Chapter

Artificial Intelligence Techniques for Political Risk Management: An NLP Analysis of the 2019 US-China Trade War

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Abstract

This chapter examines the use of artificial intelligence (AI) techniques in natural language processing (NLP) for risk management, with a particular focus on applications in the field of political economics. The aim of this analysis is to identify and measure potential political risks by conducting a textual analysis of newspapers and social media, using sentiment scores as proxies for nationalism. The study uses the 2019 US-China Trade War as a natural experiment to evaluate the impact of international disputes on political risks. One significant finding is the positive effect of the trade war on sentiment in China's media about the US, which is attributed to the Chinese government's efforts to mitigate the negative impact of the trade war on international relations. The study also reveals a negative impact on bilateral imports due to the conflict. Furthermore, the study employs a Difference-in-Difference (DID) model to investigate the impact of news censorship on media during the trade war. It is found that China's regulators attempted to soften domestic anti-US sentiment, while the US media reported more negatively about China during the conflict. Overall, this analysis demonstrates how NLP technology can be effectively used to identify changes in the management of political risks by analysing news and other media.

Keywords: international conflicts, nationalism, international trade, international political economy, textual analysis

1. Introduction

McCombs and Shaw were the first to propose the agenda-setting function of mass media, which describes how media is used to affect the political positions of the recipients of information [1]. As newspapers are the main source of information in people's daily lives, McCombs and Shaw propose that the press plays a key role in influencing citizens' attention and even shapes their views on news topics [2]. For decades, some scholars have suggested that Chinese authorities use government-controlled media to maintain the status quo by shaping the public's opinions [3, 4].

McCombs and Shaw developed the agenda-setting theory by studying the 1968 presidential election in the US, which is a country with a relatively high degree of media freedom. The media sets agendas by appealing to people's emotions [1]. For example, the 2020 coronavirus disease outbreak has caused a global health crisis. Many people in China and other regions have died from the epidemic. On 3 February 2020, the *Wall Street Journal* posted an article entitled "China is the real sick man of Asia" and we can easily sense the negative and racist emotions towards China in this narrative [5]. News sentiment is the position of the media on the subject reported and may be set by authorities or driven by the tastes of readers. When a particular news sentiment is transmitted through the traditional local media, we can deduce that most of a relatively independent media are trying to satisfy a public figure, or that the authorities are setting the agenda for the mass media.

The connection between media and nationalism has been discussed in several works. Eriksen claimed that media such as the Internet promotes ethnocentric orientations among national and ethnic [6]. Hyun et al. indicate that user-generated content in media may facilitate actions of nationalism [7]. To figure out the causal effect of media on nationalism, sentiment could be a middle variable. One example is the anti-Japanese sentiment in China nowadays. Zhou and Wang suggest political propaganda has a significant effect on negative sentiment towards Japan [8]. For this example, political propaganda is the earliest textual data to appear on public platforms. These textual data with some elements led to a negative sentiment among readers and finally led to anti-Japanese political actions in China. Today's Chinese anti-Japan activities are a good example of Chinese nationalism, and the negative sentiment driven by political propaganda as a middle variable provides a channel for researchers to quantify the degree of nationalism.

Nationalism is a popular research topic for political scientists. A large number of studies focus on the causes of nationalism and its political influence on conflict or democracy, among other issues [9–13]. However, there is relatively little quantitative research comparing nationalism in different countries or discussing the role of the authorities in promoting or supressing nationalism in international conflicts. Nationalism can have positive and negative effects on bilateral conflicts. During the South China Sea dispute, the Philippines' attempt to end Chinese fishermen's illegal poaching was stopped by a Chinese maritime reconnaissance vessel, intensifying the conflict on 8 April 2012. The *Global Times* (affiliated with the *People's Daily*) followed up on a statement by the Vice Foreign Minister of China and reported that China would not rule out the possibility of using force to resolve the conflict with the Philippines [14]. In contrast, during the Diaoyu (Senkaku) Islands dispute in 2012 between China and Japan, Fravel argues that there was no obvious trend in the frequency or timing of articles about the issue published by the *People's Liberation Army Daily* or the *People's Daily* (two official newspapers representing the attitudes of China's military and government), suggesting that China avoided mobilising public opinion when resolving the dispute [15]. In these two conflicts, the Chinese government's approach to media censorship and its attitude towards nationalism were different. Storey proposes that the weakness of the Philippine navy gave the People's Republic of China an opportunity to extend its sovereignty in the South China Sea [16]. We can infer that military power is part of the bargaining power of a party in an international conflict, so whether or not this power is invoked can affect the positive and negative effects of nationalism on the achievement of desirable negotiation outcomes.

In this chapter, I measure the level of nationalism in English and Chinese regions using sentiment consistency in the mainstream press. I also discuss the role of the news censorship system in China during the 2019 US-China trade war and compare it with the press in the US, which has a higher degree of media freedom. To study the strategies that governments adopt to manage nationalism during international conflicts, it is first necessary to find an indicator that accurately measures nationalism. I create a news consistency indicator based on the textual analysis of newspapers to capture the degree of emotional deviation between newspapers. After controlling for media bias and other macro factors, this news consistency indicator can be used to measure the level of nationalism. In addition, to examine government interference in news content, I use the 2019 US-China trade war as a natural experiment to identify the role of news censorship on nationalism and the effects of nationalism on the relations between the two parties engaged in a dispute. Identifying the position of the negotiating parties on nationalism can provide a means of determining the relative bargaining power of the parties and the possible outcome of a negotiation.

This chapter is organised as follows. Section 2 reviews the literature on nationalism and news censorship. We also discuss previous studies of the outcomes of trade wars to clearly explain the context of my natural experiment. Section 3 describes how I construct my data set to measure nationalism and relations between the US and China. Section 4 presents my approach to transform my data into metrics. Section 5 indicates the conceptual framework and key variables for empirical analysis. Section 6 presents my main results on how news censorship affects US-China relations at the time of the trade war. Section 7 tests the robustness of my main results and in Section 8 I offer suggestions.

2. Literature review

2.1 Nationalism

Nationalism is an important factor in the economy, although economists often overlook it. Breton shows that political nationalism can influence countries' capital investment in resources in nationality or ethnicity by household, business and government [9]. It is important to first define nationalism. [17] divides nationalism into four types:

> *"It stands in the first place for an actual historical process, that of establishing nationalities as political units, of building out of tribes and empires the modern institution of the national state. Secondly, the term indicates the theory, principle, or ideal implicit in the actual historical process; in this sense it signifies both an intensification of the consciousness of nationality and a political philosophy of the national state. Thirdly, it may mean, in such phrases as 'Irish nationalism' or 'Chinese nationalism', the activities of a particular political party, combining an historical process and a political theory; this meaning is clearer when the adjective 'nationalist' is employed, for example, in speaking of the historical Irish Nationalist Party. A fourth and final use of 'nationalism' is to denote a condition of mind among members of a nationality, perhaps already possessed of a national state, a condition of mind in which loyalty to the ideal or to the fact of one's national state is superior to all other loyalties and of which pride in one's nationality and belief in its intrinsic excellence and in its 'mission' are integral parts. ".*

Hayes uses the fourth definition to discuss the relationships between nationalism and economic theory, arguing that nationalism will perpetuate and exacerbate the difference between the natural sciences and the social sciences [12]. I follow the same (the fourth) definition of nationalism in the main sections to quantify and analyse the state of mind of the members of a nation. China provides an ideal case for researchers to capture nationalism among citizens based on the media activities of the Chinese Communist Party (CCP), because the CCP plays a key role in the political life of Chinese people.

Although each country has a different level of nationalism, many scholars and politicians pay special attention to Chinese nationalism because of China's important position in the economy and military affairs of East Asia and its geopolitical influence on neighbouring countries. Coenders and Scheepers reveal the mechanism that links nationalism and national economic conditions by focusing on Europe during the 19th century [10]. They describe nationalism as a tool the elite use to persuade the public to accept the established social order after industrialisation. First, nationalism helps maintain the current social order. Second, it can contribute to the short-term growth of the domestic economy. Heilmann estimate the effects of international conflicts on bilateral trade relations using several politically motivated boycotts and conclude that boycotts of consumer products are the most effective, especially of well-known brands [18]. From the authorities' point of view, a fall in demand for exports can partly translate into domestic demand and stimulate economic growth and create jobs. However, in particular situations, such as when there is political corruption or unequal international conflicts, nationalism can become an obstacle to authoritarian social stability and the progress of negotiations. Kuzio uses Ukraine's "Orange Revolution" in 2004 as a case study to illustrate the positive effects of nationalism on the democratisation of post-communist countries [11]. From the authorities' point of view, nationalism was not beneficial in maintaining the status quo of communist Ukrainian society.

