How investor sentiment and trade conflicts affect the stock markets

Kevin Gu
Deerfield Academy
Deerfield, MA, USA
kgu21@deerfield.edu

Yuxin Xie
Phillips Academy Andover
Andover, MA, USA
yxie21@andover.edu

***Abstract*—Recently, the trade conflict between the United States and China has become an international area of interest and a hot topic. This study wants to investigate the impacts of trade conflicts on both countries' stock markets.**

This research measures the changes in stock market prices from the perspective of behavioral finance. After eliminating the influence of macroeconomics through its representative indicators, this paper constructs an index reflecting investor sentiment using the principal component analysis. This work builds a regression model considering investor sentiment and the intensity of trade conflicts. The results show that there is an asymmetric influence of Chinese investor sentiment on the performance of the stock market. Comparatively, U.S. investor sentiment has a weaker impact on market performance. In order to denote the intensity of trade conflicts, this paper collects the frequencies of trade conflicts from newspapers and Google Trends. We find that trade conflicts have negative impacts on both stock markets and their major industries. Among the four selected industries, the market performance of the Chinese manufacturing industry was the most affected among all by trade conflicts, while the most affected market in the U.S. was the scientific research industry. This indicates that in the currently globalized field of production, the supply chains of the two countries are highly connected and raising tariffs will adversely affect the performance of industries in which the two countries are tightly correlated.

In addition, this paper predicts the stock prices and returns of both stock markets in the future based on Ito's process. The results show that the stock performances with high trade conflict intensity behaves badly compared to those with low intensity.

Keywords- Trade conflicts, Behavioral finance, PCA, Regression, Ito's process

I. INTRODUCTION

A. Background

In recent years, the trade conflicts between the U.S. and China have become more common and intensified. Many governments, out of different considerations, have introduced measures such as raising tariffs and restricting market access, which can cause some evident impacts on the performance of a country's stock market. For instance, Trump sent a twitter about imposing 25% tariffs on 200 billion dollar products imported from China on May 6, 2019, and this caused the stock markets of both countries to fluctuate violently with the Dow Jones Index decreasing by 1.8% while the Shanghai Composite Index decreasing by 5.58% within one day. Attracted by the trade conflicts between the U.S. and China, this paper investigates the impacts of trade conflicts on both stock markets, and more specifically, the quantitative impacts on each of their industries.

There are many factors that could influence the performance of the stock market. As previously mentioned, people are assumed to be completely rational when making decisions in traditional economics [1]. And based on the rational assumption, some theoretical frameworks, such as the Efficient Market Hypothesis (EMH), Three-Factor Model, etc., are introduced into the measurement of the stock market [2,3]. However, this rational assumption neglects human psychology and presupposes that investors are capable of faultlessly evaluating the costs and benefits of their decisions. Preferences and constraints caused by cognitive bias and emotional factors usually affect people's abilities to make decisions and do not result in choices that would endow them with optimized results that would maximize their individual satisfaction [4]. Past incidents, including the Tulip Bubble in Holland and the Internet Bubble in the U.S., show that the market is not always efficient and can be affected by such irrationalities. In the stock market, especially in China, the irrationality of investors is prevalent and obvious, which can produce inefficient markets and mispriced securities. Comparatively, behavioral economics accounts for the emotional, psychological, cognitive, cultural, and social factors of people to better simulate the actual conditions of the market where humans are largely involved. Behavioral economics and finances have thus aroused our interest in evaluating the changes in the stock market of both countries. Behavioral finances have developed in recent years, particularly by Richard Thaler, who contributed to building a bridge for economic and psychological analyses of individual decision making [5]. In this field, investment behavior is regarded as a psychological process, and investors' sentiments can potentially influence stock prices.

Researchers have previously evaluated sentiments by measuring public mood in six dimensions (calm, alert, happy, etc.) from Twitter and Weibo [6,7]. However, it is not appropriate to assess the effects of public sentiments on market prices by using information obtained from these online social platforms due to their weak economic relations. Therefore, investor sentiments hold more importance in the dynamics of the stock market because of their direct relation. As such, this paper will not include indices that reflect public sentiment, but will instead only consider the psychological states of investors and how they would impact the market.

B. Impact of Tariffs on Economy

This paper gives a simple economic analysis of imposing tariffs on imported products using our learned economic knowledge, though there are many theories correlated with international trade. Many factors are taken into consideration when a country decides the amount of tariff to impose, such as the maintenance of economic benefit, regulation of the national economy, and balance of foreign trade. Yet, tariffs always have negative effects from a consumer standpoint. Raising tariffs or imposing other restrictions regarding market accessibility could significantly impact national and consumer welfare. Based on theories of microeconomics, raising tariffs would increase product prices and subsequently decrease demand [8]. The influences are shown in the following figure:

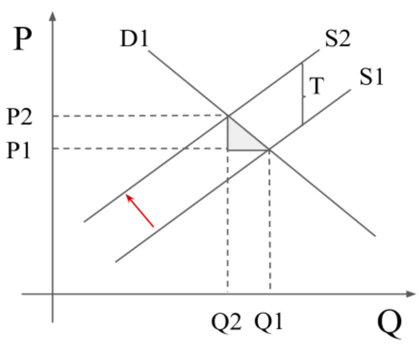


Figure 1. Impact of tariffs on equilibrium supply and price.

In the figure above, P1 and Q1 are the price and supply, respectively, at market equilibrium. After tariffs are imposed, the supply curve is vertically displaced from S1 to the position S2. When the new market equilibrium is reached, P2 and Q2 are the new equilibrium price and supply respectively. The shaded triangle area represents the unnecessary loss caused by the imposition of tariffs. And hence, the welfare of consumers in the U.S. is decreased to some extent even though the government obtains the tax revenue.

Tariffs also have a considerable impact on the export countries from a macro perspective. Based on the analysis of the aforementioned figure, tariffs decrease export supply due to the higher prices and thus weaken the economic development (GDP is comprised of consumption, investment, and exports). As the reflection of a country’s economic development, the stock market is impacted consequently. Tariffs would raise prices of products for imports. It follows that given a certain amount of wealth, the quantity of purchasable products decreases. Therefore, tariffs impact a country’s economy negatively in the macroeconomic aspect.

