The Immediate Financial Impact of Donald Trump's Tweets Related to China During the U.S.-China Trade War

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Abstract: This thesis explores the impact of Donald Trump's tweets related to China on the financial markets in the United States and China, particularly during the U.S.-China trade war period. The study collects financial variables of interest, including the USC-CNY exchange rate and several stock indices from both countries, at hourly intervals from January 2018 to December 2020, and uses OLS regression models to examine the immediate impact of Trump's tweets on these variables. The study finds that Trump's tweets related to China had an immediate impact on several financial variables, including a slight negative impact on the USD-CNY exchange rate, the U.S. stock market (S&P 500), the Chinese A-share stock market (CSI 300), and the U.S. industrials sector (MSCI USA Industrials index). Multiple regression analyses show that the number of tweets has a significant impact on the U.S. stock market and the U.S. industrials sector, while the number of retweets appears to be more market-moving than the number of favorites. The study concludes that Trump's tweets during the trade war period were perceived by the market as a signal of a potential shift in U.S. trade policy towards China, leading to uncertainty and volatility in the financial markets.

1 Introduction

Over the past few years, the global economy has seen a series of economic conflicts and trade disputes between the United States and China, which began in March 2018, when U.S. former president Donald Trump signed a memorandum directing several sanctions on China, including imposing tariffs on Chinese products and restricting investments in key technology sectors. These conflicts engendered a full-fledged trade war which was later known internationally as the United States-China trade war. The U.S.-China trade war continued furiously for almost two years, eventually leading to tariffs on some US $550 billion of Chinese goods and US$185 billion of US goods until the two nations reached a tense phase one agreement on January 2020. (Mullen, 2022) Yet, the tariffs continued through Biden's administration.

The impact of social media on various aspects of our lives cannot be underestimated. In recent years, the world has witnessed how social media has been utilized by politicians to communicate with their constituents and the wider audience. Former U.S. President, Donald Trump, was a notable example of this trend. During his presidency from 2017 to 2020, Donald Trump was keen on attempting to create a strong social network of support through the social media platform Twitter, and he was particularly passionate about posting Tweets relating to China. Trump's Tweets during the U.S.-China trade war were highly influential and controversial, which often contained bold and aggressive statements about China's trade practices and policies.

This thesis explores whether Donald Trump's public communication through Twitter on the topic of China had generated any immediate impact on the foreign exchange market and stock markets in both countries during the U.S.-China trade war, as reflected in the percent changes of the USD-CNY exchange rate and several stock indices the hour before the post and the hour after. This is one aspect to reflect and quantify mass reaction towards Trump's tweets. The thesis also analyzes whether Trump posting multiple tweets in a row, or these tweets receiving more likes and retweets, have contributed to exaggerating these financial impacts.

By analyzing the fluctuations in stock prices and exchange rates, the research will provide insights into whether the government using social media platforms to announce threats has the potential of shaping the public's opinion and thus affecting the financial statistics.

Through retrospecting back to the dramatic trade war that occurred in the near past, the research would be helpful for us to understand the potential influence of the governments' rhetorical threats on social media platforms, in the Internet era where social media contributes significantly to shaping people's opinions and causing fluctuations in the financial market. The findings of this study will be useful for policymakers, investors, and other stakeholders who are interested in understanding the impact of social media on the economy. Furthermore, this research will contribute to the existing literature on the US-China trade war and the role of social media in shaping international relations.

The overall question of how Donald Trump's social media activity on China impacted the mass society is a broad question to analyze, as it involved many related factors. One way to quantify the public's preferences and opinions is by looking at the changes in economics and financial statistics related to trade. The macroeconomic statistics, such as gross domestic product (GDP) and net exports, are usually released quarterly, while Trump's activities on social media platforms, are posted frequently and can cause a subtle but immediate impact. Therefore, it is difficult to analyze the actual long-term economic impact of these posts at the broad level using measures of macroeconomic activity like GDP and net export. Consequently, for my methodology of the research, I utilize financial variables that are updated continuously or by high frequency, including the USD-CNY exchange rate and various indices of the stock markets in the U.S. and China. I believe fluctuations in these financial variables is one aspect to reflect changes in the public's preferences and the macroeconomic context. Many existing studies have already analyzed the effects of Donald Trump's tweets on US financial and foreign exchange markets. However, few or no existing studies have concentrated the topics exclusively on the U.S.-China trade war. Therefore, my thesis is original and unique to existing studies because it is somewhat analogous to a case study on the U.S.-China trade war and aims at analyzing the effectiveness and impact of Donald Trump's tweets exclusively to China. My research topic is of great significance on the basis of existing studies because the tension in the U.S.-China relationship has continued to increase even after the pause of the trade war, and will remain competitive going forward. In addition, as Donald Trump announced a White House bid for 2024 and his Twitter account was restored, how he used rhetoric on social media and how such a remarkable manner of communicating with the public can affect mass reaction as well as the financial markets will continue to be meaningful research questions. Thus, retrospecting to the special case of the U.S.-China trade war will also provide valuable and intuitive predictions for the trend of the U.S.-China relationship and how it affects market sentiment in the future.

The findings suggest that Trump's tweets related to China had a slight negative impact on the USD-CNY exchange rate and affected the U.S. stock market, the Chinese A-share stock market, and the U.S. industrials sector. Multiple regression analyses were also conducted, which indicated that the number of tweets did not have a significant impact on the volatility change in the Chinese stock market, but did have a significant impact on the U.S. stock market and the industrials sector of the U.S. stock market. It was also found that Trump's tweets that were retweeted were more market-moving than those that were only favorited. However, the study has limitations, such as focusing only on the short-term impact of tweets and assuming no other external factors influencing financial markets. Therefore, future studies with alternative analytical methods are needed to conduct deeper analysis into how Trump's tweets on China affect market sentiments.

2 Literature Review

Many existing studies have been conducted with respect to several aspects of my research question. Some papers examine how government rhetoric on social media platforms, especially Trump's activities on Twitter, plays a role in affecting market sentiment. These research are mostly informative and helpful for me to refer to their methodologies and data sources, and I will be able to build upon the results and extend the existing knowledge to more specifically on the U.S.-China trade relationship through the case study of the U.S.-China trade war. In addition, some papers focus on analyzing the process, sanctions, as well as rhetorics used during the U.S.-China trade war, and these studies are also valuable in providing me with more detailed context knowledge about the event.

The methodology and the OLS regression model used in Nakamura and Steinsson's paper, "High-Frequency Identification of Monetary Non-Neutrality: the Information Effect," strongly influence the methodology used in my research and my construction of the regression model. This study investigates whether announcements from the Federal Reserve about monetary policy would affect high-frequency responses to macroeconomic measures, including real interest rates, expected inflation, and expected output growth. The result implies that these information effects play an important role in the overall causal effect of monetary policy shocks on output, and expected output growth increased after a monetary tightening as evidence of a Fed information effect. Though the paper focuses more on the macroeconomic policies and context compared with my research topic, the overall theme of information effect on economic shocks is similar to mine, and the methodology of using a high-frequency identification approach is significantly informative and valuable for my research. The paper uses an OLS regression with a change in an outcome variable of interest as the dependent variable, and a policy indicator as the independent variable, which measures the monetary policy news revealed in the official announcements. Nakamura and Steinsson's methodology and the OLS regression inspire me when I construct my own OLS regression model, where I change the independent variable used in the paper, a policy indicator, into a "tweet Indicator" for Trump's threats on Twitter. More details are discussed in the 3.1 Methodology section.

It is not novel in the literature to measure market sentiment using social network data and look for its impact on the financial markets. For example, Papaioannou, Russo, Papaioannou, and Siettos use Twitter information to model and predict high-frequency daily fluctuations of the EUR/USD exchange rate. The paper suggests that using information from social media platforms like Twitter can improve the accuracy of predicting short-term currency exchange rates that change frequently throughout the day. Furthermore, since Donald Trump's frequent use of social media during his presidency was unprecedented and had attracted much attention worldwide, several research papers look into Trump's use of social media platforms like Twitter affect various exchange rates and stock indices, which is similar to my research topic.