In this chapter, I study the positive and negative effects of nationalism by analysing the bilateral relations between the US and China during the 2019 US-China trade war.

2.2 Trade disputes

When Donald D. Trump was elected President of the United States he officially raised tariffs on Chinese exports, starting the 2019 US-China trade war. Liu and Woo summarise three major concerns leading to the decision to launch a trade war against China: (i) China's chronically large trade surplus slows job creation in the US; (ii) China's illegal and unfair access to US intellectual property; and (iii) China's effect on the US-led international system and its own national security [19]. Although the US launched a trade war to defend its economic interests, different scholars have different opinions on the effect of this trade war. Li, He and Lin argue that the US has more to gain than China in the trade war negotiations based on numerical stimulation results and therefore claim that the US has more bargaining power than China [20]. Conversely, using evidence of the consumption effects of trade shocks, Waugh suggests that China's retaliatory tariffs will lead to concentrated welfare loss in the US [21]. A more general argument is that neither China nor the US will win in the trade war, only cooperation can lead to a win-win situation. For example, Berthou et al. conclude that nobody wins a trade war and that global real GDP generally decreases by up to 3% after two years based on a multi-region dynamic general equilibrium model [22].

The trade war provides a natural experiment to identify the effects of nationalism on an economic conflict between the two largest economies in the world. However, an important question related to the study of nationalism is how to measure it accurately. As a state-to-state relationship is a relatively abstract concept, in this study I use textual data from newspapers to quantify nationalism. Indeed, nationalism and the mass media are tightly bound together.

2.3 Media and censorship system

Montiel et al. investigate the production of nationalism in the national media during an international conflict [23]. Nationalism also has an effect on the public media. Studying the India-Pakistan military conflict of 29 September 2016, Pandit and Chattopadhyay argue that the news media in India have always adhered to belligerent reports of patriotic nationalism and consciously obscured the disagreement of minority voices [24]. The strong correlation between media reporting and nationalism allows us to use the media as a proxy for measuring nationalism. Although using news articles allows us to measure nationalism, another problem in this measure is the effects of a news censorship system used by some governments.

China's news censorship system limits media coverage of information deemed harmful to the stability of its regime. In general, this type of media censorship is seen as part of authoritarian control of information to maintain the power of the regime and increase control over public sentiment. It is generally believed that authoritarian regimes inevitably limit media independence. For instance, Lorentzen argues that China strategically adjusts the number of reports allowed based on potential social tensions [25]. King et al. use textual analysis of social media to compare content before and after the government imposes censorship to show that censorship is designed to prevent current collective activity or activity that may occur in the future [26]. From the Chinese authorities' point of view, censorship is a means of ensuring that news content is in the interest of the government. Therefore, by comparing the differences in the effects of nationalism on the US and China during the natural experiment of the trade war, it is possible to identify the effect of the media censorship system. In addition, we can determine whether nationalism sparked by the trade war is in the interest of the government.

3. *Factiva* news and trade data

In this section, I present the main data sources I use to create meaningful indicators of US-China relations, and focus on two measures: (i) the sentiment score of news articles and (ii) bilateral imports between the US and China. For the first measure, I use the *Factiva* database to find and collect raw newspaper articles that interest us. I also apply a sentiment analysis to process the textual data and extract useful quantitative information. For the second measure, I use the annual bilateral import data from the WTO. I discuss in detail our data sources and processing methods in the next section.

Factiva is a database provided by Dow Jones & Company that allows researchers to search for global textual data, such as newspapers, journals and magazines. I use this database to collect textual data from newspapers to generate my text-based indicators.

Based on their circulation, I select the *Wall Street Journal*, the *New York Post*, *The Boston Globe*, the *Star Tribune*, *USA Today*, *The New York Times* and *The Washington Post* to construct my US news corpus, and use “China” as the keyword to find articles related to economic, financial and political topics before 5 December 2019. For the Chinese news corpus, I choose various newspapers including *Ta Kung Pao*, *Wen Wei Po*, the *Global Times*, *People’s Daily Online*, the *Sing Tao Daily* and *The Beijing News*, and use “< 001 > “(the US) as the keyword.

One challenge in cleaning the raw *Factiva* data is that the original data format downloaded from the database is in either rich text format (rtf) or portable document format (pdf). To perform textual analysis on these unstructured data, I need to convert them to comma-separated values (csv) files by date, source, title and content columns. For this data cleaning task, in the first step, I use Python codes to automatically convert textual data from pdf to txt format using “utf-8” (as some of my textual data are in Chinese, the encoder “utf-8” instead of “ascii” is required to process non-English characters). Next, I use regular expressions and the name of each newspaper to detect one complete news article from the txt data files and match the date, newspaper, title and content of each news article.

Sentiment is a qualitative value connected to people’s emotions, subjective cognition and psychological activities. To quantify sentiment in news articles, I use a dictionary approach that counts the frequency of positive and negative terms of emotional arousal (descriptions such as “amazing”, “happy”, etc.) based on the *National Taiwan University Semantic Dictionary* (NTUSD).[1] The NTUSD uses a machine learning approach to detect and collect positive and negative terms from English and Chinese documents, which can be applied to sentiment analysis on textual data of general topics.

The WTO Data portal provides statistical indicators, including bilateral imports by detailed product or service sectors from 1948 to the present. In this study, I use import data from 2002 to 2019 after China joined the WTO. Imported products and services are classified into 97 sectors, from live animals to works of art. I accumulate the US dollar value of all sectors in one year and use annual imports as my second measure of US-China relations.

4. Sampling methodology

4.1 Preprocessing for textual analysis

In this section, I present the methodology I apply to convert the large amount of news articles generated in Section 3 into more useful data by removing noise in the texts. To empirically analyse the 64,026 English news articles and 123,549 Chinese news articles in my two corpora, one major challenge is to develop appropriate measurement approaches. Before analysing the news articles, I preprocess the raw content in several steps according to the language used. For the US news corpus, the first step of preprocessing is to remove stop words such as “a” and “the” that commonly appear in English articles. Numbers and punctuation are also removed from the raw content during this step. In the second step, I convert the remaining English words to their linguistic roots, for instance, the token “save” can indicate “saving”, “savings” and

[1] Available at: http://nlg.csie.ntu.edu.tw

"saved". In the last step, I filter the remaining terms using TF-IDF proposed by Hansen, McMahon and Prat [27]. **Figure 1a** shows the TF-IDF weight of each English term. I eliminate all of the tokens ranked 100,000 or lower.

For the Chinese news corpus, the first step of preprocessing is to divide all of the Chinese texts into meaningful words. In the second step, I delete all of the Chinese stop words, numbers and punctuation, as with the US news corpus. As there is no linguistic root for each Chinese word, I skip the stemming process in the preprocessing of the Chinese news corpus. Instead, I go directly to the last step and filter the remaining terms based on the tf-idf weights of each word. **Figure 1b** shows the weight of each Chinese term. I remove all of the words ranked 200,000 or lower after inspection.

4.2 News sentiment

To interpret the opinion of each article in the US (Chinese) news corpus with regard to China (the US), I retrieve emotional information from news articles using the sentiment score. One challenge for analysing a large-scale news corpus is to design an appropriate and concordant algorithm to capture the sentiment score for each document written in different languages. Moreover, there are many more news sources available in the world than my selected newspapers providing new information at different times, so efficiency is another important criterion for the sentiment analysis algorithm. Based on these considerations, I apply the dictionary approach in textual analysis by calculating the total frequency of each word of emotional arousal based on a pre-established positive (negative) dictionary. To compute the absolute sentiment score (Σ) for article i at time t, I use the number of positive words (p) minus the number of negative words (n) divided by the total number of terms of emotional arousal ($p + n$) as follows:

