32)	(-1.202)	(-2.111)	(-2.055)	(-2.218)	(-2.454)	(-1.396)	(-1.698)	(-2.127)
$return_{t-1}$	0.1069	0.3009	0.3038	0.4991	0.092	0.1625	0.3177	0.1693	0.2234	0.3029	-0.0466
	(0.28)	(0.89)	(1.04)	(1.44)	(0.26)	(0.55)	(0.89)	(0.52)	(0.59)	(0.93)	(-0.133)
Number of	0.0003	-0.0003	-0.0002	-1.98E-05	1.31E-05	-7.92E-05	0.0004	-0.001*	6.12E-05	-0.0008	0.0003
Tweets	(0.28)	(-0.502)	(-0.403)	(-0.02)	(0.02)	(-0.164)	(0.56)	(-1.671)	(0.09)	(-1.425)	(0.46)
Number of	-0.0001	-0.0001	-9.61E-05	-0.0001	-0.0001	-0.0002**	-0.0002	-0.0002*	-0.0001	-0.0001	-0.0002**
Words	(-0.965)	(-1.577)	(-1.5)	(-0.789)	(-1.179)	(-2.194)	(-1.406)	(-1.694)	(-1.497)	(-1.241)	(-2.041)

Table 10b. Regression results of tweets mentioning U.S.: industry analysis (volatility)

	ALL										
	BankX	COND	CONS	ENRS	FINL	HLTH	INDU	INFT	MATR	TELS	UTIL
α	0.0058***	0.0038***	0.0025***	0.0058***	0.0047***	0.003***	0.0046***	0.0041***	0.0041***	0.0039***	0.0033***
	(6.79)	(7.13)	(6.36)	(6.85)	(6.83)	(6.96)	(6.95)	(7.16)	(7.16)	(7.89)	(5.87)
sentiment	-0.0009*	-0.0006*	-0.0005*	-0.0009	-0.0008*	-0.0006**	-0.0008*	-0.0007*	-0.0006	-0.0005*	-0.0006*
	(-1.691)	(-1.799)	(-1.825)	(-1.603)	(-1.719)	(-2.001)	(-1.752)	(-1.945)	(-1.516)	(-1.7)	(-1.685)
$volatility_{t-1}$	-0.0953	-0.262***	0.1139	-0.0751	-0.1185	-0.1328	-0.2786**	-0.2704***	-0.1061	-0.2889***	0.2012**
	(-1.015)	(-2.688)	(1.40)	(-0.738)	(-1.257)	(-1.483)	(-2.549)	(-2.739)	(-1.253)	(-3.052)	(2.09)
Number of Tweets	0.0009***	0.0006***	0.0004***	0.0009***	0.0007***	0.0005***	0.0007***	0.0007***	0.0007***	0.0006***	0.0004***
	(6.97)	(7.20)	(6.24)	(6.97)	(6.64)	(6.74)	(6.46)	(7.98)	(7.62)	(7.84)	(4.66)
Number of Words	-1.30E-05	5.67E-06	3.62E-06	-1.20E-05	-8.28E-06	4.75E-06	-3.49E-06	1.05E-05	-4.13E-06	6.19E-06	-6.89E-06
	(-0.604)	(0.43)	(0.37)	(-0.561)	(-0.476)	(0.43)	(-0.212)	(0.74)	(-0.283)	(0.51)	(-0.486)