(Colonescu, 2018) investigates "The Effects of Donald Trump's Tweets on US Financial and Foreign Exchange Markets," and the paper finds some evidence of short-term and persistent effects of Trump's tweets on the Dow Jones Industrial Average, US-Canadian currency exchange rate, and the "Trade Weighted U.S. Dollar Index: Major Currencies," an aggregate US dollar exchange rate index, as identified in moving average series of various window sizes. In addition, Trump's tweets are found to have resulted in lasting effects on the US dollar composite exchange rate. Another paper by Ajjoub, Walker, and Zhao explores the effects Trump's tweets on stock prices, which is also similar to my research topic, but this paper focuses on the media sector. The study demonstrates that positive tweets have a positive impact on media firms' stock prices, while negative tweets have a negative impact on non-media firms' stock prices, and that the President's attitude towards news can influence stock prices. In addition, the paper "The impact of US presidents on market returns: Evidence from Trump's tweets" (Pham, Huynh, and Duong, 2022) the consumer goods industry exhibited a negative return when Trump displayed a negative attitude toward the pandemic. Similar to my methodology, the paper by Machus, Mestel, and Theissen use high-frequency minute-by-minute data, and analyzes the effect of Trump's tweets on individual stock returns." Consistent with papers of similar topics, the result suggests "abnormal returns, increased trading volume and increased investor attention before the tweets." (Machus et al., 2022) Moreover, it's worth noting that a paper in 2020 founds that "tweets related to the US-China trade war negatively predict S&P 500 returns and positively predict VIX."(Burggraf, Fendel, and Huynh, 2020) These papers all have similar research goals to mine, providing me with insights on the data sources, such as the Trump Twitter's Archive website[1] as well as its methodology. Previous studies have shown that Trump's tweets had a significant impact on the stock markets and exchange rates. However, it remains unclear whether his tweets specifically targeting China still possess the same market-moving power. Therefore, it is essential to investigate the impact of Trump's tweets related to China on the financial markets to better understand the dynamics of US-China relations and their influence on the global economy.

Trump's Twitter activities has been a popular research topic. Besides those focusing on the impact on financial markets, many papers examine how his unique type of populist rhetoric used in his tweets gave rise to foreign policy-making and mass reaction during his presidency. Lacatus uses a relatively more qualitative methodology such as textual analysis,

[1] Trump Twitter's Archive: https://www.thetrumparchive.com/

to analyze how Trump's populist rhetoric in his official campaign communication through both Twitter and his rally speeches contributed to shaping his approach to foreign policy. "The analysis finds an inconsistency between President Trump's populist rhetoric regarding the United States foreign policy strategy regarding military interventions and his foreign policy action."(Lacatus, 2021) Such inconsistency between Trump's foreign policy rhetoric and foreign policy actions stimulates my interest to investigate in my research whether Trump's inconsistency would result in a lack of effectiveness for his rhetoric threats towards China on Twitter since the credibility of his speech was weak from an international perspective. In addition, a paper published in 2020 finds that the "general public on Twitter responds more actively to negative language (more likes and retweets), and in turn the language on Twitter employed by Trump is highly emotional with more-than-expected emotion-bearing expressions." (Elayan, Sykora, and Jackson, 2020) Given the influence of likes and retweets on Twitter, it is also worth examining whether Trump's tweets related to China generate high engagement and whether this engagement translates into market movements.

On the other hand, literature specifically focusing on the U.S.-China trade war provides me with the contextual knowledge of understanding the event in detail, which is a crucial prerequisite for conducting my research. Chong and Li introduces the U.S.-China trade war holistically by studying its causes and economic impact from a historical standpoint, and Chong and Li "hold a pessimistic view on the complete settlement of the trade war." (Chong and Li, 2019) Fajgelbaum and Khandelwal (2022) is a more recent paper focusing on the economic impact of the U.S.-China trade war, and finds that "the trade war has lowered aggregate real income in both the United States and China, although not by large magnitudes relative to GDP."(Fajgelbaum and Khandelwal, 2022) What is more, it is worth mentioning that Huang and Wang also use the U.S.-China trade war as a case study, and examine how the Chinese government use rhetoric on social media platforms of Weibo and Twitter to manage both international and domestic public opinion. The paper finds that "China's digital public diplomacy is an instrument for the CPC to legitimize and popularize its ideology, and Beijing still uses traditional propaganda-based methods for public diplomacy practices and ignores online interaction with foreign publics."(Huang and Wang, 2021) The aim of the study closely resembles mine and focuses on the opposite perspective of the Chinese government's rhetoric on social media, and the result serves as valuable information for me to compare the two countries participating in the trade war. Yet, while Huang and Wang use textual analysis as the main methodology and focus on analyzing the content of the posts on both social media platforms, I will put more emphasis on quantifying the consequences of the posts through evaluating the immediate impact on the financial markets.

There are also extensive literature works that focus on the broader topic of how government rhetoric and announcements affect mass reactions. Weiss and Dafoe assess how governmental statements and propaganda from China impact Chinese citizens' approval for their governmental performance. Similar to (Lacatus, 2021), the authors employ a qualitative approach by using surveys, and the result shows that while the citizens in China are less supportive of inactions after explicit government threats, they also approve of vague and ultimately empty threats. Moreover, Drury and Li specifically analyze the U.S. economic sanction threats against China using a quantitative approach, and conclude that "for highly salient issues, sanction threats tend to be ineffective," and it is worth noting that the MFN (most-favored nations) threats were not only ineffective but also counterproductive. In general, whether or not governmental rhetoric related to trade policies is influential to mass reaction is a sophisticated and multi-dimensional question, as they depend on the characteristics of the announcement platforms as well as the situations of countries on both sides.

Nevertheless, the findings of Drury and Li in 2006 that the U.S. sanction threats towards China tend to be ineffective is interesting and beyond my expectations, which suggests that the situation for the U.S.-China trade relationship is special and idiosyncratic and cannot be concluded from generalized studies on government trade threats, thus the importance of my case study on the U.S.-China trade war cannot be understated.

3 Background, Data, and Methods

3.1 Methodology

As mentioned in the previous section, the methodology and the regression equations used in my research are inspired by Nakamura and Steinsson (2018)'s paper on the information effect on monetary policies. Since I aim at analyzing the immediate and short-term impact after each time Donald Trump posted a tweet, I choose to use financial variables of interest as dependent variables that are updated hourly, which is a relatively high frequency. The overall methodology of my research involves constructing a time-series data set that matches the data of hourly financial variables of interest to binary Tweet indicators which I create according to timestamps of tweets, and running OLS regressions to the time-series data set to generate results. An important assumption for the regressions is that nothing else happened in the short one-hour time window, so that the regression results can refer to a causal relationship between the independent and dependent variables.

To further examine what causes fluctuations in the markets, I differentiate the hours in which Trump posted a single tweet and those with more than one tweet and analyze whether posting multiple tweets in an hour would impact the markets more. In addition, I seek to investigate whether the numbers of favorites of the Tweets and reTweets have any causal relationship with the financial impact generated by Trump's Tweets. Thus, I run multiple linear regressions to look at the influence of favorites and reTweets. However, it is important to note that the models are only approximations of the true relationship between Trump's tweets and the financial variable, and there may be other factors that the models do not account for.

3.2 Data

The collection of data for the dependent variables includes several different financial indices to capture fluctuations in the foreign exchange market and the stock markets for both the U.S. and China. The data set was exported from the Bloomberg terminal[2] and incorporates hourly data for the financial variables ranging from January 1st, 2018 to December 31st, 2020. The date range of the data set begins from the pre-heating stage of the U.S.-China trade war in 2018 to the month before the end of Donald Trump's tenure of presidency in January 2021. In addition, Trump's Twitter account was permanently suspended in January 2021, so the chosen date range of the data set is relevant for the analysis of the immediate financial impact of his tweets related to China during the U.S.-China trade war.