$$\Sigma_{it} := \frac{p_{it} - n_{it}}{p_{it} + n_{it}}. \tag{1}$$

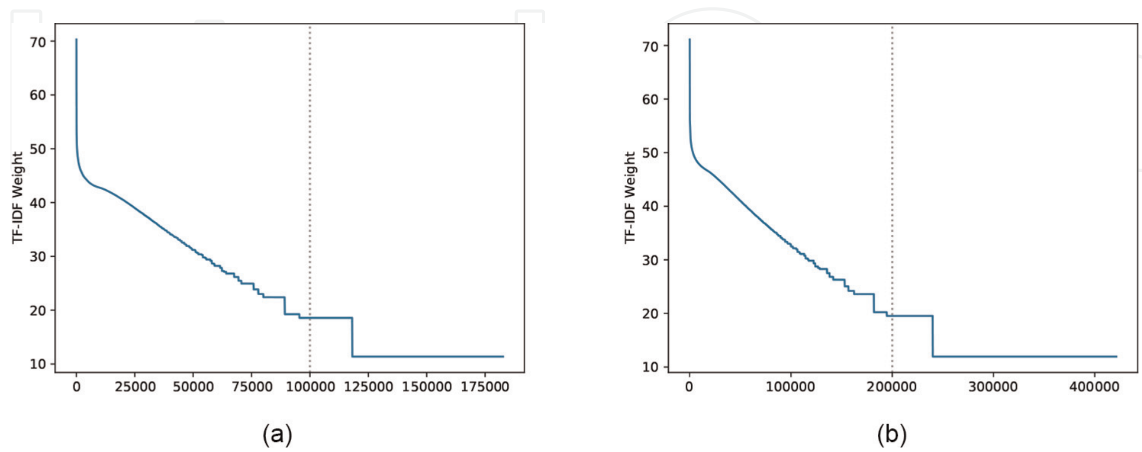


Figure 1.
Rank of Terms Ordered by TF-IDF. Note: *For each term t, the term frequency is* $tf_t := 1 + \log(n_t)$ *where* n_t *is the count of term t in the corpus. The inverse document frequency is* $idf_t := 1 + \log\left(\frac{1+N}{1+df_t}\right)$ *where N is the total number of documents in the corpus and* df_t *is number of documents where the term t appears. The product of* tf_t *and* idf_t *is the weight of tf-idf weight of term t denotes the informativeness of t in the corpus. (a) US news corpus, (b) chinese news corpus.*

Σ is scaled continuously within the range from -1 to 1. For instance, if the number of positive words in an article is 10 and there is no negative word, Σ is $(10 - 0)/(10 + 0) = 1$. The annual average absolute sentiment of each newspaper from the US and Chinese sources for the years 2009 to 2019 is presented in **Figures 2** and **3** visualises the sentiment in a heatmap.

When an article does not contain any positive or negative words, I represent this scenario with the symbol Σ as "nan" (not a number). One typical strategy for handling

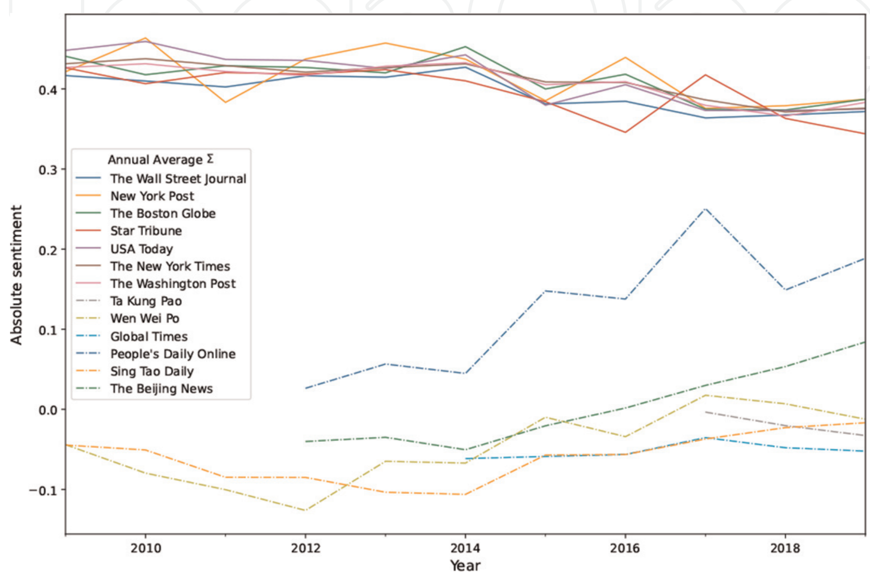


Figure 2.
Annual absolute sentiment of newspapers.

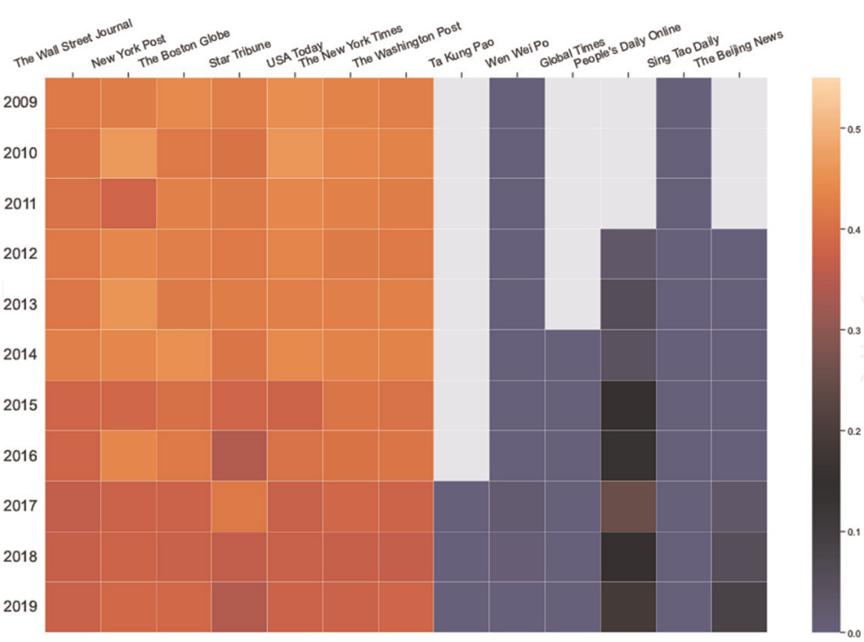


Figure 3.
Annual sentiment of newspapers. Note: This heatmap presents the annual average sentiment of each newspaper from the US and Chinese sources. For each year within the row, the colour and depth of each shading indicates the polarity and degree of the sentiment score for each newspaper within the column. Specifically, orange (blue) means the domestic media on average more positively (or negatively) reports the articles of the counter-party. Relative sentiment score is the ratio between the absolute sentiment score and the market average score and then minus one, which can be applied to measure robust relationships between different textual data sources regardless the language they used.

such “nan” values is to treat them as neutral sentiment. However, it should be noted that in my corpus, such “nan” values are a rare occurrence, accounting for only approximately 0.81% of the data. Consequently, I have chosen to exclude these observations from my analysis as part of an effort to streamline the model. Nonetheless, I believe that this exclusion will not significantly compromise the validity of my conclusions.

4.3 Topic model

The original database provides a general category for each news article and I focus on all articles marked as “economic”, “financial” and “political”. However, I am interested in specific topics and in the popularity of these topics among news media recipients. To identify the latent topics of each document, I use the Latent Dirichlet Allocation (LDA) topic model to process the textual data. As Baker, Bloom and Davis discussed, one challenge in LDA topic modelling is to choose the appropriate number of topics K [28]. Typically, a higher K increases the statistical capability of the prediction model, but sacrifices its interpretability, as each topic may be too specific to be analysed. In the extreme case where $K = D$, each document will be assigned one individual topic. Although this model fits the sample perfectly, it is useless in my case to capture the general patterns in each text, and vice versa. To resolve the trade-off between a high K and a low K, I compare the experimental results of model perplexity[2] in a 20% validation data set with different K values, as shown in **Figure A.1**. In the end, I use $K = 850$ for the textual data in English and $K = 550$ for the Chinese documents by taking into account the trade-off between the complexity of the model and the validation perplexity. I also report my empirical results for $K = 900$ for the US news corpus.

5. Analysis methodology

In this section, I describe this study’s conceptual framework and explain which set of variables I chose for analysis. **Figure 4** denotes the theoretical framework with a causal graph, and the critical variable is the media. I define media as the textual data in newspapers, the Internet, or other public platforms. These textual data can convey much information, and I mainly focus on the popularity of news topics and media sentiment on them. Censorship can be implemented under the control of the regulator, and the gap between authoritative and democratic governments also affects media consistency differently. I define media consistency as the concentration of sentiments among different media platforms. Consistency depends on the current media sentiment, as well as the interaction between censorship and topic popularity. One difficulty is to observe the censorship variable since regulators may not willing to make these data observable to the public. To address this problem, I assume the effect of regulator is relatively stable, however national conflicts such as the trade war (t-war) can shift the degree of censorship. The theoretical framework between media or sentiment and nationalism is clear from previous studies. The added literature indicates the relationships between media and sentiment [8] and the relationship between media and nationalism [6, 7].

[2] In information theory, perplexity is an indicator used to measure how well a probability model predicts a sample. Usually, a low perplexity indicates that the probability distribution is better able to fit the sample.