	During the Trade War										
	BankX	COND	CONS	ENRS	FINL	HLTH	INDU	INFT	MATR	TELS	UTIL
α	0.004***	0.0029***	0.0025***	0.0043***	0.0034***	0.0025***	0.0033***	0.0034***	0.0034***	0.0035***	0.0026***
	(11.53)	(8.94)	(12.73)	(11.52)	(12.02)	(11.81)	(11.15)	(9.56)	(11.71)	(11.17)	(14.90)
sentiment	-0.0003	-0.0002	-0.0001	-0.0002	-0.0003	-0.0002*	-0.0002	-0.0003	-0.0001	-0.0002	-0.0001
	(-1.445)	(-1.249)	(-1.137)	(-0.97)	(-1.447)	(-1.879)	(-1.129)	(-1.392)	(-0.792)	(-0.997)	(-1.062)
$volatility_{t-1}$	-0.978***	-0.8021***	-1.0932***	-1.0742***	-1.0227***	-0.9396***	-1.0649***	-0.8902***	-1.0841***	-0.9411***	-0.8955***
	(-11.674)	(-8.624)	(-12.794)	(-12.077)	(-12.139)	(-11.498)	(-11.999)	(-9.905)	(-12.158)	(-10.463)	(-13.171)
Number of Tweets	0.0006***	0.0005***	0.0002***	0.0006***	0.0005***	0.0003***	0.0005***	0.0006***	0.0005***	0.0005***	0.0002***
	(11.69)	(9.67)	(7.82)	(11.16)	(10.83)	(9.87)	(10.43)	(10.69)	(10.67)	(10.19)	(7.41)
Number of Words	0.000017**	0.000016**	0.0000104**	1.40E-05	0.00001355*	0.00001375***	0.00001536**	0.00001934**	1.13E-05	1.15E-05	0.000008469**
	(1.99)	(2.07)	(2.23)	(1.54)	(1.96)	(2.66)	(2.15)	(2.20)	(1.59)	(1.52)	(2.07)

	During the COVID-19 pandemic										
	BankX	COND	CONS	ENRS	FINL	HLTH	INDU	INFT	MATR	TELS	UTIL
α	0.0109***	0.0063***	0.004**	0.0112***	0.0086***	0.0052***	0.0085***	0.0065***	0.0069***	0.0056***	0.0069***
	(3.10)	(3.04)	(2.40)	(3.25)	(3.00)	(2.87)	(3.09)	(2.83)	(2.90)	(2.84)	(2.78)
sentiment	-0.0024	-0.0016	-0.0015	-0.0023	-0.002	-0.0015	-0.0023	-0.0019	-0.0015	-0.0016	-0.0023
	(-0.839)	(-0.983)	(-1.151)	(-0.857)	(-0.86)	(-1.037)	(-1.04)	(-1.064)	(-0.784)	(-1.002)	(-1.176)
$volatility_{t-1}$	-0.3718**	-0.4717**	0.0038	-0.4334**	-0.3836**	-0.3547*	-0.5799**	-0.3641	-0.2351	-0.3224	-0.1372
	(-1.956)	(-2.249)	(0.02)	(-2.066)	(-2)	(-1.869)	(-2.475)	(-1.6)	(-1.381)	(-1.511)	(-0.662)
Number of Tweets	0.0021***	0.0011***	0.0007**	0.0019***	0.0016***	0.0009***	0.0014***	0.0011***	0.0014***	0.0009***	0.001**
	(3.45)	(2.98)	(2.25)	(3.17)	(3.30)	(2.72)	(2.94)	(2.79)	(3.38)	(2.78)	(2.29)
Number of Words	3.10E-05	4.22E-05	3.55E-05	4.35E-05	3.35E-05	4.34E-05	3.49E-05	4.88E-05	3.07E-05	4.14E-05	3.14E-05
	(0.34)	(0.80)	(0.83)	(0.50)	(0.46)	(0.94)	(0.50)	(0.84)	(0.51)	(0.83)	(0.50)

Table 11a. Regression results of tweets mentioning China: industry analysis (return)

	ALL									
	Energy	Materials	Industrials	ConsumerDiscretionary	ConsumerStaples	HealthCare	Financials	Information Technology	Telecommunication	Utilities
α	0.0006	-0.0013	-0.0023	-0.0007	0.002	0.002	-0.0026	0.0005	-0.0019	-0.0007
	(0.19)	(-0.424)	(-0.754)	(-0.214)	(0.64)	(0.72)	(-0.901)	(0.12)	(-0.435)	(-0.288)
sentiment	-0.0009	-0.0008	-0.0003	-0.0004	0.0002	-0.0014	0.0011	-0.0007	0.0006	-0.0011
	(-0.547)	(-0.441)	(-0.192)	(-0.232)	(0.13)	(-0.916)	(0.66)	(-0.282)	(0.26)	(-0.779)
$return_{t-1}$	0.1392	0.1226	0.6025	0.2365	0.2655	0.117	0.299	-0.0365	0.0088	0.0093
	(0.33)	(0.32)	(1.44)	(0.62)	(0.64)	(0.34)	(1.05)	(-0.099)	(0.02)	(0.02)
Number of Tweets	-0.0006*	-0.0007**	-0.0007**	-0.0008**	-0.0008**	-0.0004	-0.0006**	-0.0004	-0.001**	-0.0006**
	(-1.851)	(-2.038)	(-2.049)	(-2.163)	(-2.222)	(-1.202)	(-1.997)	(-0.978)	(-2.239)	(-2.194)
Number of Words	-1.32E-05	6.13E-05	7.03E-05	3.50E-05	-4.73E-05	-3.25E-05	7.76E-05	2.14E-05	7.57E-05	2.78E-05
	(-0.196)	(0.88)	(1.00)	(0.47)	(-0.654)	(-0.513)	(1.17)	(0.22)	(0.78)	(0.51)