The 5 different financial variables of interest as dependent variables of the OLS regressions include the following:

1. USD to CNY exchange rate in the foreign exchange market, which is the value of the US dollar relative to the Chinese yuan.

2. S&P 500 index, which is a stock market index that tracks the performance of 500 large-cap companies listed on the New York Stock Exchange (NYSE) or the NASDAQ. It is a

[2] Bloomberg Terminal: https://www.bloomberg.com/professional/solution/bloomberg-terminal/

widely recognized and commonly used measure of the U.S. stock market's performance.

3. CSI 300 index (SHSZ300), which is a stock market index comprised of the 300 largest and most liquid A-share stocks. It is the equivalent index of the S&P 500 index and represents the overall price of China's A-share market.

4. MSCI USA Industrials Index, which is a market cap-weighted index and captures large and mid-cap segments of equities in the U.S. stock market. All securities in the index are classified in the Industrials sector as per the Global Industry Classification Standard;

5. MSCI China Industrials Index, which is the equivalent index of the MSCI USA Industrials Index in China's A-share stock market.

The data for compiling the tweet indicators as the main independent variables comes from the Trump Twitter Archive website[3], a collection of around 33,000 tweets, all of which Donald Trump has posted since 2009 in the official personal account @realDonaldTrump. My research only looks at about 500 tweets that Donald Trump posted with the keyword "China" between January 1st, 2018 to December 31, 2020. The exported data set of tweets contains the post date of each tweet with precision to seconds, the number of favorites, and the number of retweets of each tweet. All of these information are then used to construct the data set for running regressions. Based on the data of tweets, I create several time series data sets with dummy variables as indicators for Trump's tweets, and the tweet indicator variables take the value 1 when Trump posted one or more tweets with the keyword "China" during the corresponding hour, and the value 0 if there is no relevant tweet in the hour.

[3] Trump Twitter's Archive: https://www.thetrumparchive.com/

The timestamps of the dependent variables vary since the stock indices' data are available only during the trading hours of the United States and China stock markets. The New York Stock Exchange (NYSE) is open from Monday through Friday from 9:30 a.m. to 4:00 p.m. Eastern time, and the Shanghai and Shenzhen Stock Exchange is open Monday through Friday from 9:30 am to 11:30 am and 1:00 pm to 3:00 pm China Standard Time. To prevent confusion, I unify all timestamps of the data sets to show in Eastern Standard Time. Accordingly, I change the timestamps of the tweet indicator data set to correspond to each financial variable with a different trading hour. For example, the tweet indicator for the S&P500 index only includes timestamps for the U.S. trading hours. However, not all of the tweets were posted during trading hours. Therefore, I created two versions of tweet indicators to account for tweets posted outside of trading hours.

1. The first version of tweet indicator (variable name: $TweetFlagv1$) simply ignores all tweets posted outside of the trading hour. In this case, only the tweets posted during the trading hour are taken into account.

2. The second version of tweet indicator (variable name: $TweetFlagv2$) transfers the tweets posted outside of the trading hour to be counted in the next available trading hour after the time of post, looking at the effect of the tweets on the financial markets as soon as the markets opened.

Comparing the regression results of the two versions of tweet indicators allows me to find out whether the financial market fluctuations caused by Trump's tweets were particularly from tweets that are posted within trading hours or those outside of trading hours.

I merged financial data updated hourly with binary tweet indicators based on timestamps. These indicators are dummy variables, meaning their values are 1s even if Trump posted more than one tweet related to China during a given hour.

The following are the summary statistics for all of the financial variables as dependent variables for the regression models as well as the statistics for favorites and retweets of each Tweet. According to Trump Twitter Archive, both favorites and retweets are the most recent values to the date of January 8th, 2021 when Twitter permanently suspended Trump's account.

Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
USD-CNY Rate	9727	6.81	0.24	6.25	7.18
S&P 500	5276	2959.75	287.54	2209.62	3750.01
USA Industrials	5289	290.21	24.31	189.35	349.98
SHSZ 300	4380	3912.82	500.42	2940.19	5210.55
China Industrials	4362	120.81	9.99	94.49	152.4
Favorites	546	79453	74347.88	0	764501
ReTweets	546	19454	14639.32	67	143066

3.3 Regression Models

Inspired by Nakamura and Steinsson (2018)'s paper, I construct the following OLS regression equation:

$$\begin{gathered}\frac{\ln s_t - \ln s_{t-1}}{z} = \alpha + \beta TweetFlag_t + \epsilon_t \\ \text{where } z = \frac{\sum_{i=1}^{n} \mid \ln s_t - \ln s_{t-1} \mid}{n}\end{gathered} \tag{1}$$

On the left-hand side of the regression equation, s_t is the closing price of the financial variable of a trading hour in which a tweet by Donald Trump with the keyword "China" was posted, and s_{t-1} is the opening price of the financial variable of the same trading hour. The term $\ln s_t - \ln s_{t-1}$ captures the percentage change in price from the beginning to the end of the trading hour when the tweet was posted. Since the changes in prices of the financial variables within an hour are typically small, a standardized term z is used to scale the changes in the financial variable. z is calculated as the average of the absolute values of the percent changes. By using z, the magnitude of the percent changes is standardized relative to the average magnitude of percent changes, and the effects of small changes within an hour can be magnified and thus become more comparable. The dependent variable term is named $rPercentChange$ in the regression result tables.

On the right-hand side of the regression equation, $TweetFlag_t$ is a binary tweet indicator on whether any Trump's tweets were posted during the trading hour or counted in the hour. The variable has two versions in different regression models, $TweetFlagv1$ and $TweetFlagv2$, which are explained in Section 3.2. α is a constant estimate parameter, β is the estimate parameter of the immediate effect that captures the difference in percent change in the dependent variable before and after the hour of each tweet relative to the average of all percent changes across all hours, and ϵ_t is an error term that captures the part of the variation in the dependent variable that is not explained by $TweetFlag_t$.

The null hypothesis for regression in the above equation is that Trump posting a tweet related to China has no statistically significant relationship with the percent change of the financial variables before and after the hour in which Trump posted tweets relative to the average of all percent changes across all time. If the null hypothesis is rejected, the regression model will also indicate whether the impact of Trump's tweets related to China is positive or negative through the sign of the β coefficient.

Alternatively, I can look at the impact of market volatility by changing the dependent variable into the square root of the original one, which is the standard deviation of the percent change. The new dependent variable, representing market volatility, ignores the signs of impact (positive or negative) and only focuses on the incremental amount of change in the financial variable. The dependent variable in Model (2) is named $rVolatility$ in the regression result tables.

$$\begin{gathered} |\frac{\ln s_t - \ln s_{t-1}}{z}| = \alpha + \beta TweetFlag_t + \epsilon_t \\ \text{where } z = \frac{\sum_{i=1}^{n} \mid \ln s_t - \ln s_{t-1} \mid}{n} \end{gathered} \tag{2}$$

In the above regression model, the beta parameter estimates the impact of Trump's tweets related to China on market volatility relative to the average of all percent changes across time, by looking at the absolute value of the percent change in the financial variables. For consistency across different regression models, I use the same standardized term z to magnify the value for percent change in market volatility. The null hypothesis for the regression in the above equation is that Trump posting a tweet related to China has no statistically significant relationship with the amount of percent change of the financial variables before and after the tweet.