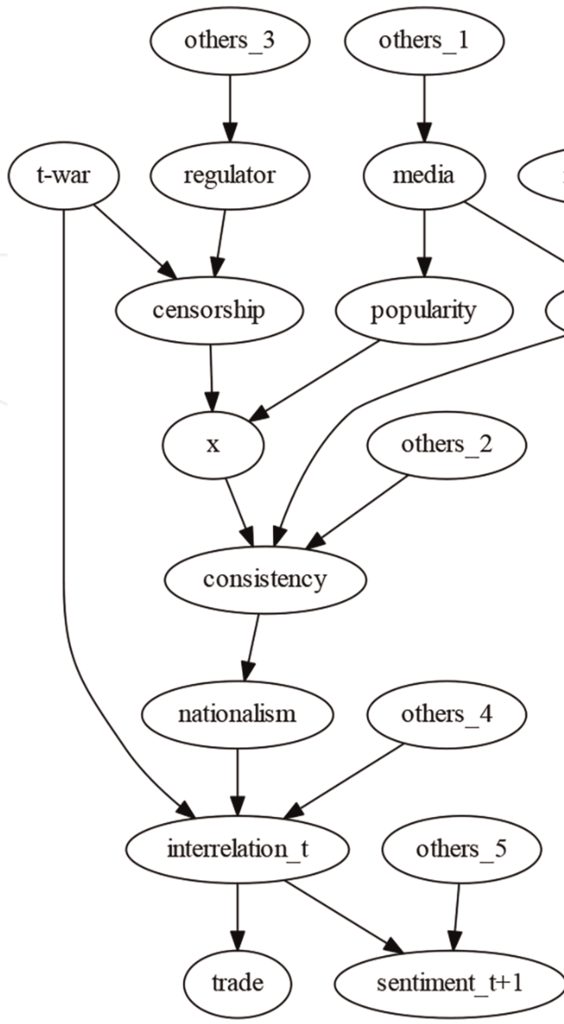


Figure 4.
Theoretical Framework with Causal Graph. Note: *I draw a causal system as a directed graph to denote all causes of the outcome of interest in this study, based on past literature and assumptions grounded in theory and empirical findings. Each graph node indicates a variable, and single-headed arrows represent causal effects. The parent of the directed edge leads to the variable at the child's position. Variable x denotes the interaction effects of popularity and censorship on media consistency.*

5.1 From trade war to interrelation

The basic model I build to study the effects of the trade war on the relations between the US and China is as follows:

$$y_{it} = \beta_0 + \beta_1 D(T - war)_t + \gamma \boldsymbol{X}_t + \alpha_i + \varepsilon_{it}, \tag{2}$$

where y_{it} is a dependent variable indicating the measures of US-China relations for entity i at time t. I use lagged media sentiment as a proxy variable of the degree of national relations. The causal path can be interpreted by the previous national relations affecting the government's attitude towards regulating the media, as well as the sentiment in the media narrative. As a result, current media sentiment can be used to measure national relations approximately. The model incorporates a fixed effect for each entity, denoted by α_i, and a constant term, denoted by β_0. The parameter of interest, β_1, is estimated to examine the impact of the trade war on national relations. Additionally, the vector of macro-level control parameters is denoted by γ. I employ panel data regression with entity fixed effects to estimate the model parameters.

Table 1 denotes the descriptive statistics of the effects of the trade war on national relations. Sentiment_{t+1} is the proxy of national relations between China and the US, and I set it as the dependent variable. *D(T-war)* is a dummy variable indicating whether the date of publication is during the US-China Trade War (1 after May 2016, and 0 before), and vector $\boldsymbol{X}_t$ controls the political, financial and other effects related to y_{it}. For the political control, I include the Chinese Political Uncertainty (CPU) index discussed by [29]. The CPU index is a text-based index focusing on specific terms related to uncertainty in US-China bilateral relations expressed in the *People's Daily*. As mentioned above, the *People's Daily* started publishing in 1948 as an official publication of the CCP and reflects the position of the Chinese government. Both the CPU index and my news sentiment measures use a dictionary approach that considers the frequency of terms or the number of documents containing specific words found in a pre-established dictionary. In particular, the CPU index captures information on public uncertainty about national policy and the economy, which can be considered as a quantitative proxy for people's perception of the monthly level of systematic risk in national relations. For the financial control (Market Return), I consider the stock market returns on the day before the publication of a given article. It is easy to imagine that people's short-term gain or loss in a financial market can influence their emotions. For the US market, I use the S&P 500 market index as a proxy for the performance of the US financial market. For China, I use the SSE Composite Index to reflect the performance of the Chinese financial market.

In addition, I include certain specific controls to measure US-China relations. For the news sentiment measures, whether a news topic is popular or not can influence the writers' use of words that trigger emotional arousal. If a publisher agrees with the tastes of the public, this publisher will be more motivated to make a positive or

Variables	Obs.	Mean	Median	Std. Dev.	Min	Max	Remark
US							
Sentiment_{t+1}	42,144	0.401	0.404	0.119	−1	1	dep
D(T-war)	42,145	0.401	0	0.49	0	1	indep
CPU Index	42,145	148.405	139.035	47.237	63.877	284.136	indep
$\text{MarketReturn}_{t-1}$	42,145	0.000265	0.000697	0.0105	−0.0666	0.0707	indep
D(Popular)	42,145	0.577	1	0.494	0	1	indep
D(Unpopular)	42,145	0.110	0	0.313	0	1	indep
China							
Sentiment_{t+1}	81,861	−0.0119	−0.0303	0.444	−1	1	dep
D(T-war)	81,862	0.552	1	0.497	0	1	indep
CPU Index	81,862	525.577	403.254	423.448	160.821	2787.628	indep
$\text{MarketReturn}_{t-1}$	81,862	0.000277	0.000645	0.0137	−0.0849	0.0612	indep
D(Popular)	81,862	0.467	0	0.499	0	1	indep
D(Unpopular)	81,862	0.208	0	0.406	0	1	indep

Notes. This table reports the descriptive statistics of variables in my observations. I use "dep" to denote the dependent variable and "indep" which means the independent variables in my model.

Table 1.
Descriptive statistics of the trade war on national relations.

negative description. Conversely, if a publisher is seeking to manipulate public sentiment by using emotionally arousing language, popular and unpopular news topics are not the ideal target. On the one hand, overly popular topics can easily lead to widespread discussion and expose the purpose of the publisher. On the other hand, unpopular topics do not arouse the interest of readers, leading to failed manipulation. Accordingly, I add a topic-specific control for the news sentiment measures using two dummy variables, *D(Popular)* and *D(Unpopular)*, indicating whether a news-based item covers a popular or unpopular topic, respectively. I classify a news article discussing a latent topic with a popularity index (see Section 6.3 for more details) in the top 35% as popular news ($D(Popular) = 1$, and 0 otherwise). Conversely, I define an article as unpopular if its topic has a popularity index in the bottom 35% ($D(Unpopular) = 1$, and 0 otherwise). This control allows us to identify the effect of readers' interest on how the news is presented.

Table 2 denotes the descriptive statistics of the effects of the trade war on bilateral imports between the US and China from 2017. On the one hand, the direct effect of the trade war on bilateral trading is an interesting study. On the other hand, bilateral trading could approximately be a proxy variable of national relations besides the lagged media sentiment. Therefore, the two different proxy variables of national relations provide a robust estimation of the impact of the trade war on bilateral relations.

For the measure of bilateral imports, I add two controls, the total annual population (Population) and the monthly number of WTO dispute cases between the US and China (D(Dispute)), instead of the topic controls. The population control (unit: billion) allows us to capture the effect of the natural increase in people's demand for foreign products and services. The WTO dispute case dummy $D(Dispute)$ controls the effects of other bilateral trade disputes besides the US-China trade war on people's demand for the other party's products and services. $D(Dispute) = 1$ if there is one or more WTO dispute cases between the US and China, and 0 otherwise.

Finally, I add a source fixed effect α_i to represent the heterogeneity of each newspaper (for the sentiment measures) or of each country (for the import measure). For the

Variables	Obs.	Mean	Median	Std. Dev.	Min	Max	Remark
US							
Import	36,428	0.355	0.420	0.161	0.0	0.498	dep
D(T-war)	36,428	0.265	0	0.442	0	1	indep
$MarketReturn_{t-1}$	36,428	0.000205	0.000575	0.0107	−0.0666	0.0708	indep
Population	36,428	0.318	0.318	0.00680	0.306	0.327	indep
D(Dispute)	36,428	0.195	0	0.396	0	1	indep
China							
Import	70,113	0.105	0.134	0.0622	0.0	0.153	dep
D(T-war)	70,113	0.406	0	0.491	0	1	indep
$MarketReturn_{t-1}$	70,113	0.000221	0.000652	0.0137	−0.0849	0.0612	indep
Population	70,113	1.373	1.379	0.0174	1.331	1.393	indep
D(Dispute)	70,113	0.171	0	0.377	0	1	indep

Table 2.
Descriptive statistics of the trade war on imports.