	During the Trade War									
	Energy	Materials	Industrials	ConsumerDiscretionary	ConsumerStaples	HealthCare	Financials	Information Technology	Telecommunication	Utilities
α	0.0052**	0.0016	0.0002	0.003	0.0036	-0.0001	0.0005	0.0035	0.0012	0.0015
	(2.14)	(0.63)	(0.08)	(1.09)	(1.20)	(-0.044)	(0.17)	(0.88)	(0.31)	(0.90)
sentiment	0.0007	0.0009	0.0021	0.0018	0.0026	0.0004	0.0034**	0.0018	0.0033	0.0001
	(0.46)	(0.64)	(1.43)	(1.14)	(1.52)	(0.24)	(2.11)	(0.81)	(1.41)	(0.11)
$return_{t-1}$	-0.2562	0.1356	0.2068	-0.0445	-0.1404	0.3324	-0.0175	0.0492	0.2182	-0.2006
	(-0.694)	(0.43)	(0.58)	(-0.136)	(-0.332)	(0.80)	(-0.066)	(0.12)	(0.47)	(-0.585)
Number of Tweets	-0.0004	-0.0005*	-0.0004*	-0.0004	-0.0004	-0.0002	-0.0004	-6.55E-05	-0.0006	-0.0003*
	(-1.559)	(-1.79)	(-1.694)	(-1.617)	(-1.222)	(-0.791)	(-1.544)	(-0.168)	(-1.616)	(-1.916)
Number of Words	-0.0001**	-1.14E-05	9.31E-06	-6.40E-05	-0.0001	-1.18E-05	-1.58E-06	-7.06E-05	-2.07E-05	-2.44E-05
	(-2.102)	(-0.197)	(0.17)	(-1.027)	(-1.558)	(-0.168)	(-0.025)	(-0.792)	(-0.227)	(-0.633)

	During the COVID-19 pandemic									
	Energy	Materials	Industrials	ConsumerDiscretionary	ConsumerStaples	HealthCare	Financials	Information Technology	Telecommunication	Utilities
α	-0.012	-0.0101	-0.0063	-0.0086	0.0033	0.0085	-0.0088	-0.0068	-0.0108	-0.0053
	(-1.231)	(-0.993)	(-0.6)	(-0.819)	(0.35)	(1.29)	(-1.039)	(-0.524)	(-0.849)	(-0.598)
sentiment	-0.0067	-0.0072	-0.008	-0.0075	-0.0064	-0.0065*	-0.0058	-0.0095	-0.0093	-0.0055
	(-1.384)	(-1.43)	(-1.537)	(-1.406)	(-1.319)	(-1.974)	(-1.385)	(-1.469)	(-1.473)	(-1.293)
$return_{t-1}$	0.0236	-0.7651	0.4827	0.3818	0.4598	-0.3015	0.8314	-0.3455	-0.6176	-0.2669
	(0.02)	(-0.639)	(0.42)	(0.33)	(0.43)	(-0.472)	(0.98)	(-0.439)	(-0.783)	(-0.239)
Number of Tweets	-0.0022	-0.0022	-0.003*	-0.003*	-0.0037***	-0.0012	-0.0024*	-0.003	-0.0036*	-0.0025*
	(-1.562)	(-1.488)	(-1.956)	(-1.959)	(-2.7)	(-1.29)	(-1.972)	(-1.594)	(-1.951)	(-1.99)
Number of Words	0.0003	0.0003	0.0002	0.0003	5.89E-05	-9.78E-05	0.0003	0.0003	0.0004	0.0002
	(1.45)	(1.41)	(1.01)	(1.35)	(0.29)	(-0.683)	(1.54)	(1.04)	(1.38)	(0.98)