To conduct a more detailed analysis of the impact of Trump's tweets on the financial markets, I also differentiate the hours in which Trump posted one tweet and those with more than one tweets using an additional independent variable named $Multiple\_Tweets$. The value for this new independent variable is calculated using this formula:

$$Multiple\_Tweets = \max(Total\#ofTweets - 1, 0) \tag{3}$$

This variable takes the value of the actual number of tweets minus one if multiple tweets on China were posted by Trump within an hour or were counted in the hour, and takes the value 0 if one or no tweet was counted. For example, if Trump posts 3 tweets during a weekend, the value of $Multiple\_Tweets$ for S&P500 that corresponds to the timestamp of 9:00-10:00 a.m. on the next Monday is 2, because it is the next trading hour of NYSE after the weekend.

$$\frac{\ln s_t - \ln s_{t-1}}{z} = \alpha + \beta_1 TweetFlag_t + \beta_2 Multiple\_Tweets_t + \epsilon_t \tag{4}$$

$$|\frac{\ln s_t - \ln s_{t-1}}{z}| = \alpha + \beta_1 TweetFlag_t + \beta_2 Multiple\_Tweets_t + \epsilon_t \tag{5}$$

By comparing the regression results in models (3) and (4) with models (1) and (2), I control the variable $Multiple\_Tweets$ in order to distinguish between hours with one tweet and those with multiple tweets and thus determine whether the number of tweets posted during a given hour has a statistically significant impact on the financial variables. The null hypothesis is that the number of tweets posted during a given hour does not have a statistically significant impact on the dependent variables, after controlling for all other variables in the model. The β_2 coefficients represent the additional effect of posting multiple tweets in a given hour on percent change and volatility of the financial variables, compared to Trump posting only one tweet in the same hour or no tweet at all. A positive β_2 would indicate that posting multiple tweets in a given hour is associated with a larger percent change or volatility of the financial variables, while a negative beta coefficient would indicate the opposite.

In addition to differentiating one tweet and multiple tweets to break down the impact of Trump's tweets on the financial markets, I also included the number of favorites and retweets of the tweets as two additional independent variables in my multiple regression models. Due to the potential issue of multicollinearity between the number of likes and retweets, I opted to include each variable in separate regression models instead of combining them together in one model.

$$\frac{\ln s_t - \ln s_{t-1}}{z} = \alpha + \beta_1 TweetFlag_t + \beta_2 Favorites_t + \epsilon_t \tag{6}$$

$$|\frac{\ln s_t - \ln s_{t-1}}{z}| = \alpha + \beta_1 TweetFlag_t + \beta_2 Favorites_t + \epsilon_t \tag{7}$$

$$\frac{\ln s_t - \ln s_{t-1}}{z} = \alpha + \beta_1 TweetFlag_t + \beta_2 ReTweets_t + \epsilon_t \tag{8}$$

$$|\frac{\ln s_t - \ln s_{t-1}}{z}| = \alpha + \beta_1 TweetFlag_t + \beta_2 ReTweets_t + \epsilon_t \tag{9}$$

Similar to the previous simple regression models of (1) and (2), models (5) and (7) test the difference in percent change of the financial variables, and models (6) and (8) test the volatility of the financial variables, and the dependent variables are all magnified by the standardized term z.

After adding the independent variables representing favorites and retweets, issues of varying values occur, so the variables are standardized to ensure accurate interpretations of results. If the tweet indicator is 1 in the data set for regression, the values for retweets and favorites corresponding to each hour are shown as the sum of the retweets and likes of all the tweets posted during the hour. As a result, the number of likes and retweets for each of Trump's tweets can be quite high if the tweet indicator is 1, while for most hours there are no tweets posted, resulting in a value of 0 for those hours. To address this issue of varying values, I standardize the favorites and retweets variables by dividing the values of likes and retweets by the average number of likes/retweets that each of Trump's tweet receives. This standardization ensures that the beta coefficients for the likes and retweets variables reflect how they compare with the average likes/retweets received by a Trump tweet. The standardization also facilitates easier interpretation of the impact of favorites and retweets on the markets in terms of one average tweet by Trump. In models (5) and (6), the β_2 coefficients are used to test for the additional impact on the percent change and volatility of financial markets caused by the total number of favorites of all tweets posted during hour t, relative to the average number of favorites that Trump's tweets typically receive. However, standardization reduces the influence of outliers in the data, which means that the impact of tweets with exceptionally high numbers of favorites or retweets might be underestimated.

4 Results

4.1 USD-CNY FX Rate

USD-CNY FX Rate Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
USD-CNY Rate	9727	6.81	0.24	6.25	7.18
rPercentChange	9,727	0.018825	1.568939	-18.98338	13.30281
rVolatility	9,727	0.0009378	0	0.0032103	0.1372935

The USD-CNY exchange rate represents the value of the US dollar relative to the Chinese yuan, and is one of the most influential foreign exchange rate in the FX market. Changes in the exchange rate can reflect market expectations about the trade relationship between the US and China, and can signal the degree to which Trump's tweets are perceived as affecting that relationship.

Regression results in Table 1 suggest that there is a statistically significant relationship between Trump's tweets related to China and the volatility of the USD-CNY exchange rate at a 1% significance level. It means that Trump's tweets on China had indeed generated some immediate fluctuations in the foreign exchange market in the following trading hour. In addition, Trump posting tweets related to China is significant with the percent change of the financial variables relative to the average percent change before and after the tweet at a 10% significance level. The negative beta coefficient suggests that Trump's tweets had negative impact on the USD-CNY exchange rate. In other words, on average, the U.S. dollar slightly depreciated relative to the Chinese yuan immediately after President Trump posted tweets related to China during the U.S.-China trade war. Trump's tweets were often related to trade negotiations and other economic issues between the two countries, and these tweets could be interpreted by investors and traders as a sign of increased uncertainty or instability in the market. This could lead to a decrease in demand for the U.S. dollar relative to the Chinese yuan, which would result in a lower exchange rate. However, it is important to note that the negative impact of Trump's tweets on the exchange rate may be small or negligible, as the significance level is only 10%. The result also suggests that it is likely that most of the positive and negative impacts of the Tweets offset each other, but the negative impacts were slightly higher than the positive ones. The negative impact of Trump's tweets on the USD-CNY exchange rate can be explained by the fact that these tweets were often related to trade negotiations and other economic issues between the US and China. Such tweets could create the impression of increased uncertainty or instability in the market, which can lead to a decrease in demand for the US dollar relative to the Chinese yuan. This could result in a lower exchange rate, as observed in the study.

As for the multiple regression results in Table 6, Table 7, and Table 8 (see Appendix A), no statistically significant relationship is found in the regressions with $Multiple\_Tweets$, $Favorites$ or $ReTweets$. This implies that the cumulative amount of tweets posted by Trump within an hour as well as the likes or retweets a tweet receives are not good predictors of changes in the USD-CNY exchange rate volatility during the US-China trade war period. It is possible that other factors are driving changes in USD-CNY exchange rate volatility caused by Trump's tweets on China that were not captured in the statistical model.

Even though the regression results of the second independent variables are not significant, these additional variables might still contribute to the model. Accordingly, I use F-test to test for the null hypothesis that the coefficients of $TweetFlagv2$ and $Multiple\_Tweets$ (or $Favorites$ or $ReTweets$) are equal to zero. Performing a joint hypothesis test (F-test) can help assess whether the independent variables are multicollinear and determine whether the variable is adding any significant explanatory power to the model, despite not being individually significant. The F-test results for the three additional independent variables respectively are $F(2, 9724) = 32.54, p = 0.000$, $F(2, 9724) = 33.03, p = 0.000$, and $F(2, 9724) = 32.43, p = 0.0000$. All of the joint hypothesis tests are statistically significant at the 99% confidence level, indicating that we reject the null hypothesis and conclude that both tweet flag and $Multiple\_Tweets$ (or $Favorites$ or $ReTweets$) have significant effects on the percent change of the financial variables, even when taken together in the model. It's possible that the lack of significance for the additional independent variable in the individual regression was due to its correlation with the $TweetFlagv2$ variable, since the values of both variables are 0 when there is no Trump's tweets related to China during the hour, which is most of the circumstances. In general, the findings suggest that Trump's tweets related to China may have a significant impact on the exchange rate, and that the frequency and popularity of the tweets may also be important factors to consider.