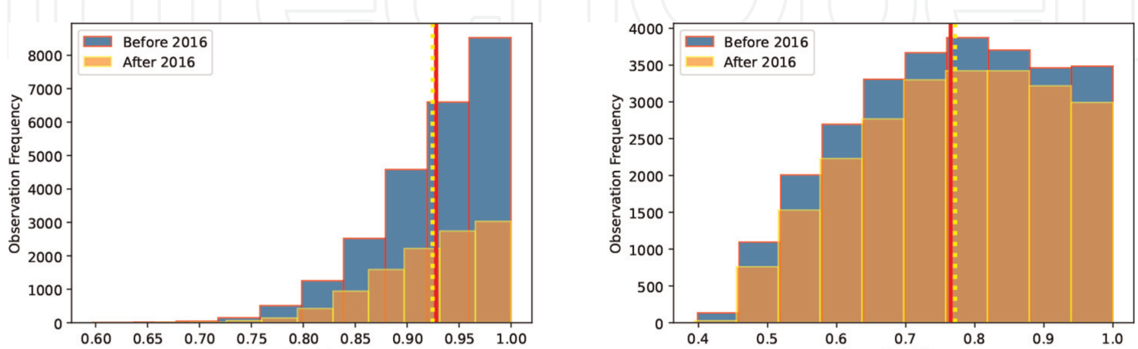
sentiment measures, one major driver of heterogeneity is media bias. Different newspapers may have a specific and consistent tendency to subjectively report news in a way that favours certain institutions, organisations or political parties. Other possible reasons for heterogeneity include the linguistic characteristics of the articles and the demographic characteristics of the target customers. Articles in different languages and from different regions may use sentimental terms at different frequencies. For the import measure, each country's national import demand will lead to heterogeneity. My main concern is the estimated coefficient β, which indicates the average change in sentiment across all entities in a region before and after the trade war event.

5.2 From censorship to nationalism

I use media consistency as a proxy of nationalism. Sentiment consistency in newspapers is an important factor that I need to take into account when explaining the dynamics of daily emotions in different newspapers. Newspapers may naturally or forcibly focus on the common voice of some or entire public groups due to sponsorship or censorship by a third party. On the one hand, news consistency depends on the current media sentiment. On the other hand, I measure news consistency by aggregating sentiment among massive media platforms and under the pressure of the media censorship system. In other words, news consistency should better interpret generalised nationalism than traditional media sentiment. Therefore, I choose news consistency as an instrumental variable of nationalism. For each country, I define a proxy for sentiment consistency $c_{it} \in]0, 1]$ in newspaper i at time t as follows:

$$c_{it} := \frac{1}{1 + |\Sigma_{it} - \overline{\Sigma}_t} |, \tag{3}$$

where Σ_{it} is the average sentiment of newspaper i at time t, as discussed in Section 4.2, and $\overline{\Sigma}_t$ is the mean value of all news articles at time t. If c_{it} is close to 1, it means that the sentiment of newspaper i is more likely to be consistent with the common voice of the public media, and vice versa. In **Figures 4** and **5**, I use two histograms of variable c_{it} showing the frequency distribution of selected observations from all newspapers in my US news corpus (5a) and Chinese news corpus (5b) before and after the 2016, which is the year of the Trade War.



(a) (b)

Figure 5.
News Consistency Histogram (c_{it}). Note: *These histograms show the frequencies of selected observations in my corpus of variable c_{it} in the US and China. The yellow dot indicates the average media consistency after 2016, whereas the red line denotes the average consistency from 1989 to 2016. (a) The United States, (b) China.*

Next, I discuss the characteristics of news consistency using a linear model as follows:

$$c_{it} = \beta_0 + \beta_1 \rho_{it} + \beta_2 D(T - war)_t \times \rho_{it} + \boldsymbol{\beta_x} \boldsymbol{X}_t + \varepsilon, \tag{4}$$

where ρ_{it} is the corresponding average popularity index of newspaper i at time t. To compute ρ_{it}, it is crucial to have knowledge of the popularity index of each topic to which the newspaper pertains. It is evident that some news topics are more appealing than others, and therefore people may show more interest in discussing them. As the topics produced by the topic model are not arranged in any specific order (see Section 4.3), I establish a popularity index for each topic by ranking them. The initial step in developing this index involves constructing distinct social network corpora for users who speak English and Chinese.

I collected a total of 15,236,749 tweets from the English corpus between 10 October 2018 to 8 August 2019 using the *Twitter* API. The specific keywords used to query the API were “tradewar”, “tradewars”, “MAGA”, “trade”, and “USChina”. Subsequently, a subset of 30,473 unique narratives was constructed by random selection. It is assumed that the chosen tweets related to the 2019 US-China trade war encompass current economic and political narratives, which are of interest for this study. For the Chinese corpus, I utilised the *Weibo* public timeline API, a popular social networking platform in China similar to *Twitter*, to collect 3,194,226 unique narratives from the general population between May 29, 2018, and October 17, 2018, although not strictly in real-time. Subsequently, I chose 9539 unique comments to create my subset. Unlike the *Twitter* API, the *Weibo* API does not offer a keyword query feature to the public users. Therefore, I collected data on general topics to build my Chinese corpus.

In the second step of the analysis, I construct a p by q matrix $\boldsymbol{T}$, where p denotes the number of topics selected in the topic model and q represents the top q terms generated by the model that are of interest. For the primary analysis, I set $p = 850$ for the English corpus, $p = 550$ for the Chinese corpus, and $q = 12$. $\boldsymbol{T}_{\mu\nu}$ is utilised to capture the count of words in row μ and column ν in **Figure 6** or **Figure** 7, as presented in Section 6.1, for each social network corpus. Next, I compute the popularity score for each topic μ,

$$\boldsymbol{P}_{\mu} := \sum_{\nu=1}^{q} \boldsymbol{T}_{\mu\nu} \times \boldsymbol{W}_{\mu\nu}, \tag{5}$$

where $\boldsymbol{W}_{\mu\nu}$ represents the estimated probability that a word in column ν belongs to topic μ, as generated by the topic model. It should be noted that $\boldsymbol{P}$ is a column vector with p dimensions. To obtain the popularity index vector, $\boldsymbol{P}$ is normalised.

$$\boldsymbol{P}^* := \frac{\boldsymbol{P}}{\|\boldsymbol{P}\|_2} = \left[\rho_1, \rho_2, \ldots, \rho_p\right]^{\mathrm{T}}, \tag{6}$$

where $\|\boldsymbol{P}\|_2$ is the l^2-norm of $\boldsymbol{P}$, and the average popularity index ρ_i at time t can be expressed as

$$\rho_{it} = \frac{\sum_{x \in \boldsymbol{T}_x} \rho_x}{N_{it}} \quad \text{s.t.} \quad \mathbf{card}(\boldsymbol{T}_x) = N_{it}, \rho_x \in \boldsymbol{P}^*, \tag{7}$$

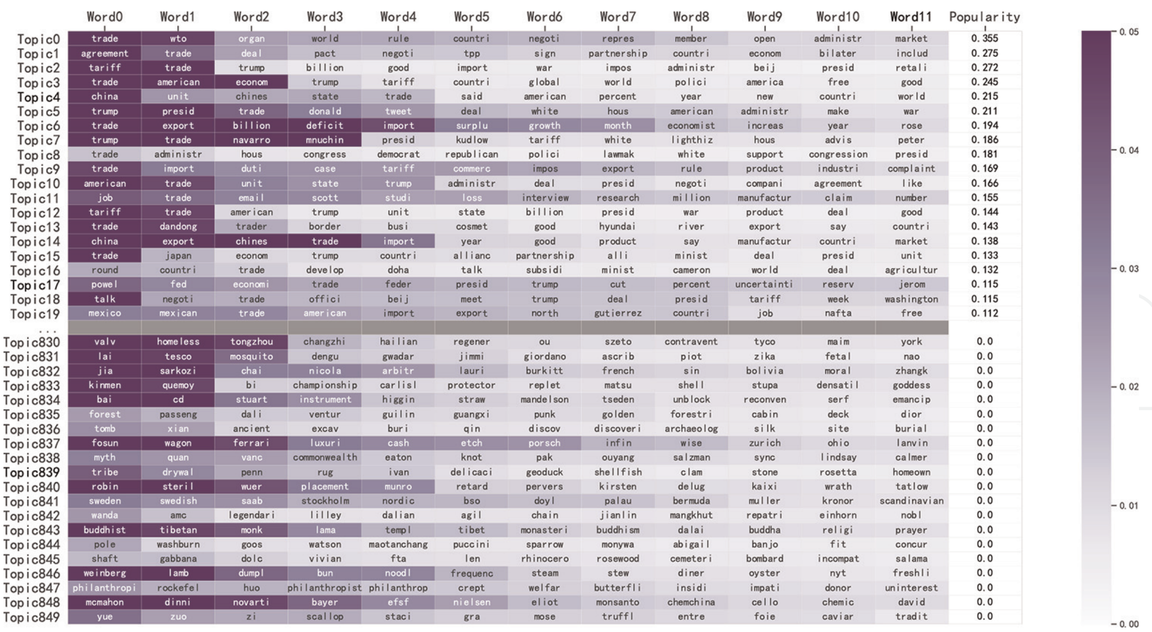


Figure 6.
Topics in the US News Corpus Ranked by Popularity. Note: *This figure denotes the 850 separate distributions over news vocabulary that LDA model learns to indicate topics. According to a popularity index that captures term frequencies of the top 12 vocabulary terms in each LDA topic in social networks, I order these distributions from 0 (the most popular) to 849 (the least popular).*