Table 11b. Regression results of tweets mentioning China: industry analysis (volatility)

	ALL									
	Energy	Materials	Industrials	ConsumerDiscretionary	ConsumerStaples	HealthCare	Financials	Information Technology	Telecommunication	Utilities
α	0.0054***	0.0057***	0.0049***	0.0064***	0.0065***	0.0063***	0.0056***	0.0104***	0.0101***	0.0029***
	(5.12)	(4.55)	(4.22)	(5.41)	(5.40)	(6.66)	(5.82)	(7.68)	(7.30)	(3.06)
sentiment	-0.0004	-0.0002	-0.0005	-0.0006	-3.16E-05	-0.0002	-0.0005	-0.0005	-0.0009	-0.0001
	(-0.724)	(-0.333)	(-0.861)	(-0.896)	(-0.05)	(-0.475)	(-1.027)	(-0.689)	(-1.202)	(-0.29)
$volatility_{t-1}$	0.4536	-0.0935	0.0777	-0.2324	-0.1937	-0.1689	0.1435	-0.7137**	-0.4237	0.6001
	(1.25)	(-0.285)	(0.21)	(-0.651)	(-0.56)	(-0.609)	(0.50)	(-2.545)	(-1.603)	(1.46)
Number of Tweets	0.0001	0.0002*	0.0002	0.0002*	0.0002	0.0001	0.0002**	0.0002	0.0002*	3.90E-05
	(1.22)	(1.72)	(1.58)	(1.89)	(1.64)	(1.52)	(2.17)	(1.19)	(1.67)	(0.44)
Number of Words	1.61E-05	2.85E-05	3.55E-05	2.85E-05	3.43E-05	2.68E-05	2.09E-05	2.45E-05	2.03E-05	2.71E-05
	(0.77)	(1.08)	(1.48)	(1.15)	(1.36)	(1.37)	(1.06)	(0.88)	(0.71)	(1.46)

	During the Trade War									
	Energy	Materials	Industrials	ConsumerDiscretionary	ConsumerStaples	HealthCare	Financials	Information Technology	Telecommunication	Utilities
α	0.0053	0.0043	0.0037	0.0051	0.0051	0.0049	0.005	0.0089	0.0085	0.0029
	(6.54)	(4.35)	(4.44)	(5.68)	(4.49)	(5.30)	(6.04)	(7.41)	(7.04)	(4.97)
sentiment	-0.0004	-0.0003	-0.0005	-0.0004	-0.0001	-0.0003	-0.0005	-0.0005	-0.0008	-8.05E-05
	(-0.861)	(-0.509)	(-1.166)	(-0.79)	(-0.209)	(-0.606)	(-1.258)	(-0.808)	(-1.19)	(-0.277)
$volatility_{t-1}$	0.1718	0.1533	0.293	0.015	0.3116	0.1554	0.1546	-0.5415	-0.1834	0.2667
	(0.63)	(0.63)	(1.07)	(0.05)	(0.95)	(0.55)	(0.64)	(-2.039)	(-0.764)	(1.11)
Number of Tweets	0.0001	0.0002	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002	0.0003	5.34E-05
	(1.78)	(2.59)	(2.79)	(2.85)	(1.92)	(1.52)	(2.66)	(1.87)	(2.37)	(1.06)
Number of Words	1.91E-05	3.84E-05	4.08E-05	3.51E-05	4.61E-05	4.60E-05	2.88E-05	3.07E-05	2.63E-05	2.78E-05
	(1.20)	(1.87)	(2.38)	(1.90)	(1.94)	(2.44)	(1.71)	(1.30)	(1.07)	(2.46)