Table 1: Regression of USD-CNY FX Rate on Tweet Indicators

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.197*	0.00109***		
	(0.119)	(0.000243)		
TweetFlagv2			0.221**	0.00144***
			(0.0885)	(0.000181)
Constant	0.0224	0.000918***	0.0114	0.000890***
	(0.0161)	(0.0000328)	(0.0162)	(0.0000330)
Observations	9727	9727	9727	9727
Adjusted R^2	0.000	0.002	0.001	0.006

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

4.2 S&P 500 Index

S&P 500 Index Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
S&P 500	5,276	2959.754	287.5655	2209.62	3750.01
rPercentChange	5,276	0.000721	1.653367	-12.33826	20.56049
rVolatility	5,276	0.0062741	0.0277077	0	0.970423

The S&P 500 is a stock market index that tracks the performance of 500 large-cap companies listed on the New York Stock Exchange (NYSE) or the NASDAQ. The S&P 500 is often used as a benchmark for the overall performance of the U.S. stock market because it includes a diverse set of companies across various industries and sectors. As such, changes in the S&P 500 index are seen as indicative of the overall state of the U.S. economy and can influence investor sentiment and decision-making. Using the S&P 500 can help to capture the immediate and short-term financial impact of Donald Trump's tweets related to China during the U.S.-China trade war on the broader U.S. economy, as represented by the stock market.

In Table 2, only the regression that test the volatility of the S&P 500 index is statistically significant at a 1% significance level means that Trump's tweets with the keyword "China" has contributed to impacting the S&P 500 index, but whether the impact is positive or negative cannot be concluded. This is consistent with the notion that Trump's tweets on China during the trade war period were often unpredictable and could send mixed signals to the market. Moreover, only the second version of the tweet indicator is statistically significant while the first version is not. The result implies that the significance comes from the tweets posted outside of the U.S. stock market trading hours, since the first version of $TweetFlag$ only accounts for the tweets posted during the trading hour. This suggests that the impact of Trump's tweets on the S&P 500 index was most significant when the tweets were posted outside of US stock market trading hours. This may be because traders and investors have more time to react and adjust their positions to the information contained in the tweets when the market is closed. It can also be explained by the Donald Trump's personal preference of using social media. It is intuitive that he probably has posted relatively irrational tweets at night more frequently, which is outside of the trading hour, and irrational statements on Twitter were more likely to have generated market fluctuations.

In Table 9, the beta coefficients for the controlled variable $Multiple\_Tweets$ are both significant. It suggests that the cumulative number of tweets during a trading hour or between two non-consecutive trading hours has statistically significant impacts on the prices of the S&P 500 index. What's more, the beta coefficient in regression (3) is negative, which can be interpreted as ceteris paribus, on average each hour in which Trump posted more than one tweet is associated with a negative percent change in the price of the S& P 500 index. This finding suggests that there may be a negative reaction from investors in the

Table 2: Regression of S&P 500 on Tweet Indicators

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.0917	0.00111		
	(0.153)	(0.00256)		
TweetFlagv2			0.0251	0.00465***
			(0.0983)	(0.00165)
Constant	0.00281	0.00625***	-0.000706	0.00601***
	(0.0230)	(0.000386)	(0.0234)	(0.000393)
Observations	5276	5276	5276	5276
Adjusted R^2	-0.000	-0.000	-0.000	0.001

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

U.S. stock market towards Trump posting multiple tweets within an hour. It could indicate that multiple tweets within a short period of time lead to increased uncertainty or volatility in the market, which in turn affects investor confidence and leads to a decline in stock prices. However, further analysis is needed to determine the specific mechanisms driving this relationship and to assess its broader implications for financial markets.

In addition, the regression results in Tables 10 and 11 indicate that the variables of retweets and favorites are statistically significant in explaining the percent change and volatility of the S&P 500 index in response to Trump's tweets on China. The coefficient for retweets is more significant, with levels of 5% and 1%, while the coefficient for favorites is significant at a relatively small 10% level. This suggests that the number of retweets has a stronger influence on the changes in the S&P 500 index compared to the number of favorites, and can partially explain the effects of Trump's tweets on the U.S. stock market in general. Furthermore, the beta coefficients show that a higher number of favorites or retweets for Trump's tweets related to China during a trading hour or between non-consecutive trading hours is associated with a decrease in the price of the S&P 500 index. It reflects that investors in the U.S. stock market perceived Trump's influential tweets with more likes and retweets as having a negative impact on the ongoing trade negotiations between the US and China or on the overall relationship between the two countries. As a result, investors may become more cautious and sell off their stocks, leading to a decrease in the S&P 500 index.

4.3 CSI 300 Index

CSI 300 Index Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
CSI 300	4,380	3912.818	500.476	2940.19	5210.55
rPercentChange	4,380	0.0406899	1.498307	-8.510251	10.03232
rVolatility	4,380	0.0061944	0.0152611	0	0.2775765

The CSI 300 is a stock market index that represents the top 300 companies listed on the Shanghai and Shenzhen stock exchanges in China. The index is widely regarded as a benchmark for the Chinese stock market and is used by investors to track the performance of China's major publicly traded companies. It provides a measure of the overall performance of the Chinese stock market, and therefore may be sensitive to changes in investor sentiment caused by Donald Trump's tweets related to China during the U.S.-China trade war. By analyzing the immediate financial impact of these tweets on the CSI 300, I am able to gain insights into how investors react to political events and news related to trade tensions between the U.S. and China.

The Chinese stock market also appears to have been affected by Donald Trump's tweets related to China during the trade war period. However, regression results in Table 3 implies contradictory findings as the ones for S&P 500. While the independent variable

$TweetFlagv2$ is significant at a relatively high 1% level, $TweetFlagv1$ is not significant at levels above 10%. The results show that the impact of Trump's tweets on the Chinese stock market in general was most significant when the tweets were posted outside of China's stock market trading hours. Nevertheless, the regression model for S&P 500 in Table 2 also shows a difference between the two versions of the tweet indicator, but the trading hours for the Chinese stock market are almost opposite to that of NYSE. This implies two things: Firstly, the hypothesis that tweets posted outside of trading hours are the tweets that resulted in fluctuations in the stock markets may be incorrect, and there may be other factors or noise at play. Secondly, the tweets that had the greatest impact on both stock markets were those posted during times that were neither Chinese nor U.S. trading hours. On the other hand, the regression of $rPercentChange$ on $TweetFlagv2$ is positive. It means that Trump posting Tweets related to China increases the stock price of the CSI 300 index. Investors in the Chinese stock market may have perceived Trump's tweets as a positive signal for China. Though this result is counter-intuitive given the context of the U.S.-China trade war and the tensions between the two countries, it's possible that investors in the Chinese stock market interpreted Trump's tweets as a sign that the trade tensions between the U.S. and China could potentially ease or that a trade deal could be reached. This could have led to increased confidence in the Chinese economy and higher demand for Chinese stocks, which would have driven up the stock price of the CSI 300 index.

In the multiple regression analysis, it's counterintuitive that the beta coefficients for the variables $Multiple_Tweets$ (Table 12), $Favorites$ (Table 13), and $ReTweets$ (Table 14) are significant for the percent change in the CSI 300 index ($rPercentChange$), but not significant for the volatility of the CSI 300 index ($rVolatility$). This can only be explained by the presence of noise in the data. As Twitter is not permitted in China, it is likely that

Chinese investors had limited and delayed access to the information contained in Trump's tweets. As a result, the impact of Trump's tweets on the volatility of the CSI 300 index should have been less immediate and significant compared with the S&P 500 index, and may have been influenced by other factors such as global economic conditions or government policies. Thus, it may be necessary to revise my approach to better understand the impact of Trump's tweets on the Chinese stock market.