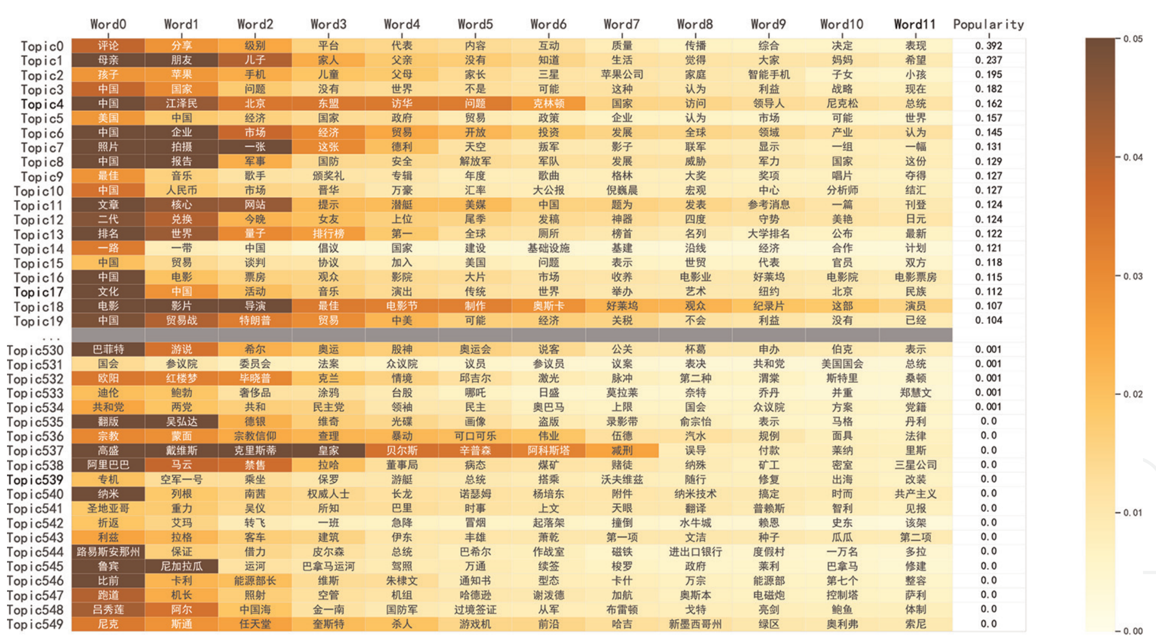


Figure 7.
Topics in the Chinese News Corpus Ranked by Popularity. Note: This figure denotes the 550 separate distributions over news vocabulary that LDA model learns to indicate topics. According to a popularity index that captures term frequencies of the top 12 vocabulary terms in each LDA topic in social networks, I order these distributions from 0 (the most popular) to 549 (the least popular).

where N_{it} represents the total number of articles in newspaper i at time t, $\boldsymbol{Tx}$ maps the set of articles $d_1, d_2, \ldots d_{N_{it}}$ to their corresponding topic categories generated by the LDA algorithm, and $\mathbf{card}(\cdot)$ denotes the cardinality of a set. The elements ρ_x belong to the vector $\boldsymbol{P}^*$, which contains the popularity index of each topic x.

$D(T - war)_t$ is the dummy variable for the US-China Trade War period, as discussed in Section 6.2. I assume the parent variables of consistency include the current media sentiment, the interaction between topic popularity and media censorship, and other factors, including politics and demographic characteristics. I add this interaction term because of an assumption that regulators may have stronger censorship over the news with high popularity, so there is a potential interaction effect between popularity and censorship. Once regulators' impact on censorship is relatively constant, external events such as the trade war as an instrumental variable should sufficiently explain the degree of censorship. **Table 3** reports the descriptive statistics of news consistency.

As in **Figure 4**, I assume media censorship only depends on two factors: one is regulators' will, and another is the external interrelation shock, such as the Trade War's impact on Sino-US relations. Within my study period, it is reasonable to consider the regulators' will is relatively stable, therefore I recognise it as a constant term. As a result, the dynamic of censorship meanly depends on the Trade War effect. Vector $\boldsymbol{X}_t$ controls for regional factors in the US, including political bias in the media[3] (using a dummy equal to 1 for a right biased source and 0 for a left biased source) and the proportion of Chinese people (excluding Taiwanese) in the state.[4] Notice that the Chinese ratio is only suitable in the US region. I do not create the US ratio because China is not an immigration country, and the percentage of US immigrants in China is trivial. In addition, I do not use the Chinese ratio in my sentiment regression model because I assume the sentiment variable depends on the media and previous international relations per se. This is a reasonable assumption because the media's primary purpose is to report new information regardless of demographic interests, especially since my sample sources are well-known US newspapers. However, I consider the Chinese ratio could affect the media consistency because a higher number of Chinese clients might lead to lower media consistency to report Chinese if the US media generally tend to report Chinese news negatively but still care about the local Chinese immigrants.

Variables	Obs.	Mean	Median	Std. Dev.	Min	Max	Remark
US							
Consistency	42,145	0.924	0.935	0.0553	0.465	1	dep
D(T-war)	42,145	0.401	0	0.490	0	1	indep
Popularity	42,145	0.0309	0.00776	0.0594	0.0	0.355	indep
D(Political Bias)	42,145	0.459	0	0.49800	0	1	indep
Chinese Ratio	42,145	0.0280	0.0328	0.00918	0.00512	0.0328	indep
China							
Consistency	85,617	0.771	0.778	0.135	0.388	1	dep
D(T-war)	85,617	0.572	1	0.495	0	1	indep
Popularity	85,617	0.0321	0.0195	0.0356	0	0.392	indep

Table 3.
Descriptive statistics of news consistency.

[3] Data source: *Media Bias/Fact Check*, https://mediabiasfactcheck.com.
[4] Data source: U.S. Census Bureau, 2011–2015 American Community Survey 5-Year Estimates.

5.3 DID model

Furthermore, I employ news consistency as a proxy for media censorship by regulators, as it can more accurately capture nationalist sentiments in countries with varying political systems. To mitigate potential biases introduced by external factors when measuring nationalism through news consistency and to examine the impact of censorship on international conflicts, I utilise a natural experiment involving the 2019 US-China Trade War in my empirical analysis. To determine the change in the measures of national relations associated with the trade war due to news consistency in each entity, I use a Difference-in-Difference (DID) model. DID model is a statistical technique used to assess the causal impact of an intervention or treatment by comparing changes in the outcome variable of interest between a treatment group and a control group before and after the intervention. The DID model estimates the difference in the average change in the outcome variable between the treatment and control groups before and after the intervention, and this difference is considered as the treatment effect. This methodology is widely employed in economics, public health, and social sciences to evaluate the impact of policies, programs, or interventions [30–32].

The DID model I construct with entity and time effects is as follows:

$$y_{it} = \theta_0 + \theta_1 D(T - war)_t \times c_{it} + \omega c_{it} + \zeta_i + \varepsilon_{it}, \tag{8}$$

where y_{it} is the dependent variable for the measures of US-China relations. In my empirical study, I choose the lagged media sentiment as the proxy for interrelations. $D(T - war)_t$ is the dummy indicator of the US-China Trade War period and ζ_i is source fixed effects. I allow the entity-fixed effects to capture the heterogeneity of each entity measured. I assume that if omitted variables change over time but are constant across all newspapers, the daily media sentiment and consistency indicators should absorb the effect. Therefore, I do not use time-fixed effects. ω is the estimated coefficient to explain how news consistency affects my measures of national relations. ω can be interpreted as the effect of the respective nationalism of the US and China on their bilateral relations without significant authorities' control during a period without conflict. θ_0 is a constant term.