As the trade conflicts between the U.S. and China continue to escalate, the stock markets of both countries will undergo several changes. The heightened tariffs, a result of the recent conflicts, impact the economic output of imports and exports. In turn, sustained damage would directly weaken the development of related industries, which would be reflected in the performance of the stock market. These issues also affect investor sentiment. During periods of tense U.S.-China relations, irrational behaviors are likely to be prevalent in investors. Herd behavior is one such example of collective investor irrationality and extreme sentiment. Individuals, acting sequentially on the behavior of others, can reduce the efficiency of the market [1]. These induced investor irrationalities can thereby cause abnormal development in stock prices. And their relations are shown as follows:

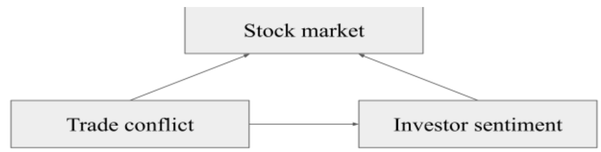


Figure 2. The influencing mechanisms of trade conflict, investor sentiment, and the stock market.

C. Purpose and Structure

The purpose of this paper is to measure the impacts of trade conflicts between the U.S. and China on their stock market performances based on behavioral finance. Additionally, analyzing the differing impact trade conflicts have on various industries holds great significance for our analysis of the trade conflicts. When trade conflicts occur, stock markets do not simply react to those corresponding fluctuations temporarily, and thus the impact of trade conflicts on stock markets that we are addressing in this paper refers to the long-term impacts.

The basic structure of this paper is as follows: the first section introduces background information and previous research on this aspect. Using a simple microeconomic model, we can theoretically demonstrate the mechanism by which trade conflicts affect stock market performance and investor sentiment; the second section incorporates several assumptions; and the third section illustrates sources of data cited in this paper and the methods that we adopt to process these data, which provides statistical support for the econometric models used later in this paper; the fourth section, which is the focus of this paper, incorporates the models and results, also including the construction for investor sentiment index, some econometric models, and the specific results derived from them; the fifth section is a simulation regarding the future intensity level of the trade conflicts by analyzing stock market performances of both countries under different circumstances; and the sixth section is a summary for this research.

II. ASSUMPTIONS AND JUSTIFICATIONS

1) ***Assumption 1****: The indicators selected in this work could reflect the macroeconomic conditions in the economy.*

Justification*:* Only macroeconomics is needed to represent the markets of industries as a whole since microeconomic factors only impact individual companies instead of the overall condition of industries.

2) ***Assumption 2****: The sources of the data are reliable.*

Justification*:* The data was obtained from government released sources and well-known databases. The websites used for the internet crawler are reputable and used by investors. In addition, these sources are often utilized by data-analysts and researchers.

3) ***Assumption 3****: When simulating future stock market trends, assume that it is subject to a random process and does not consider major macroeconomic changes.*

Justification*:* Many scholars have different methods for forecasting the stock market, but the most common is to assume that the stock price obeys the Wiener process and then simulate the stock market. Based on this theory, this paper simulates the changes of the future stock market under different levels of trade conflicts. Since major macroeconomic changes will significantly affect the overall development of the stock market, therefore, in the simulation, the impact of major macroeconomic changes will not be considered.

III. Data Collecting and Preprocessing

To analyze the effect of investor sentiment on stock markets, we choose four indicators to represent the macroeconomic effects on the stock markets: consumer price index (CPI), producer price index (PPI), unemployment rate (UR), and business confidence index (BCI). The annual percentage change in the CPI can be used as a measure of inflation; the PPI, which measures the average changes in prices received by domestic producers for their output, can reflect the overall condition of the manufacturers and producers; the UR has an inverse linear relationship with economic growth, according to Okun's law [9]; and the BCI reflects how positively the investors view the current economic situation. The data sources of these variables are all from official databases.

A. Sources of Data

To evaluate the impact of investor sentiment and trade conflicts on market prices, we need to collect and preprocess data. Based on previous research, the variables to measure investor sentiment are primarily closed-end fund discounts, IPO quantities, IPO first-day returns, market turnover rates, and quantities of A-share newly opened accounts. And the data sources are shown as follows:

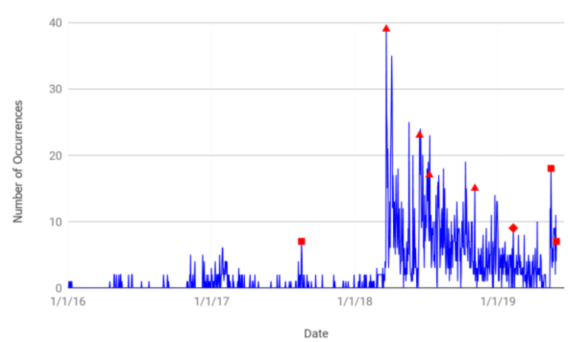
TABLE I. Table Type Styles

Investor sentiment index	Sources of data	Macroeconomic indicators	Sources of data
Closed-end fund discount	Wind	Consumer price index	National Bureau of Statistics
IPO quantity	Wind	Producer price index	National Bureau of Statistics
IPO first-day return	Wind	BCI (business confidence index)	National Bureau of Statistics
Market turnover rate	Wind	Unemployment Rate	National Bureau of Statistics
Quantity of A-share newly opened accounts	Wind	-	-

Note: National Bureau of Statistics includes the Chinese Statistics Bureau and U.S. Bureau of Labor Statistics.

As for the data of trade conflicts between China and the U.S., we need some approaches to estimating it. Previous studies have used dummy variables to evaluate the effects of political events [10]. Previous to the declaration, scholars assign the value 0 to the dummy variable D; after an event, the value of the dummy variable changes to 1. However, regulations of different severities can bring about impacts that vary significantly. For instance, raising the tariff value by 5%, 10%, or restricting access, etc. all impact the market in distinct ways. Simply employing dummy variables can be difficult to reflect impact. Hence, to increase the accuracy of our model, we use the frequency of occurrence of news including the keywords "trade conflict" and "trade war" as proxy variables to precisely measure the extent of the impact of the trade conflicts. The greater the frequency with which relevant news occurs, the more information can become accessible to investors, and thus, the greater the effect is on the stock market. The number of articles pertaining to trade can then be assessed using methods such as regression.