Table 3: Regression of CSI 300 Index on Tweet Indicators

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.0117	0.00190		
	(0.254)	(0.00259)		
TweetFlagv2			0.276^{***}	0.00531^{***}
			(0.0957)	(0.000973)
Constant	0.0408^{*}	0.00618^{***}	0.0243	0.00588^{***}
	(0.0227)	(0.000232)	(0.0233)	(0.000237)
Observations	4380	4380	4380	4380
Adjusted R^2	-0.000	-0.000	0.002	0.007

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

4.4 MSCI USA Industrials Index

MSCI USA Industrials Index Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
USA Industrials	5,289	290.2103	24.31002	189.35	349.98
rPercentChange	5,289	-0.0108093	1.676308	-32.70927	15.42791
rVolatility	5,289	0.0078634	0.0533407	0	2.994394

The MSCI USA Industrials Index is a stock market index that tracks the performance of companies in the industrial sector of the US economy, which includes companies involved in a wide range of industries, such as aerospace and defense, machinery, construction materials, and transportation. The industrials sector is particularly sensitive to trade, since many industrial companies rely on international trade to source materials and sell their products. Changes in trade policy can have a significant impact on their bottom line. In particular, the US-China trade war had a significant impact on the industrials sector as China is a major market for many US industrial companies, and the imposition of tariffs and other trade barriers had a ripple effect throughout the sector. Thus the MSCI USA Industrials Index can serve as a useful proxy for measuring the impact of Donald Trump's tweets related to China during the US-China trade war period. Additionally, there is a corresponding index in the Chinese stock market for the MSCI USA Industrials Index, which makes it convenient for conducting comparisons between the two markets.

The results of the regression analysis in Table 4 suggest that Trump's tweets related to China have a statistically significant impact on the industrials sector of the U.S. stock market. The beta coefficient for the regression testing the volatility of the S&P 500 index is statistically significant at a 1% significance level, indicating that Trump's tweets with the keyword "China" have contributed to impacting the U.S. industrials sector. However, it is difficult to determine whether the impact is positive or negative. The variable $TweetFlagv2$ has a high level of significance at 1% for measuring volatility, whereas $TweetFlagv1$ is only significant at levels below 10%. The findings indicate that either Trump's tweets had the greatest impact on the industrials sector when they were posted outside of U.S. stock market trading hours, or there exists noise and external factors contributing to the significance. Interestingly, the beta coefficient value for the industrials index is almost five times greater than that of the S&P 500. This suggests that the industrials sector responded more strongly to Trump's tweets related to China compared to the overall market. One possible explanation for this is that the industrials sector is particularly sensitive to trade issues, which were a major focus of the U.S.-China trade war period studied in this research, as mentioned in the previous paragraph. Another possible explanation is that the industrials sector may be more volatile in terms of stock prices compared to the average stock market, leading to a larger response to external factors such as Trump's tweets.

Table 4: Regression of MSCI USA Indutrials on Tweet Indicators

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.142	0.00230		
	(0.154)	(0.00491)		
TweetFlagv2			-0.0206	0.0221^{***}
			(0.0995)	(0.00315)
Constant	-0.00757	0.00781^{***}	-0.00963	0.00660^{***}
	(0.0233)	(0.000742)	(0.0237)	(0.000752)
Observations	5289	5289	5289	5289
Adjusted R^2	-0.000	-0.000	-0.000	0.009

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Furthermore, Table 15 indicates that the variable $Multiple\_Tweets$ is statistically significant at a 1% level in the regression. This suggests that the number of tweets posted by Trump during a trading hour or between two non-consecutive trading hours has a significant impact on the stock prices of the industrials sector in the U.S. stock market. Additionally, the negative beta coefficient in regression (3) implies that, on average, each hour in which Trump posted more than one tweet is associated with a negative percent change in the industrial market sector of the U.S. stock market, holding all other factors constant. This finding is similar to that of the S&P 500, which is intuitive because many companies in the MSCI USA Indstrials Index are also included in the S&P 500, so the two indices are correlated with each other. This finding suggests that the impact of Trump's tweets on the industrials sector of the U.S. stock market is not limited to a single tweet but can accumulate over multiple tweets. In addition, the negative coefficient may be because the U.S.-China trade war created significant uncertainty and unpredictability for the industrials sector, and the tweets amplified that uncertainty. Additionally, the negative impact may reflect market concerns about the potential negative consequences of Trump's tweets on U.S.-China trade relations, and ultimately, on the industrial sector. Overall, the findings suggest that the cumulative effect of Trump's tweets on the industrial market sector may have been negative, and this effect was compounded when multiple tweets were posted during a trading hour.

The regression results for the impact of the number of favorites and retweets on the US industrials sector, as shown in Tables 16 and 17, indicate a difference in their significance. The number of favorites does not appear to have a significant impact on the sector's volatility, as the regression for volatility is insignificant. This may suggest that external factors or noise not captured by the model could be contributing to the significance in the regression for the number of favorites. On the other hand, the number of retweets has a significant impact on the US industrials sector, as shown by the significant beta coefficient for $ReTweets_v2$ at a 1% significance level. This suggests that Trump's tweets are indeed influential and worth retweeting, and the more retweets, the more impact it has on the financial markets, especially on the industrials sector. One possibility to explain the difference in significance between favorites and retweets is that retweets indicate a higher level of engagement and interest from Twitter users, compared to favorites which may simply be an indication of approval or agreement without necessarily leading to further dissemination of the tweet. This higher level of engagement could result in a greater influence on the financial markets.

Another possibility is that the content of Trump's tweets that were retweeted were more market-moving than those that were only favorited. For example, a tweet that contains a specific policy announcement or threat to impose tariffs may be more likely to be retweeted and have an impact on financial markets than a tweet expressing a general opinion about trade with China.

4.5 MSCI China Industrials Index

MSCI China Industrials Index Summary Statistics					
Variable	Obs	Mean	Std. Dev.	Min	Max
China Industrials	4,362	120.8103	9.997437	94.49	152.4
rPercentChange	4,362	-0.0460881	1.51834	-17.44334	13.27002
rVolatility	4,362	0.0059087	0.0206111	0	0.7793097

The MSCI China Industrials Index is a financial index that measures the performance of the industrial sector of publicly traded companies in China. It includes companies engaged in various industries, such as aerospace, defense, construction, engineering, machinery, and transportation. It also enables me to assess how Trump's tweets about China have affected the Chinese industrial sector. Moreover, by comparing the behavior of the this index with the MSCI USA Industrials Index, I can gain insights into the potential impact of the trade war on the industrial sectors of both countries and how they are interconnected.

Table 5 shows that Trump's tweets about China, particularly those outside of trading hours, have a significant positive impact on the MSCI China Industrials Index, with a significance level of 1%. However, the same regression for the volatility of the index is only significant at a 10% level. This unexpected result could indicate that there are other external factors or noise affecting the significance of percent change. It is possible that there is a correlational relationship between Trump's tweets on China and the Chinese industrials sector, but further analysis is needed to confirm this. Since we cannot confirm that Trump's tweets related to China have any immediate impact on the stock price of the Chinese industrials sector, it may not be necessary to conduct multiple regressions with additional variables, $Multiple\_Tweets$, $Favorites$, and $ReTweets$. Regarding the additional variables, if the initial regression analysis did not establish a significant relationship between Trump's tweets related to China and the stock price of the Chinese industrials sector, it may not be necessary to conduct multiple regressions with additional variables. Unsurprisingly, these regression results appear to be counter-intuitive with significance on $rPercentChange$ but no significance on $rVolatility$ at levels above 10%.