The coefficient θ_1 is my parameter of interest to explain the change in news consistency after the US-China Trade War. The dummy variable $D(T - war)_t$ is used to distinguish between the treatment and control groups. The coefficient θ_1 on the treatment indicator variable represents the difference in the outcome variable between the treatment group ($D(T - war)_t = 1$) and the control group ($D(T - war)_t = 0$) at the baseline (the trade war). The coefficient θ_1 in Eq. (3) captures the marginal effect of daily news consistency of newspaper i at time t on my measures of national relations, indicating the extent to which the common voice of mass media after the trade war affects the outcome variable. A positive (negative) value of θ_1 suggests an increase (decrease) in the effect of news consistency on the outcome variable. Any significant difference in θ_1 between the United States and China can be primarily attributed to the level of media freedom. Notably, China has a system of official news censorship, which ensures that most media reports align with, or at least do not contradict, the government's position. Therefore, news consistency in China during a conflict is likely to reflect to some extent the stance of the central government on particular issues. In contrast, countries with higher media freedom may experience less government interference and therefore may not adequately represent the official position. Consequently, the value of θ_1 is mainly attributable to the change in nationalism caused by the trade war. The sign of θ_1 reveals whether the news consistency during the trade war had a positive (improving international relations) or negative effect (harming international relations) on the outcome variable.

6. Empirical results

This section presents the main results of this chapter. For my main results, I focus on news articles published during the terms of President Barack Obama and President Donald Trump from 2009 to 2019. Using observations from the two presidential terms reflects the stability of US political and diplomatic strategies towards China before and after the trade war. Unlike the competition between Republicans and Democrats in the US, members of the United Front in China fully obey the CCP and must accept its "leadership role" as a condition of their continued existence. Therefore, China's policy towards the US depends mainly on the position of the CCP, which is relatively consistent. Therefore, the relations between China and the US can be effectively measured during the study period.

6.1 LDA results

The main objective of the topic model is to identify news topics, and the results are presented in **Figures 6** and **7** for the US and Chinese news corpora, respectively. The heatmaps in these figures represent the top 12 terms for each topic in the respective corpus after preprocessing, and the darker shades indicate a higher probability that the terms can explain the topics in their respective rows. Although each topic is not assigned a name during the unsupervised learning process of the topic model, the terms grouped in each topic provide a natural annotation. For instance, Topic 2 in the US news corpus, as shown in **Figure 6**, corresponds to "trade war", which is Topic 19 in the Chinese news corpus presented in **Figure 7**.

When the popularity index is closer to 1 (0), it indicates that the topic receives more (less) attention from the masses. In the US news corpus, the most popular topics are "trade negotiation" (1) and "trade war" (2) and the least popular topics are "Wanda Group" (842) and "Dalai Lama" (843). For the Chinese news corpus, the most popular topics are "family" (1), "Belt and Road Initiative" (14) and "trade war" (19), and the least popular topics are those related to the "US Congress" (531) and "US political parties" (534). The distribution of news topics from US and Chinese newspapers in my data set is depicted in two histograms in **Figure 8a** and **b**. It can be observed that news topics with higher popularity indices tend to have more reports, which aligns with my expectations. Popular topics are more likely to be reported by the media, and thus the popularity index can accurately reflect readers' interest in the topics.

6.2 Trade war effects

To accurately estimate the significance of the β coefficient, I use cluster-robust standard errors because within-individual media error correlations may still remain.

Table 4 presents the estimates of the news sentiment Σ_{it} (see Section 4.2 for more details) associated with all of the news topics in my corpora. For Chinese news articles related to the US, we can see a significant increase in sentiment after the trade war, leading to an overall increase in sentiment among Chinese newspapers towards the

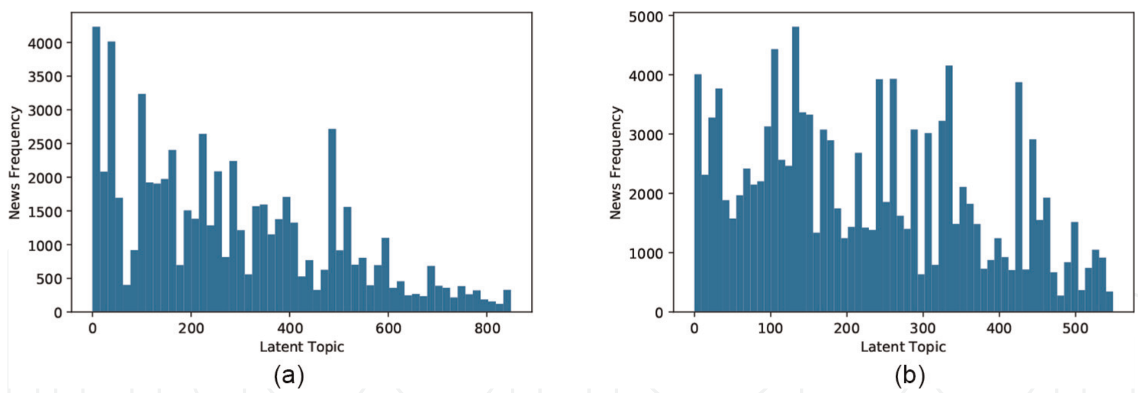


Figure 8.
Distribution of News Topics. Note: *These histograms figure out the distribution of latent topics generated by the Topic Model over my news corpus. There are 64,026 relevant news reports in the US from 1980 to 2019 and 123,549 records in China from 1999 to 2019. The topic number starting from zero is in the sequence of its popularity index (from highest to lowest). (a) The United States, (b) China.*

US. For all articles published between 2009 and 2019, we can see a significant decrease in news sentiment in US newspapers and a significant increase in Chinese newspapers. The decline in news sentiment in US newspapers towards China is in line with my expectations, as the rise of nationalism during conflicts between two nations often triggers negative emotions against the other country. In contrast, the rise of positive descriptions of the US in Chinese newspapers deserves our attention. After controlling the macro factors and the topic-specific factor, I find the main difference between US and Chinese newspapers is media freedom. Therefore, I attribute the positive effects of the trade war on sentiment in Chinese newspapers to the government's efforts to weaken the negative impact of the trade conflict on international relations with the US.

Among my control variables, we observe that the degree of political uncertainty is significantly negatively correlated with news sentiment in US and Chinese newspapers (except for non-negative Chinese news articles), whereas financial market performance is generally positively correlated with news sentiment. On exception is negative Chinese news articles, which are negatively correlated with market performance. This can be explained as follows. When the financial market does not perform well in China, dissatisfaction with the domestic financial market prompts citizens to aspire to a free capital market like the US. Conversely, when the financial market is overheated, a higher sense of national superiority makes people more confident in the country's economy and increases disdain for its main competitors. For the topic-specific control, I find that both popular and unpopular topics are significantly related to news sentiment (except for negative Chinese news articles). One interesting observation is that for popular news articles, US newspapers are more likely to negatively describe China-related issues. In contrast, Chinese media tend to positively present news related to the US in both popular and unpopular topics. I attribute this phenomenon to newspapers meeting readers' tastes. If the constant effect can fully control the specific reporting bias of each newspaper, we can infer that US readers in general are more interested in negative Chinese news, whereas Chinese readers are more interested in positive US news. Furthermore, if the topic is not interesting, for example, religious topics, the media in both countries do not report it negatively.

To clarify the economic importance of my estimated coefficients, I use the term "t-war effect" to represent the value of trade war coefficient $\hat{\beta}_1$ as a percentage of the average measures of US-China relations before the US-China trade war and use stars

Main Regressors	US (1)	China (2)
D(T-war)	−0.037***	0.054***
	[.002]	[.009]
CPU Index	−0.000085***	0.000013**
	[.000]	[.000]
Market Return$_{t-1}$	0.35***	0.40***
	[.090]	[.195]
D(Popular)	−0.0051***	0.011
	[.000]	[.008]
D(Unpopular)	−0.0017	0.0020
	[.001]	[.003]
Constant	0.43***	−0.054***
	[.001]	[.011]
Observations	42,144	81,861
Source FE	Yes	Yes
Pre-war avg	0.42	−0.034
T-war effect	−8.9***	−158.6***

Notes. This table reports the estimating results on newspaper overall sentiments from the US and Chinese sources. Dependent variables include the average sentiment of total articles. Cluster-robust standard errors in parentheses. Coefficients are labelled based on significance ($p < .1$, ** $p < .05$, ***$p < .01$). The T-war effect indicates the estimated coefficient on a dummy D(T-war) as a percentage of the average score of the daily average newspaper sentiment in the region before May 2, 2016. I report the same significant star labels as the level of estimated coefficient on D(T-war) within the column.*

Table 4.
Results of the effects of the trade war on national relations.

to indicate the statistical significance of the estimated effect. This indicator aims to measure the degree and direction of the trade war's influence on media sentiment. If the value is positive, the trade war amplifies the media sentiment. If the value is higher, the amplified effect will be more significant. For instance, the estimated t-war effect in **Table 4**, Column (1), is $\frac{-0.037}{0.42} \times 100 \approx -8.9$. As the sign of the corresponding pre-war average is negative, the t-war effect represents the average effect of the trade war, contributing to an 8.9% opposite change in the overall sentiment in US newspapers about China after the trade war period. Comparing the empirical results in the US and China, the t-war effect of China sources dominates that of the US sources, indicating that the trade war event had a more significant impact on descriptions of average sentiment in Chinese media during the sampling period. Moreover, although the US and China media changed their attitude during the trade war, this conflict significantly reduced the number of negative narratives in Chinese newspapers about the US.