Due to the different policies of media regulation in the U.S. and China, the content and quantity of the news corresponding to trade conflicts differ in each country. Therefore, it is necessary to observe and collect data from several reputable sources of finance and economics to measure the level of social recognition and public attention to trade issues. For statistics in China, we use an internet crawler using the phrases "贸易摩擦" and "贸易战" as key terms to find the number of relevant news on Sina Finance, China's largest portal website (https://finance.sina.com.cn/). We apply a similar strategy for U.S. statistics with the crawler to attain the frequency of the appearance of the terms on the business paper Wall Street Journal. (https://wsj.com/). The results are shown as follows:



Note: ◇ denotes public statements, □ denotes policy changes, △ denotes imposed tariffs..

Figure 3. Occurrences of "贸易摩擦" and "贸易战" in Sina Finance from 2016 to 2019.

In the above figure, it can be seen that the occurrences of the phrases "贸易摩擦" and "贸易战" are largely correlated with trade conflict development and intensity. For instance, on March 23rd of 2018, the U.S. imposed a 25% tariff on all steel imports and a 10% tariff on all aluminum imports. On that day, Sina Finance mentioned the aforementioned terms 39 times that day, mirroring the intensity of the imposed tariffs.

B. Data Preprocessing

When constructing the investor sentiment index, the varied units of the different variables would affect the calculation of the investor sentiment index. In order to eliminate the effects of the units, this paper will first normalize the selected data, which can be categorized into two types: the processing of continuous data and the processing of scattered data.

For continuous data, such as price-earnings ratio (PE) and market turnover rate, the way to normalize the data is shown as follows:

$$X_i^* = \frac{X_i^* - \bar{X}}{S_X}$$

$$\text{Note: } \bar{X} = \frac{\sum X_i}{n}, S_X = \frac{1}{n-1}\sum (X_i - \bar{X})^2$$

For discrete data, such as NIPO (number of IPO) and the quantity of reports related to trade conflicts, the way to normalize the data is as follows:

$$X_i^* = \frac{X_i - \min_i X_i}{\max_i X_i - \min_i X_i}$$

The representation of the performance of the stock markets is the return rate. To ensure congruity, for this paper, we will take the logarithm of the return rate. The formula is shown as follows:

$$R_t = \ln \frac{P_t}{P_{t-1}}$$

By using these aforementioned methods to normalize the data, we can eliminate the effects of the varied units of the variables, which makes the calculation of the investor sentiment index more reasonable. This data can support the analysis of the impact of investor sentiment and trade conflicts on stock markets later in this paper.

IV. Modeling

A. Principal Component Analysis

Since the market and sentiment are influenced by macroeconomic factors, it is critical to eliminate the influences of these variables when measuring the impact of investor sentiment on the stock market. This paper will use consumer price index (CPI), producer price index (PPI), unemployment rate (UR), and business confidence index (BCI) as major variables to evaluate macroeconomic factors. The selected investor sentiment variables are then regressed to these factors, and the form is as follows:

$$y_z = \beta_0 + \beta_1 \mathrm{CPI}_t + \beta_2 \mathrm{PPI}_t + \beta_3 \mathrm{UR}_t + \beta_4 \mathrm{BCI}_t + \varepsilon_{it}$$

In this equation, the subscript i represents the i^{th} index of the investor sentiment variable. The residual series from the linear regression in the aforementioned equation can be used to eliminate the influences of macroeconomics. Principal component analysis can then be employed according to the investor sentiment variable.

Since there's a certain degree of collinearity among the variables for investor sentiment, we use principal component analysis to change these variables to those that are not linearly correlated. X_{it} can be used to represent the investor sentiment variable without influences of macroeconomics, and the following formula can be applied to linearly transform the aforementioned variable:

$$\mathbf{Sent} = \boldsymbol{\mu}^T \boldsymbol{X}$$

$$\text{s.t.}\, \boldsymbol{\mu}_i' \boldsymbol{\mu}_i = 1$$

In the formula, $sent_i$ represents the i^{th} investor sentiment index after processing. $sent_1$ is the index with the maximum variance while satisfying the aforementioned restriction; $sent_2$ has the second maximum variance among all linear combinations that are not correlated to $sent_1$, etc. Using the principal component analysis, the overall investor sentiment indices for this paper can be constructed.

Among the investor sentiment indices constructed, if the investor sentiment index (sent) > 0, then it can be inferred that the general investor sentiment in the market is relatively positive (a bullish sentiment); if investor sentiment index (sent) < 0, then it shows that the general investor sentiment in the market is relatively negative (a bearish sentiment). The comparison between the investor sentiment index and the Chinese stock market is as follows:

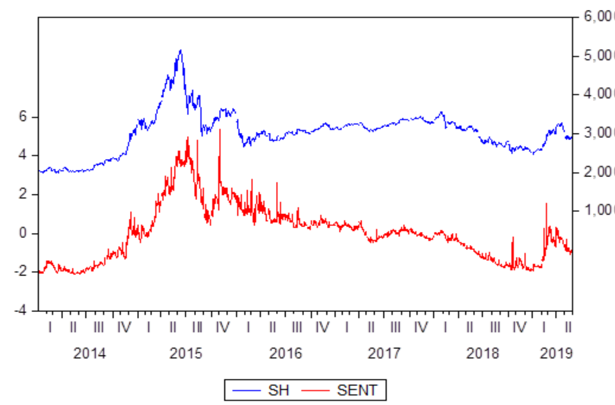


Figure 4. The trends of the Shanghai Composite Index and investor sentiment.

B. Stock Market Returns and Investor Sentiment

In order to evaluate the relationship between investor sentiment and return rate in the Chinese stock market, we construct a linear regression model to represent the relations between the stock market returns and investor sentiment using the least-squares method. The constructed model is as follows:

$$r_t = c + \alpha_1 sent_t d_{1t} + \alpha_2 sent_t (1 - d_{1t}) + \varepsilon_t$$

In the formula, d_{1t} is a dummy variable and is defined as follows:

$$d_{1t} = \begin{cases} 1, & sent_t \geq 0 \\ 0, & sent_t < 0 \end{cases}$$

That is, we assume that various investor sentiments have different impacts on the stock market. The investor sentiments are mainly divided into two categories: one is positive sentiment

(d_{1t}=1); the other is negative sentiment ($d_{1t} = 0$), which could cause different effects on investors' decisions.