Table 5: Regression of MSCI China Industrials on Tweet Indicators

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	0.250	-0.00243		
	(0.258)	(0.00350)		
TweetFlagv2			0.335***	0.00242*
			(0.0970)	(0.00132)
Constant	-0.0481**	0.00593***	-0.0661***	0.00576***
	(0.0231)	(0.000313)	(0.0237)	(0.000322)
Observations	4362	4362	4362	4362
Adjusted R^2	-0.000	-0.000	0.003	0.001

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

The lack of immediate response from the Chinese industrial sector to Donald Trump's tweets on China in the study could be due to various factors. Firstly, Twitter is banned in mainland China, which may result in a delay in the reception of Trump's tweets by the market. This delay may not be captured in the study, which examines a high-frequency one-hour time window, leading to a lack of significance in the results. Additionally, the Chinese market may not have access to complete information about these tweets, which may result in the market perceiving Trump's activity in social media as less important compared to the U.S. market. Another possible explanation is that Trump's tweets may not contain any new information that would significantly impact the sector. The Chinese market may also not react as strongly to political events or statements as other markets do, which could dampen the impact of Trump's tweets. It is also possible that there are external factors at play, such as domestic economic policies, that overshadow the effects of the tweets.

5 Conclusion

As the first and the second largest economies in the world, it is no doubt that the United States and China will remain in a long-term competing relationship, similar to the relationship between the United States and the Soviet Union during the Cold War era, since "the chances of a settlement (of the U.S.-China trade war) in the short run are slim."(Chong and Li, 2019) Moreover, as Donald Trump announces to run for president again in 2024, it is of great significance to study how he uses rhetorical tactics and threats to influence the financial markets via both social media and official platforms from a historical standpoint and analyze the dramatic trade war occurred during his presidency as a case study. The result will provide a valuable guide to predict the market sentiments to similar possible rhetoric and threats by the U.S. government in the future. Many existing studies have analyzed the impact of the government's rhetoric and trade threats through both quantitative and qualitative approach, and the success of sanction threats tend to be multi-factorial. Drury and Li (2006) suggests the ineffectiveness of the U.S.'s sanction threats towards China and the

U.S.-China relationship is extraordinarily unique and complex. Therefore, the significance of studying the U.S. government's rhetoric and trade threats using the case study of the U.S.-China trade war cannot be undermined.

The aim of this study is to examine the immediate impact of Donald Trump's tweets on the foreign exchange and stock markets in the U.S. and China. Financial variables of interest, including the USC-CNY exchange rate and several stock indices from both countries, were collected in hourly intervals from the Bloomberg terminal for the period of January 2018 to December 2020. These variables were used as dependent variables in OLS regression models. The tweet indicator, created using data from Trump's Twitter posts with the keyword "China" obtained from the Trump Twitter Archive website, served as the primary independent variable. To further analyze the impact, three additional variables were included in multiple regression models: the number of tweets posted within a trading hour or between non-consecutive trading hours, the number of favorites, and the number of retweets. The second and third variables examined whether the number of favorites or retweets in an hour, in relation to the average number of retweets, had a correlational relationship with the percent change or volatility in the financial variables.

The study assumes that no other events occurred during the one-hour time frame under analysis, and the simple OLS regression results indicate that Trump's tweets related to China had an immediate impact on several financial variables. Specifically, the tweets had a slight negative impact on the USD-CNY exchange rate which means the U.S. dollar depreciated relative to the Chinese yuan immediately after Trump's tweets on China. The tweets also affected the U.S. stock market (S&P 500), the Chinese A-share stock market (CSI 300), and the U.S. industrials sector (MSCI USA Industrials index). However, the direction of the impact on these markets cannot be determined. The tweets don't appear to have immediately impacted the industrials sector of the Chinese stock market. Generally speaking, Trump's tweets on China during the trade war period were indeed perceived by the market as a signal of a potential shift in U.S. trade policy towards China, which could have created uncertainty and volatility in the financial markets, leading to the observed impact on the USD-CNY exchange rate and stock indices. However, the Chinese industrials sector doesn't seem to be more sensitive to these tweets compared with the overall Chinese stock market, which contradicts with my previous hypothesis that the industrials sector might respond more to his tweets since it is the industry that is particularly sensitive to change in trade policies. The impact of Trump's tweets on the Chinese industrials sector may be delayed, and it may take some time longer than an hour for the effects to be observed.

To answer the question of whether multiple tweets have a greater impact than single tweets, multiple OLS regression analyses were conducted on a time series data set with a one-hour interval. The results indicate that the number of tweets does not have a significant impact on the volatility change in the exchange rate and the CSI 300 of the Chinese stock market. Accordingly, F-tests are conducted since there might be multicolinearity between the two independent variables. Results show that the tweet indicator and the number of tweets are jointly significant, which means that it's possible that the combined effect of these variables provides a stronger explanatory power than any of them individually, even if their individual effects were not significant. However, for the U.S. stock market and the industrials sector of the U.S. stock market, the number of tweets does have a significant impact. The number of favorites of the tweets appears to have no bearing on their impact, while the number of retweets appears to be significant in affecting the S&P 500 and the MSCI USA Industrials Index. The difference in significance between favorites and retweets indicates that Trump's tweets that were retweeted were more market-moving than those that were only liked.

Regardless of the findings, a considerable amount of noise is exhibited in the results, so there are a few limitations to this study that should be acknowledged. Firstly, the study only focuses on the immediate impact of tweets, and does not examine the long-term effects or sustainability of the impact on financial markets. Secondly, the study assumes that no other external factors are influencing financial markets during the one-hour time frame, which may not be a valid assumption in reality. Finally, the study only uses OLS regression analysis, which may not account for non-linear relationships or other complex factors that may affect the impact of tweets on financial markets. Thus, future studies with alternative analytical methods are needed to conduct deeper analysis into how Trump's tweets on China affect market sentiments. For instance, future studies can use time-series models or machine learning techniques to capture non-linear relationships and other complex dynamics that may exist between the tweet indicators and financial variables.

As the use of social media by government officials continues to be prevalent, and the impact of such tweets on financial markets has far-reaching consequences. This study can be generalized to other political leaders and social media platforms, and future research can investigate the impact of social media posts on different sectors of the financial markets and the long-term effects of such posts. Even though Trump is not the President of the United States anymore, he remains active in the political field of the U.S., and his influence on financial markets cannot be underestimated. Furthermore, with Trump's pledge to stay in the 2024 presidential race, understanding the impact of his tweets on financial markets will continue to be a crucial area of research in the future.

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Appendices

A Appendix

Table 6: Regression of USD-CNY FX Rate on Tweet Indicators and Multiple Tweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv2	0.221**	0.00144***	0.170*	0.00137***
	(0.0885)	(0.000181)	(0.0955)	(0.000195)
Multiple_Tweets			0.0761	0.000112
			(0.0537)	(0.000110)
Constant	0.0114	0.000890***	0.0114	0.000890***
	(0.0162)	(0.0000330)	(0.0162)	(0.0000330)
Observations	9727	9727	9727	9727
Adjusted R^2	0.001	0.006	0.001	0.006

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Regression of USD-CNY FX Rate on Tweet Indicators and Favorites

	(1)	(2)	(3)	(4)
	rPercentChange	rVolatility	rPercentChange	rVolatility
TweetFlagv1	-0.268	0.000876**		
	(0.167)	(0.000341)		
Favorites_v1	0.0580	0.000171		
	(0.0953)	(0.000195)		
TweetFlagv2			0.168	0.00120***
			(0.123)	(0.000250)
Favorites_v2			0.0330	0.000152
			(0.0524)	(0.000107)
Constant	0.0224	0.000918***	0.0114	0.000890***
	(0.0161)	(0.0000328)	(0.0162)	(0.0000330)
Observations	9727	9727	9727	9727
Adjusted R^2	0.000	0.002	0.000	0.007

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Regression of USD-CNY FX Rate on Tweet Indicators and ReTweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.324*	0.00128***		
	(0.190)	(0.000388)		
ReTweets_v1	0.104	-0.000160		
	(0.121)	(0.000246)		
TweetFlagv2			0.156	0.00129***
			(0.123)	(0.000250)
ReTweets_v2			0.0398	0.0000973
			(0.0524)	(0.000107)
Constant	0.0224	0.000918***	0.0114	0.000890***
	(0.0161)	(0.0000328)	(0.0162)	(0.0000330)
Observations	9727	9727	9727	9727
Adjusted R^2	0.000	0.002	0.000	0.006