	During the COVID-19 pandemic									
	Energy	Materials	Industrials	ConsumerDiscretionary	ConsumerStaples	HealthCare	Financials	Information Technology	Telecommunication	Utilities
α	0.0052	0.0097	0.0086	0.0104	0.0099	0.0096	0.0071	0.0161	0.0149	0.0031
	(1.44)	(2.36)	(2.14)	(2.59)	(2.75)	(3.51)	(2.22)	(4.34)	(3.72)	(0.86)
sentiment	-0.001	0.0017	0.0011	0.0008	0.0013	0.0005	-0.0002	0.002	0.0009	-0.0003
	(-0.554)	(0.76)	(0.48)	(0.36)	(0.69)	(0.38)	(-0.129)	(1.05)	(0.45)	(-0.18)
$volatility_{t-1}$	2.4682	-1.3879	-1.0295	-1.2213	-1.7104	-0.8476	0.4255	-1.982	-1.5814	2.1561
	(1.69)	(-1.011)	(-0.742)	(-1.111)	(-1.693)	(-1.189)	(0.38)	(-3.01)	(-2.264)	(1.14)
Number of Tweets	0.0003	0.0002	7.98E-05	0.0003	0.0002	0.0002	0.0003	1.79E-05	0.0002	5.55E-05
	(0.60)	(0.41)	(0.14)	(0.54)	(0.40)	(0.56)	(0.71)	(0.03)	(0.28)	(0.12)
Number of Words	-2.14E-05	1.08E-05	2.17E-05	4.73E-06	6.23E-06	-2.24E-05	-1.21E-05	1.97E-05	1.68E-05	1.77E-06
	(-0.29)	(0.12)	(0.25)	(0.06)	(0.08)	(-0.387)	(-0.183)	(0.25)	(0.20)	(0.03)

Table 12a. Regression results of tweets : frequency of one hour (return)

	ALL			During the Trade War			During the COVID-19 pandemic		
	SSEC	CSI300	SZI	SSEC	CSI300	SZI	SSEC	CSI300	SZI
α	9.10E-05	-0.0005	0.0015	0.0024	0.0026	0.0032	-0.0076	-0.0108	-0.0048
	(0.03)	(-0.135)	(0.38)	(0.81)	(0.78)	(0.84)	(-0.816)	(-1.04)	(-0.434)
sentiment	0.0002	0.0006	0.0003	0.0028*	0.0033*	0.0035	-0.0086*	-0.0089	-0.0101*
	(0.13)	(0.32)	(0.14)	(1.67)	(1.70)	(1.58)	(-1.775)	(-1.647)	(-1.743)
$return_{t-1}$	0.1701	0.1429	0.0721	0.2249	0.1613	0.153	0.1335	0.1757	0.0249
	(1.12)	(0.89)	(0.46)	(1.41)	(0.94)	(0.83)	(0.40)	(0.50)	(0.08)
Number of Tweets	-0.0005	-0.0006	-0.0005	-0.0003	-0.0004	-0.0003	-0.0021	-0.0021	-0.0022
	(-1.544)	(-1.531)	(-1.287)	(-1.007)	(-1.075)	(-0.816)	(-1.657)	(-1.494)	(-1.449)
Number of Words	1.82E-05	4.14E-05	1.63E-05	-4.88E-05	-3.98E-05	-4.44E-05	0.0003	0.0003	0.0002
	(0.25)	(0.51)	(0.18)	(-0.73)	(-0.519)	(-0.51)	(1.29)	(1.46)	(1.01)

Table 12b. Regression results of tweets: frequency of one hour (volatility)

	ALL			During the Trade War			During the COVID-19 pandemic		
	SSEC	CSI300	SZI	SSEC	CSI300	SZI	SSEC	CSI300	SZI
α	0.006***	0.0072***	0.0068***	0.0051***	0.006***	0.0063***	0.008***	0.0099***	0.0095***
	(6.66)	(7.51)	(6.43)	(6.77)	(6.85)	(6.54)	(2.72)	(3.42)	(2.94)
sentiment	-0.0002	-0.0004	-0.0004	-0.0004	-0.0004	-0.0006	0.0008	0.0005	0.0007
	(-0.509)	(-0.709)	(-0.763)	(-1.182)	(-0.924)	(-1.204)	(0.58)	(0.34)	(0.42)
$volatility_{t-1}$	0.1637	0.1158	0.2923***	0.2977***	0.288**	0.2852**	-0.0396	-0.1297	0.1607
	(1.44)	(1.02)	(2.66)	(2.69)	(2.48)	(2.48)	(-0.148)	(-0.517)	(0.65)
Number of Tweets	0.0001	0.0002	0.0002	0.0002**	0.0002**	0.0002**	-3.40E-05	6.18E-05	-3.44E-05
	(1.41)	(1.63)	(1.64)	(2.42)	(2.40)	(2.59)	(-0.085)	(0.16)	(-0.08)
Number of Words	1.74E-05	1.54E-05	1.98E-05	1.66E-05	1.66E-05	2.10E-05	1.65E-05	1.03E-05	1.13E-05
	(0.93)	(0.77)	(0.92)	(1.12)	(0.97)	(1.15)	(0.26)	(0.16)	(0.16)