C. *Impact from Trade Conflicts*

As mentioned in the abstract, trade conflict impacts both investor sentiment and the stock market. Therefore, this paper will consider the impacts that trade conflicts have on both the U.S. and Chinese stock markets. Because the data dimensions vary greatly, the collected data regarding trade must first be normalized. The normalization is as follows:

$$x_i^* = \frac{x_i - \min_i x_i}{\max_i x_i - \min_i x}$$

Using this formula, the data range can be mapped to [0, 1], which can avoid issues of the regression coefficients being overly small due to the large values of the data and facilitate the analysis. Taking all these factors into consideration, we construct the model with the trade conflict factors included:

$$r_t = c + \alpha_1 sent_t d_{1t} + \alpha_2 sent_t (1 - d_{1t}) + \beta_1 trade_t + \beta_2 trade_t \times sent_t + \varepsilon_t$$

This formula takes into consideration the influence of trade conflicts on the stock market. Generally speaking, when the U.S. or China declare an increment in tariffs or implement other regulations regarding access restrictions, the amount of relevant news increases. Hence, we will not incorporate dummy variables in the aspect of the trade conflict.

The relationship between term frequencies and market indices is shown as follows:

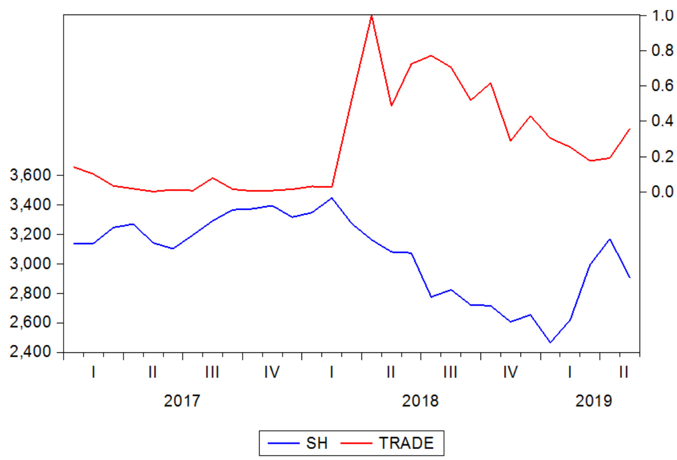


Figure 5. Relationship between Sina Finance term frequency and Shanghai market.

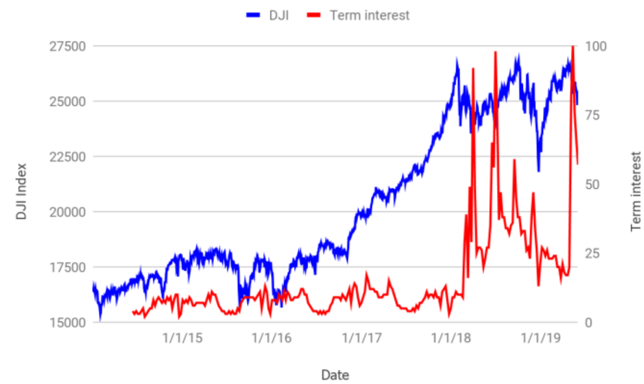


Figure 6. Relationship between Google term interest and DJI.

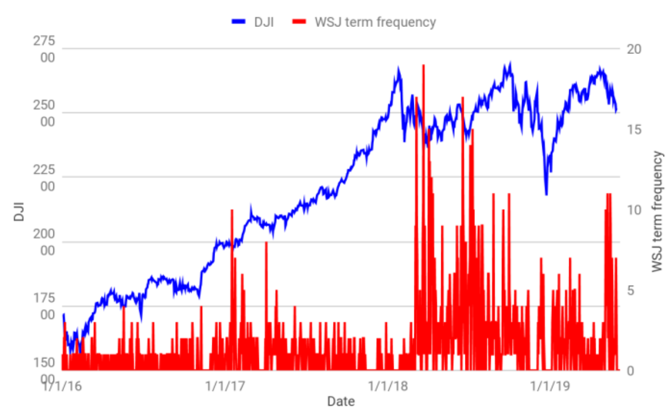


Figure 7. Relationship between Wall Street Journal term frequency and DJI.

From the graphs above, we can see that there exists an inverse relationship between term frequency and the overall performance of the stock market. When the frequency with which the terms related to trade conflicts occur increase, the stock market indices follow a decreasing trend in correspondence.

V. RESULTS AND DISCUSSION

A. *China*

1) *Principal component analysis results*

After processing the data, we can find the relative correlation among the variables. The results are shown in the figures below:

TABLE II. CORRELATION OF VARIABLES.

	ADD ACCOUNT	FIRST DAY RETURN	IPO	STOCK TURNOVER
ADD ACCOUNT	1.000000			
FIRST DAY RETURN	0.010779	1.000000		
IPO	0.469691	-0.039520	1.000000	
STOCK TURNOVER	0.687480	0.072061	0.383502	1.000000

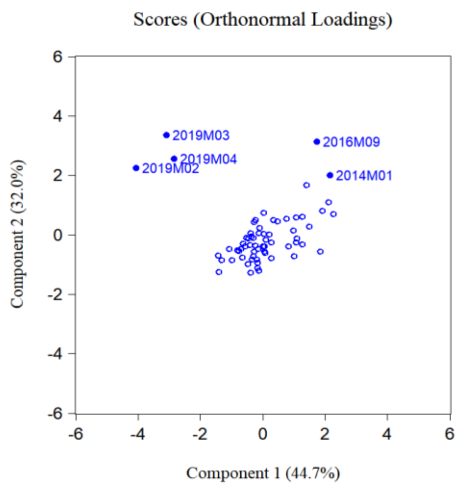


Figure 8. Scores of principal component analysis.