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Regression of S&P 500 on Tweet Indicators and Multiple Tweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv2	0.0251	0.00465***	0.188*	0.00324*
	(0.0983)	(0.00165)	(0.106)	(0.00178)
Multiple_Tweets			-0.203***	0.00176**
			(0.0495)	(0.000830)
Constant	-0.000706	0.00601***	-0.000706	0.00601***
	(0.0234)	(0.000393)	(0.0234)	(0.000392)
Observations	5276	5276	5276	5276
Adjusted R^2	-0.000	0.001	0.003	0.002

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Regression of S&P 500 on Tweet Indicators and Favorites

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.100	-0.000381		
	(0.226)	(0.00378)		
Favorites_v1	0.00649	0.00110		
	(0.123)	(0.00206)		
TweetFlagv2			0.196	0.00230
			(0.136)	(0.00227)
Favorites_v2			-0.107*	0.00148
			(0.0589)	(0.000987)
Constant	0.00281	0.00625***	-0.000706	0.00601***
	(0.0230)	(0.000386)	(0.0234)	(0.000392)
Observations	5276	5276	5276	5276
Adjusted R^2	-0.000	-0.000	0.000	0.002

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 11: Regression of S&P 500 on Tweet Indicators and ReTweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.0783	-0.00107		
	(0.242)	(0.00405)		
ReTweets_v1	-0.0103	0.00167		
	(0.144)	(0.00242)		
TweetFlagv2			0.309**	0.000838
			(0.136)	(0.00229)
ReTweets_v2			-0.181***	0.00243**
			(0.0603)	(0.00101)
Constant	0.00281	0.00625***	-0.000706	0.00601***
	(0.0230)	(0.000386)	(0.0234)	(0.000392)
Observations	5276	5276	5276	5276
Adjusted R^2	-0.000	-0.000	0.001	0.002

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 12: Regression of CSI 300 Index on Tweet Indicators and Multiple Tweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv2	0.276***	0.00531***	0.186*	0.00531***
	(0.0957)	(0.000973)	(0.104)	(0.00106)
Multiple_Tweets			0.0823**	0.000000445
			(0.0370)	(0.000377)
Constant	0.0243	0.00588***	0.0243	0.00588***
	(0.0233)	(0.000237)	(0.0233)	(0.000237)
Observations	4380	4380	4380	4380
Adjusted R^2	0.002	0.007	0.003	0.006

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Regression of CSI 300 Index on Tweet Indicators and Favorites

	(1)	(2)	(3)	(4)
	rPercentChange	rVolatility	rPercentChange	rVolatility
TweetFlagv1	0.0679	0.00206		
	(0.308)	(0.00313)		
Favorites_v1	-0.0580	-0.000115		
	(0.126)	(0.00128)		
TweetFlagv2			0.0116	0.00471***
			(0.128)	(0.00130)
Favorites_v2			0.128***	0.000292
			(0.0410)	(0.000417)
Constant	0.0408*	0.00618***	0.0243	0.00588***
	(0.0227)	(0.000232)	(0.0233)	(0.000237)
Observations	4380	4380	4380	4380
Adjusted R^2	-0.000	-0.000	0.004	0.006

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 14: Regression of CSI 300 Index on Tweet Indicators and ReTweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	0.0493	0.00274		
	(0.327)	(0.00334)		
ReTweets_v1	-0.0384	-0.000530		
	(0.130)	(0.00132)		
TweetFlagv2			0.0674	0.00489***
			(0.126)	(0.00129)
ReTweets_v2			0.102**	0.000206
			(0.0402)	(0.000409)
Constant	0.0408*	0.00618***	0.0243	0.00588***
	(0.0227)	(0.000232)	(0.0233)	(0.000237)
Observations	4380	4380	4380	4380
Adjusted R^2	-0.000	-0.000	0.003	0.006

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 15: Regression of MSCI USA Indutrials on Tweet Indicators and Multiple Tweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv2	-0.0206	0.0221***	0.208*	0.0153***
	(0.0995)	(0.00315)	(0.107)	(0.00339)
Multiple_Tweets			-0.286***	0.00849***
			(0.0501)	(0.00159)
Constant	-0.00963	0.00660***	-0.00963	0.00660***
	(0.0237)	(0.000752)	(0.0237)	(0.000750)
Observations	5289	5289	5289	5289
Adjusted R^2	-0.000	0.009	0.006	0.014

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 16: Regression of MSCI USA Indutrials on Tweet Indicators and Favorites

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	-0.468**	0.00318		
	(0.223)	(0.00710)		
Favorites_v1	0.267**	-0.000715		
	(0.132)	(0.00419)		
TweetFlagv2			0.275**	0.0224***
			(0.137)	(0.00436)
Favorites_v2			-0.186***	-0.000171
			(0.0597)	(0.00189)
Constant	-0.00757	0.00781***	-0.00963	0.00660***
	(0.0233)	(0.000742)	(0.0237)	(0.000752)
Observations	5289	5289	5289	5289
Adjusted R^2	0.001	-0.000	0.001	0.009

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 17: Regression of MSCI USA Indutrials on Tweet Indicators and ReTweets

	(1)	(2)	(3)	(4)
	rPercentChange	rVolatility	rPercentChange	rVolatility
TweetFlagv1	-0.460*	0.00233		
	(0.239)	(0.00760)		
ReTweets_v1	0.272*	-0.0000220		
	(0.156)	(0.00496)		
TweetFlagv2			0.490***	0.00722*
			(0.138)	(0.00437)
ReTweets_v2			-0.325***	0.00950***
			(0.0610)	(0.00193)
Constant	-0.00757	0.00781***	-0.00963	0.00660***
	(0.0233)	(0.000742)	(0.0237)	(0.000750)
Observations	5289	5289	5289	5289
Adjusted R^2	0.000	-0.000	0.005	0.013

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 18: Regression of MSCI China Industrials on Tweet Indicators and Multiple Tweets

	(1)	(2)	(3)	(4)
	rPercentChange	rVolatility	rPercentChange	rVolatility
TweetFlagv2	0.335***	0.00242*	0.426***	0.000883
	(0.0970)	(0.00132)	(0.105)	(0.00143)
Multiple_Tweets			-0.0834**	0.00141***
			(0.0375)	(0.000510)
Constant	-0.0661***	0.00576***	-0.0661***	0.00576***
	(0.0237)	(0.000322)	(0.0237)	(0.000321)
Observations	4362	4362	4362	4362
Adjusted R^2	0.003	0.001	0.003	0.002

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 19: Regression of MSCI China Industrials on Tweet Indicators and Favorites

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	0.440	-0.00415		
	(0.335)	(0.00455)		
Favorites_v1	-0.264	0.00238		
	(0.298)	(0.00404)		
TweetFlagv2			0.449***	-0.000427
			(0.129)	(0.00176)
Favorites_v2			-0.0551	0.00138**
			(0.0416)	(0.000565)
Constant	-0.0481**	0.00593***	-0.0661***	0.00576***
	(0.0231)	(0.000313)	(0.0237)	(0.000322)
Observations	4362	4362	4362	4362
Adjusted R^2	-0.000	-0.000	0.003	0.002

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 20: Regression of MSCI China Industrials on Tweet Indicators and ReTweets

	(1) rPercentChange	(2) rVolatility	(3) rPercentChange	(4) rVolatility
TweetFlagv1	0.250	-0.00435		
	(0.442)	(0.00600)		
ReTweets_v1	-0.000701	0.00226		
	(0.424)	(0.00575)		
TweetFlagv2			0.426***	-0.000593
			(0.128)	(0.00174)
ReTweets_v2			-0.0440	0.00147***
			(0.0408)	(0.000554)
Constant	-0.0481**	0.00593***	-0.0661***	0.00576***
	(0.0231)	(0.000313)	(0.0237)	(0.000322)
Observations	4362	4362	4362	4362
Adjusted R^2	-0.000	-0.000	0.003	0.002

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$