Table 13a. Regression results of tweets: daily data (return)

	ALL			During the Trade War			During the COVID-19 pandemic		
	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ
α	0.0016	0.0013	0.0012	0.0004	0.0001	-8.27E-05	0.0093*	0.0088*	0.0087*
	(1.42)	(1.27)	(1.14)	(0.54)	(0.18)	(-0.1)	(1.88)	(1.91)	(1.95)
sentiment	-0.0008	-0.0006	-0.0004	5.88E-06	0.0001	0.0002	-0.0059	-0.0047	-0.004
	(-1.073)	(-0.821)	(-0.615)	(0.01)	(0.34)	(0.47)	(-1.524)	(-1.292)	(-1.144)
$return_{t-1}$	-0.1864***	-0.2516***	-0.2535***	0.0484	0.0437	0.0129	-0.2134*	-0.2945***	-0.3128***
	(-3.525)	(-4.818)	(-4.718)	(0.74)	(0.68)	(0.19)	(-1.876)	(-2.62)	(-2.807)
Number of Tweets	-0.0002	-0.0001	-0.0002	-3.28E-05	-1.34E-05	-3.56E-05	-0.001	-0.001	-0.001
	(-0.989)	(-1.007)	(-1.13)	(-0.34)	(-0.147)	(-0.313)	(-1.302)	(-1.451)	(-1.462)
Number of Words	-3.19E-05	-2.40E-05	-1.80E-05	-7.84E-06	-1.59E-06	4.69E-06	-0.0002	-0.0002	-0.0002
	(-1.14)	(-0.919)	(-0.652)	(-0.441)	(-0.095)	(0.22)	(-1.504)	(-1.491)	(-1.415)

Table 13b. Regression results of tweets: daily data (volatility)

	ALL			During the Trade War			During the COVID-19 pandemic		
	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ	DJIA	SPX	NASDAQ
α	0.0027***	0.0023***	0.0027***	0.0029***	0.0026***	0.0037***	0.0055**	0.0047**	0.0043**
	(4.63)	(4.20)	(5.00)	(9.03)	(8.32)	(9.41)	(2.23)	(2.05)	(2.00)
sentiment	-0.0003	-0.0003	-0.0003	-0.0001	-0.0001	-0.0002	-0.0015	-0.0012	-0.001
	(-0.885)	(-0.896)	(-0.982)	(-0.646)	(-0.829)	(-0.848)	(-0.813)	(-0.7)	(-0.617)
$volatility_{t-1}$	0.7985***	0.8178***	0.7159***	0.1643***	0.1971***	0.0293	0.6905***	0.7179***	0.7482***
	(21.07)	(22.15)	(19.20)	(3.01)	(3.69)	(0.55)	(7.74)	(8.27)	(9.04)
Number of Tweets	0.0006***	0.0006***	0.0007***	0.0004***	0.0004***	0.0005***	0.0012***	0.0012***	0.0011***
	(7.39)	(7.62)	(9.09)	(9.53)	(9.86)	(9.81)	(3.25)	(3.29)	(3.43)
Number of Words	-0.00002471*	-2.09E-05	-1.50E-05	6.24E-06	7.31E-06	1.15E-05	-3.70E-05	-2.97E-05	-2.93E-05
	(-1.736)	(-1.566)	(-1.105)	(0.82)	(1.00)	(1.24)	(-0.589)	(-0.507)	(-0.541)

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