By applying principal component analysis to these variables, we eventually get that the cumulative contribution rate of the variances of the first three constructed principal components reaches 92.44%, which proves that the variables are sufficiently uncorrelated. By using the coefficient of the first principal component as the weight, we can construct the overall investor sentiment index, and the result is as follows:

$$Sent_t = 0.6233 \times acc_t + 0.0289 \times fir_t$$
$$+0.5016 \times ipo_t + 0.5993 \times turn_t$$

Now we can compare the overall investor sentiment index with the stock market index, which reflects the overall condition in the Chinese stock market (Shenzhen stock exchange and Shanghai stock exchange, the only two authoritative exchanges in China, have similar indices for stock markets; hence, only one is needed), and stock market return rate. The comparison graphs are shown below:

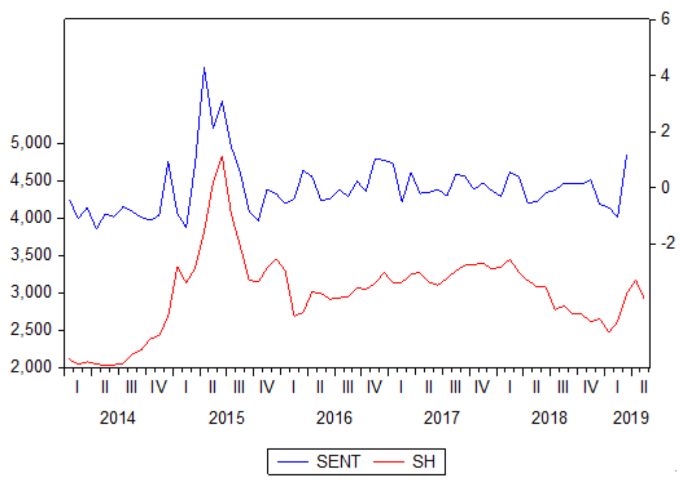


Figure 9. Impact of investor sentiment on Shanghai market index..

From the figure above, we can see that the constructed investor sentiment index in this paper is highly correlated with the changes in the Chinese stock market. The graph shows the fluctuations and trends that resemble each other. Using the investor sentiment index and the stock market return to conduct the Granger causality test, we can find that the investor sentiment causes changes in the returns of the Chinese stock market.

TABLE III. GRANGER CAUSE TEST.

Null Hypothesis:	Obs	F-Statistic	Prob.
RETURN does not Granger Cause SENT	60	0.17804	0.8374
SENT does not Granger Cause RETURN		5.95167	0.0046

Since the significance level is 1%, the result of the Granger causality test can be considered significant. This demonstrates that investor sentiment is a critical cause of changes in the Chinese stock market.

2) *Effects of investor sentiment on the stock markets*

Based on the models constructed in the modeling section, we can derive the impact of investor sentiment on the stock markets by using linear regression in Eviews. The result is shown in the chart below:

TABLE IV. RESULT OF INVESTOR SENTIMENT ON STOCK MARKET RETURNS.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.011250	0.013337	-0.843515	0.4023
SENT*D1	0.034940**	0.012338	2.831980	0.0063
SENT*(1-D1)	-0.012429	0.021778	-0.570703	0.5704

Note: ***, **, * represent the coefficient is significant at 1%, 5% and 10% significance level.

As the results from the regression show, when the investor sentiment is relatively positive (sent > 0), the coefficient is 0.03494, which is significant since 1% is a significant level. Every one-unit rise in positive investor sentiment index would cause the Chinese stock market return rate to increase by 0.03494 units. Comparatively, when the investor sentiment is relatively negative (sent < 0), the coefficient is -0.012429, which is to say that every one unit increase in negative investor sentiment would cause the Chinese stock market return rate to decrease by 0.012429 units. Therefore, the negative investor sentiment does not impact the stock market significantly, which is most likely due to the fact that when investors experience emotional distress, they tend to reevaluate the costs and benefits of their investment and consequently normalize their behaviors.

According to the results given from regression, we can conclude that sentiment significantly impacts stock returns in the Chinese stock market. Specifically, positive sentiment holds more significance in the stock market than negative sentiment. Therefore, it is possible that the herd effect is prevalent among Chinese investors.

3) *Analysis*

After substituting the frequency of search for “trade conflict” and “trade war” into the aforementioned model of regression (using the stock returns of the Chinese stock market as the dependent variable), we can get the results as shown below:

TABLE V. CONSIDERING TRADE CONFLICTS.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.003517	0.014723	-0.238865	0.8121
SENT*D1	0.031588**	0.012592	2.508626	0.0149

SENT*(1-D1)	-0.005840	0.022354	-0.261258	0.7948
TRADE*D2	-0.046333	0.038052	-1.217621	0.2283

Note: ***, **, * represent the coefficient is significant at 1%, 5% and 10% significance level.

From the chart above, we can see that the coefficient before the variable TRADE*D2 is -0.046333, which is less than 0. This reflects that the trade conflict has some extent of negative impact on the Chinese stock market. In addition, for this paper, we use both investor sentiment and trade conflicts as variables for regression. From the results, we find that trade conflicts also negatively impact investors' sentiment, and the coefficient of their correlation variable is -0.14886. However, limited by the amount of data that could be collected, the result is not significant under the 5% significance level. Yet, we still find that trade conflicts cause Chinese investors' sentiment indices to decrease, which is to say investors tend to negatively react to news of trade conflicts.

4) The degree of impact on different industries

More specifically, in order to analyze the impact of investor sentiment and trade conflicts on the stock markets of different industries, this paper includes data of the stock markets of different industries (the data employed are the sub-industry indices based on the stock market performance of companies in different industries. The source of the data is Wind database and the categorization of the companies is according to the official Chinese (CSRC China Securities Regulatory Commission) industry classification standard. We take agriculture, forestry, and fishery; manufacturing; information technology; and scientific research industries as examples since they are the industries most concerned by the general public. The impact that investor sentiment and trade conflicts have on these different industries is shown in the chart below:

TABLE VI. IMPACT OF SENTIMENT AND TRADES ON VARIOUS INDUSTRIES.

Industries	Sent*d1	Sent*(1-d1)	Trade*d2
Agriculture, Forestry, Fishery	0.051005	-0.013385	-0.073864
Manufacturing	0.050364	-0.016222	-0.134486
Information Technology	0.070676	-0.056144	-0.064813
Scientific Research	0.069307	-0.038881	-0.091891

When the investor sentiment index changes to negative, the stock markets of information technology and scientific research industries are negatively impacted to the greatest extent, and the stock markets of agriculture (forestry and fishery) and manufacturing industries are less negatively impacted in comparison. This reflects that when investors sentiment is negative,

As we can see from the graph above, investor sentiment and trade conflicts impact different industries in distinct ways. Comparatively, the information technology industry is impacted most significantly when the investor sentiment is positive. The positive investor sentiment and the stock market of the information technology industry are significantly correlated; for every unit of increase in the constructed investor sentiment index, the return rate of the stock market in the information technology industry also increases by 0.070676 units in response. In addition, positive investor sentiment also has a relatively significant impact on scientific research industries. Every unit of increase in investor sentiment would result in a 0.069307-unit increase in the stock return rate of the stock market of the scientific research industry. This reflects that when the investor sentiment is positive, investors generally hold optimistic perspectives towards technology-based companies.

When the investor sentiment index changes to negative, the stock markets of information technology and scientific research industries are negatively impacted to the greatest extent, and the stock markets of agriculture (forestry and fishery) and manufacturing industries are less negatively impacted in comparison. This reflects that when investor sentiment is negative, the basic industries, such as agriculture (forestry and fishery) and manufacturing are impacted by a relatively small amount, which is to say that the investor sentiment hardly impacts the stock markets of these aforementioned industries.

For impact from trade conflicts, the results show that stock markets of the manufacturing industry are impacted most significantly. Every unit of increase would cause the return rate of the stock markets of the manufacturing industry to decrease by 13.4486%. This is possibly due to the structure of the Chinese export system, which is that the majority of exports are products related to manufacturing. Therefore, when trade conflicts occur, the export of these departments would be impacted; hence, the reflection in the stock market is that the return rate decreases. Secondly, the stock markets of scientific research industries also appear to be impacted relatively significantly, which is possibly due to the specific content of the trade conflicts. When the U.S. blockades Chinese technology, the stock market of the corresponding industry would seem to be affected.

On the other hand, the information technology and agriculture (forestry and fishery) industries are impacted less significantly. This can be possibly explained by the peculiar condition of China. The information technology companies have a relatively weak influence abroad, while the possession rate is much higher in China, which makes it reasonable that trade conflicts barely affected the stock markets of this industry. For agriculture (forestry and fishery), the restriction imposed on the import of U.S. agricultural products stimulates the development of this industry in China, and thus the stock markets of agriculture are also hardly affected by trade conflicts. On the other hand, the information technology and agriculture (forestry and fishery) industries are impacted less significantly. This can be possibly explained by the peculiar condition of China. The information technology companies have a relatively weak influence abroad, while the possession rate is much higher in China, which makes it reasonable that trade conflicts barely affected the stock markets of this industry. For agriculture (forestry and fishery), the restriction imposed on the import of U.S. agricultural products stimulates the development of this industry in China, and thus the stock markets of agriculture are also hardly affected by trade conflicts.

B. United States

1) Effects of investor sentiment on the stock markets

Reapplying the process used previously for the Chinese stock market (), we can also estimate the return rate in U.S. stock markets. The formula is as follows:

$$r_t = c + \alpha_1 sent_t d_{1t} + \alpha_2 sent_t (1 - d_{1t}) + \varepsilon_t$$

Using linear regression on EViews, we can find results as shown in the table below:

TABLE VII. RESULT OF INVESTOR SENTIMENT ON STOCK MARKET RETURNS.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007891	0.004094	1.927309	0.0587
SENT*D1	0.003991	0.006052	0.659483	0.5121
SENT*(1-D1)	0.005197	0.006210	0.836878	0.4060

From the chart above, we can see that the coefficient before the constructed investor sentiment index is 0.003991, which is to say that for the U.S. stock markets, when the investor sentiment is positive, every unit of increase in investor sentiment index would result in a 0.399% increase in the return rate of U.S. stock markets. Comparatively, when the investor sentiment is negative, every unit of increase in investor sentiment index (to become less negative) would cause the return rate of U.S. stock markets to increase by 0.5197%. The performance of the stock markets is better when negative investor sentiment index increases in comparison to that when positive investor sentiment index increases.

2) Analysis

Similar to what was mentioned before, this paper uses the frequency of search for the keywords, “trade conflict” and “trade war” as the variable to measure the impact of trade conflicts. The results are shown in the chart below from the data obtained from Google Trends.

TABLE VIII. CONSIDERING TRADE CONFLICTS.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.009587	0.004429	2.164429	0.0345
SENT*D1	0.005054	0.006144	0.822562	0.4141
SENT*(1-D1)	0.005522	0.006219	0.887987	0.3782
TRADE*TRADE_DUMMY	-0.010276	0.010242	-1.003301	0.3198

From the chart above, we can see that the coefficient before trade conflicts is -0.010276, which shows that trade conflicts and the U.S. stock markets are inversely related to each other. In other words, when the increment in tariffs or other restriction regulations is declared, the U.S. stock markets would be negatively impacted. However, in comparison, the negative impact of trade conflicts on the U.S. stock markets is less significant than that on the Chinese stock markets. A potential explanation for this phenomenon is that the trade conflicts incite a greater reaction from the Chinese investors. The greater fluctuation in their sentiment causes the stock market to be affected by a greater extent.

3) The degree of impact on different industries

For this paper, we choose to use Dow Jones’ indices for different industries. In particular, we take the indices of food production, technology, and the industrial average as examples. By using regression, we can calculate the impact of trade conflicts on the stock markets of different industries. The result is shown in the chart below:

TABLE IX. IMPACT OF SENTIMENT AND TRADES ON VARIOUS INDUSTRIES.

Industries	Sent*d1	Sent*(1-d1)	Trade*d2
Food production	0.001566	0.010818	-0.010239
Technology	0.004989	0.009569	-0.020038
Industrial average	0.007234	0.001839	-0.017666

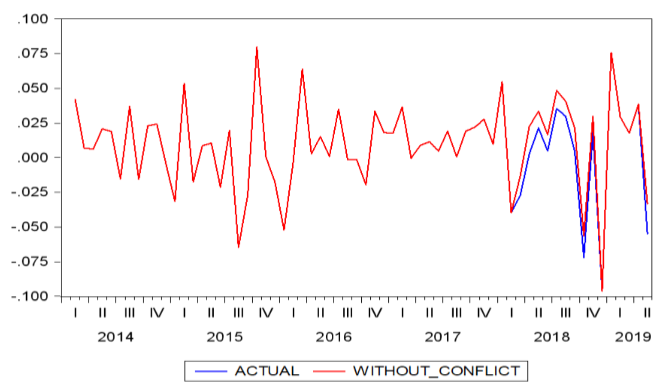
From the graph above, we can see that the coefficients (impacted by the trade conflicts) before the Dow Jones indices of food production, technology, and industrial average industries are -0.010329, -0.020038, -0.017666, respectively. The stock markets of the technology industry are impacted most significantly, and second to that is the industrial industry, while the food production industry is impacted by trade conflicts least significantly. This demonstrates that in the highly globalized current society, the production chains of the industries of all the countries are tightly connected; therefore, heightening tariffs would negatively impact the industries in which the two countries are highly related.

The industrial average is impacted most by investor sentiment, as indicated by the magnitude of the coefficient in comparison to technology and food production. It follows that positive sentiment and the performance of U.S. industries are significantly correlated. This can be explained by the investors’ view of the market holistically - trade conflicts are perceived to impact a wide breadth of industries.

The technology sector is impacted to a greater extent than food production by investor sentiment. Similar to that of China’s, during moments of positive investor sentiment, there is a trend of higher optimism and therefore a market index of technology-based companies in reference to the food industry. Since the U.S.’ market of agriculture is stable and therefore relatively independent of sentiment, it could account for the smaller correlation. The technology sector is largely based on communications and relations, so the respective index is likely to be largely impacted by tariffs and sentiment.

C. Comparison

Based on these analyses above, we predicted the virtual stock market return of both the U.S. and China without trade conflicts. The graph of the left-hand side represents the actual and virtual stock market return of the U.S. while the right-side represents those of China.



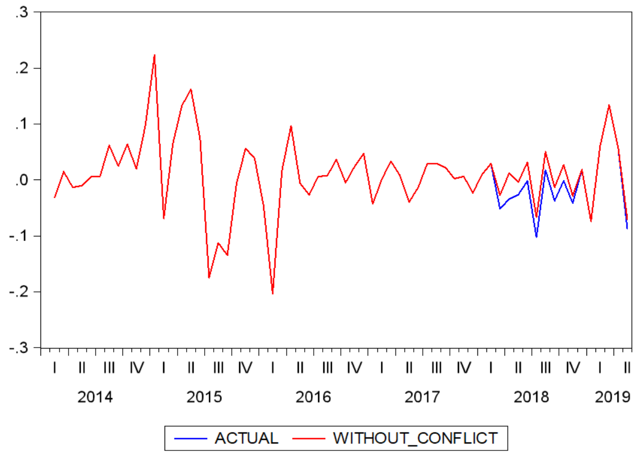


Figure 10. The actual stock market return and the predicted return without trade conflicts.

From the figure above, we could clearly see that the blue lines of both countries have kept lower than the red lines since 2017, which represents that the trade conflicts have decreased the stock market returns in both countries and proves that the markets could have performed better without the tense trade conflicts.

VI. Further Analysis and Extensions

A. *Generalized Wiener Process for Simulation*

The environment of the stock markets is constantly changing. Many factors affect the performance of the stock markets collectively, and this section will take into consideration the impact of different extents of trade tension on the stock markets. Since the purpose of this simulation part is to forecast fluctuations in the stock markets, which include many uncertainties, we will assume the stock market prices follow the Ito process.

The Wiener process is a special stochastic process with zero drift and variance proportional to the length of the time interval. The Ito process can be expressed as:

$$dx_t = u(x_t, t)dt + \sigma(x_t, t)dw_t$$

The w_t here is a Wiener process, whose differential form satisfies, $\Delta w_t = \varepsilon\sqrt{\Delta t}$.

Using $G(x)$ as a function of x and y, which are both differentiable and then expanding $G(x)$ with Taylor series, we can get the result as follows:

$$\Delta G = G(x+\Delta x, y+\Delta y) - G(x,y) = \frac{\partial G}{\partial x}\Delta x + \frac{\partial G}{\partial y}\Delta y$$

$$+\frac{1}{2}\frac{\partial^2 G}{\partial x^2}(\Delta x)^2 + \frac{1}{2}\frac{\partial^2 G}{\partial y^2}(\Delta y)^2 + +\frac{1}{2}\frac{\partial^2 G}{\partial x \partial y}(\Delta x \Delta y) \ldots$$

Assume that y presents t, and x_t follows the form of Ito process as shown below:

$$dx_t = udt + \sigma dw_t$$

Then G becomes a function of x_t, and t, and its first-order approximation is:

$$dG = \frac{\partial G}{\partial x}dx + \frac{\partial G}{\partial t}dt + \frac{1}{2}\frac{\partial^2 G}{\partial x^2}\sigma^2 dt$$

$$= \left(\frac{\partial G}{\partial x}u + \frac{\partial G}{\partial t} + \frac{1}{2}\frac{\partial^2 G}{\partial x^2}\sigma^2\right)dt + \frac{\partial G}{\partial x}\sigma dw_t$$

Let P_t represent the stock market price at time t, and the price P_t follows the Ito process as follows:

$$dP_t = \mu P_t dt + \sigma P_t dw_t$$

The μ and σ here are both constants. Let $G(P_t, t) = \ln(P_t)$ represent the price of the stocks in logarithm, and we can deduce that:

$$\frac{\partial G}{\partial P_t} = \frac{1}{P_t}, \frac{\partial G}{\partial t} = 0, \frac{1}{2}\frac{\partial^2 G}{\partial {P_t}^2} = \frac{-1}{2 \cdot \partial {P_t}^2}$$

Through Ito process, we can attain that:

$$d\ln(P_t) = \left(\frac{1}{P_t}uP_t + \frac{-1}{2 \cdot \partial {P_t}^2}\sigma^2 {P_t}^2\right)dt$$

$$+\frac{1}{P_t}\sigma P_t dw_t = \left(u - \frac{\sigma^2}{2}\right)dt + \sigma dw_t$$

Based on the formula above, we can know that the return rate of the stock can be expressed as $r_t = \ln(P_t) - \ln(P_{t-1})$. The expected value and variance of the stock market return rate can be written as:

$$u_r = E(r_t) = (u - \frac{\sigma^2}{2}) \cdot \Delta$$

$$\sigma_r^2 = \mathrm{var}(r_t) = \sigma^2 \cdot \Delta$$

From the previous models, we can see that trade conflicts can impact stock market performance. Therefore, in the simulation for changes in future stock market return rate, we deem the intensity level of trade conflicts as an exogenous variable. Including the trade conflict factor into the aforementioned Wiener process, the differential changes to the form as follows:

$$d\ln(P_t) = \left(u - \frac{\sigma^2}{2} + \beta_1 trade_t \cdot d_{2t}\right)dt + \sigma dw_t$$

Integrating the equation above, the logarithmic expression of price becomes:

$$\ln(P_t) = \int_0^t \left(u - \frac{\sigma^2}{2} + \beta_1 trade_t \cdot d_{2t}\right)dt + \int_0^t \sigma dw_t$$

Afterward, we will employ this part as the basics, and by changing the variable $trade_t$, which represents the intensity level of the trade conflicts between the U.S. and China, from 0.6 to 1.4 (which is to say that the intensity level of future trade conflicts is 0.6-1.4 times the current value) we can thereby simulate the stock trends and returns in the future.

B. *Results and Analysis*

Based on the model constructed in section 6.1, we can analyze the possible changes in U.S. and Chinese stock markets in the next 1.5 years under trade conflicts of different intensity levels by coding with MATLAB (The previous ones are the stock market indices from 2014.5-2019.5, and the ones after time 65 are the results of simulation). The resulting changes in stock markets of U.S. and China are shown as follows:

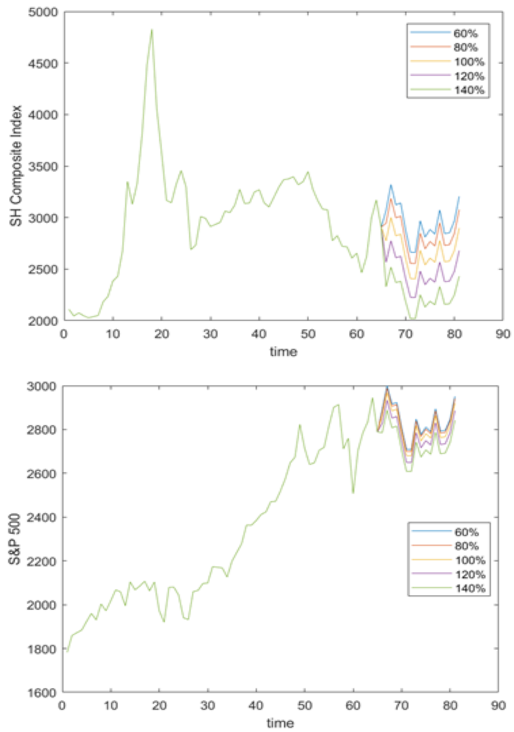
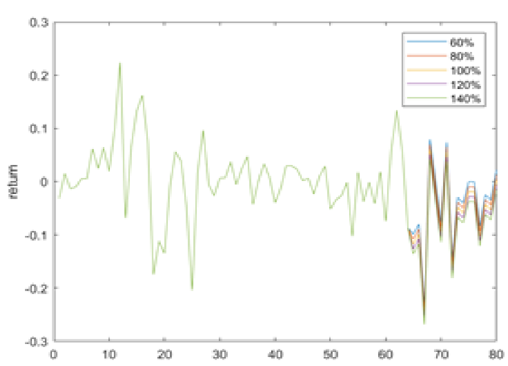


Figure 11. The future stock price of China (Left) and the U.S. (Right).

From the graph above, we can see that in comparison with the situation when the intensity level of trade conflicts is relatively low, the stock market follows a greater downward trend when the intensity level is higher. In other words, the stock market performance is associated with the intensity level of the trade conflicts-the more intense the trade conflicts are, the worse the stock markets perform. Similarly, we can calculate the stock market return rate under trade conflicts of different intensity levels. The results are shown as follows:



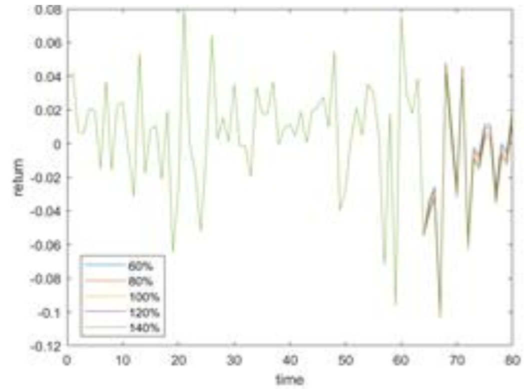


Figure 12. The future stock return of China (Left) and the U.S. (Right).

VII. Conclusion

Considering the recent heated topics, we investigated the impact of investor sentiment and trade conflicts on the stock markets of the U.S. and China. By collecting data from Wind and other official databases, we can summarize our investigation into the following points:

1. Investor sentiment and the stock markets are positively related. There are two types of investor sentiment: positive sentiment and negative sentiment. Under different type of sentiment, investors' behavior differs greatly, which thus causes changes in the stock markets. Based on the method employed to process data in the paper, when the investor sentiment index is greater than 0, it means that the investor sentiment is within the positive range; when the investor sentiment index is less than 0, the investor sentiment is within the negative range.

For Chinese markets, when the investor sentiment is positive, aggressive (prone to risk-taking) involvement in the markets stimulates an overall upward trend in the stock markets, which causes the return rate of the stock markets to increase dramatically. When the investor sentiment is negative, irrational investors usually exit the market. Therefore, although the negative investor sentiment negatively impacts the stock markets, the impact on the stock market is not significant in comparison to the impact that positive investor sentiment has on the stock market.

For U.S. stock markets, positive and negative investor sentiment have almost an equivalent impact on the stock market. This is to say, in comparison, there's more irrationality among investors in Chinese stock markets, and the "herd effect" is easily prevalent.

2. Trade conflicts and the overall condition of the stock markets are negatively correlated. Through analyzing the relationship between the frequency of search of trade conflicts on several reputable websites and the stock markets, we can find that trade conflict has a negative impact on both countries. From the perspective of microeconomics, the ongoing trade conflicts impact the Chinese manufacturing industry relatively significantly, and the second industry most affected is the scientific research industry. This is due to the fact that the tariffs imposed on China by the U.S. are usually concentrated on manufacturing companies. Simultaneously, the stock markets of

the U.S. technology industry are also impacted negatively by trade conflicts. This can be explained by the correlation between the production chain of U.S. technology companies and several Chinese industries. Therefore, trade conflicts affect the regular development of technology-based companies in the U.S.

3. By incorporating the intensity level of trade conflicts into the Ito process, we simulated the stock market trends of U.S. and China under different intensity levels of trade conflicts, including the stock market indices and return rate. Through analysis, we can see that when all of the other conditions are equivalent, the more intense the trade conflicts are, the more negatively impacted the stock markets would. This demonstrates that the intensity level of the trade conflicts is closely related to the future performance of the stock markets of U.S. and China.

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