Table 5 shows the results of the Trade War's effects on bilateral imports. Unsurprisingly, I observe that the trade war had a significant negative effect on US and Chinese bilateral imports. We can see that the trade war had a significantly stronger negative effects on US demand for Chinese products and services. If we only focus on the economic consequences of the trade war, it seems that US customers suffered

Main regressors	US (1)	China (2)
D(T-war)	−0.20***	−0.045***
	[.003]	[.001]
CPU index	−0.00025***	−0.000032***
	[.000]	[.000]
Market return_t-1	0.25***	0.049***
	[.057]	[.012]
Population	3.79***	−0.39***
	[.102]	[.019]
D(Dispute)	−0.030***	−0.017***
	[.002]	[.001]
Constant	−0.75***	0.69***
	[.033]	[.025]
Observations	36,428	70,113
Source FE	No	No
News region	US	China
Pre-war avg	0.41	0.14
T-war effect	−50.2***	−33.0***

Notes. This table reports the estimating results on imports in the US (China) from China (the US). Dependent variable is the total value of all types of imported goods (in trillions of dollars). Standard errors in parentheses. Coefficients are labelled based on significance (p < .1, ** p < .05, ***p < .01). The T-war effect indicates the estimated coefficient on a dummy D(T-war) as a percentage of the average value of the dependent variables before May 2, 2016. I report the same significant star labels as the level of estimated coefficient on D(T-war) within the column.*

Table 5.
Results for the effects of the trade war on imports.

greater losses, which is consistent with Waugh [21]. However, as the trade war was launched by President Trump, I attribute the stronger negative effect on US imports of Chinese products and services to a trade-off with the objective of gaining more bargaining power during the negotiation process.

Based on the content of the Phase One trade deal, my results support the argument that the US has stronger bargaining power during the negotiations. Based on the estimated coefficients of the macro controls, I observe a significantly negative effect of political uncertainty and WTO dispute cases on imports and a positive effect of the domestic population and financial market performance. One interesting observation is that in the US, the population determines the level of imports of Chinese products and services, while this effect is not significant in China. I attribute this result to the fact that China has a relatively complete industrial system, so there is less demand for importing daily consumer products from the US.

6.3 News consistency effects

In **Table 6**, I report how the popularity of news topics affects sentiment consistency, with all features in my model being significant. One interesting result is that popular news topics tended to be more consistent after the trade war in China as β_1

Main regressors	US (1)	China (2)
$D(T - war) \times Popularity$	-0.021^{**}	0.259^{***}
	[0.009]	[0.020]
Popularity	0.038^{***}	-0.070^{***}
	[0.008]	[0.018]
D (Political Bias)	-0.003^{***}	—
	[0.001]	—
Chinese Ratio	-0.125^{***}	—
	[0.034]	—
Constant	0.929^{***}	0.768^{***}
	[0.001]	[0.001]
Observations	42,145	85,617

Notes. Standard errors in parentheses. Coefficients are labelled based on significance ($^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$).

Table 6.
News consistency results.

from Eq. 4 in Column (2) is significantly positive, whereas in the US the result is the opposite. Moreover, from the constant terms, we see the newspapers about China topics have higher media consistency in the US. We may also find similar conclusions since the average media consistency in the US (**Figure 5a**) is higher than China's (**Figure 5b**), and the average media consistency after 2016 (yellow dot line) slightly increased in China whereas it decreased in the US. The news censorship system in China may provide a plausible explanation for these differences. Although all published news articles are subject to censorship in China, the degree of censorship varies depending on the objectives of the authorities. It is reasonable to believe that if a news topic is more popular, media regulators expend more energy on reviewing its content and in removing any "unwanted" description. However, it also increases its influence on content manipulation because it attracts more readers' attention. Therefore, using the trade war, we observe different strategies adopted by the Chinese government in response to hot news topics in different periods. Newspapers in the US provide a mixed sample of a news system without central management. As most media in the US are profit oriented, to a large extent, the more popular the news, the more it needs to respond to the tastes and ideologies of subscribers. However, different groups of American readers had different opinions on whether to launch or continue the trade war. Therefore without central control by the central government, US newspapers should have low news consistency if other factors are the same as the Chinese media. However, as we see from the constant terms in **Table 6** and the average consistency in **Figure 5**, the US's coefficient is significantly higher than China's. One explanation is that albeit the Chinese regulators could censor the media topics and contents, they still have some limitations in their ability to control the sentiments of news about the US. Except for a few media with official backgrounds, regulators might not fully control most of the media's reporting sentiments during non-special periods. Another explanation is that although the US media is less manipulated by the regulators, the US media has a more unified sentiment towards China in terms of market or profit-driven purposes. For example, if the US public generally believes that the US should decouple or should maintain good relations with China, then market forces will naturally drive media consistency in coverage of China. It can be seen from the empirical results that the market has a stronger impact on media consistency than regulators.

Table 7 reports the DID estimates of the lagged media sentiment in Eq. (8) based on my data set after 2009. An important result is the positive coefficient θ_1 in Column (2), indicating that the public media in China systematically reported US news more positively during the trade war. As the Chinese government has a strong influence on the national media and some Chinese media abroad, we can reasonably conclude that Chinese regulators tried to soften domestic anti-US sentiment amid the Sino-US trade conflict, which can be seen as an effort by Chinese regulators to repair Sino-US relations. In opposite, the negative coefficient θ_1 in Column (1) denotes the public media in the US spontaneously reported China news more negatively during the trade war.

To clearly explain the role of news consistency after the trade war in the US-China relations, I create an indicator called "unity effect" to estimate coefficient $\hat{\theta}_1$ as a percentage of $\hat{\theta}_1$ multiplied by a parameter κ divided by the average of the observations of the dependent variable y_{it} before the trade war. κ is a threshold value used to determine whether a news article should be recognised as consistent with that of other media. I choose $\kappa = 0.9$ for US newspapers and $\kappa = 0.8$ for Chinese newspapers as these values are close to the mean of the frequency distribution of the documents in **Figure 8**. Therefore, $\kappa\hat{\theta}_1$ indicates consistent news articles, with the estimated measures of US-China relations changing by at least this amount due to the trade war. For instance, the unity effect in **Table 7**, Column (2), is $0.8 \times \frac{0.072}{-0.034} \times 100 \approx -167.9$. I add stars next to the unity effect values estimated based on the significance level of $\hat{\theta}_1$ that I use to generate the indicator. Based on the unity effect in **Table 7**, I conclude that the impact of Chinese and US nationalism on international relations has undergone opposite changes during the trade war. Before the trade war, nationalism in China, represented by media consistency, could more significantly reflect Sino-US relations changes. The negative ω in Column (2) denotes Chinese nationalism weakening

Main regressors	US (1)	China (2)
D(T − war) × Consistency	−0.043***	0.072***
	[.002]	[.013]
Consistency	0.033***	−0.063***
	[.012]	[.013]
Constant	0.39***	0.0058
	[0.011]	[0.005]
Observations	42,144	81,866
Source FE	Yes	Yes
Pre-war avg	0.42	−0.034
Unity effect	−9.3***	−167.9***

Notes. Cluster-robust standard errors in parentheses. Coefficients are labelled based on significance (p < .1, ** p < .05, ***p < .01).*

Table 7.
DID Results for the Sentiment Measures.

China's relations with the US. During the trade war, the θ_1 in Column (2) became significantly positive and contributed to China's relations with the US. Note the Chinese regulators partly censor the media consistency as a proxy of nationalism. Therefore, one explanation of nationalism's positive international relations effect is regulators' willing of the improving Sino-US relations. In opposite, I do not observe a similar result in the US. From the US perspective, the escalating trade conflict between the US and China has naturally soured relations with China.

6.4 Placebo-controlled study

To address concerns regarding the impact of pre-existing factors on the results presented in **Table 7**, a placebo-controlled study is conducted to assess the news sentiment as described in Eq. (8) in US and Chinese newspapers prior to the 2019 US-China trade war. The same DID model employed in Section 6.3 is utilised, with θ_1 representing the difference in the outcome variable between the treatment group $(D(T - war)_t = 1)$ and the control group $(D(T - war)_t = 0)$ at the baseline. However, the placebo test differs from the original analysis in that the baseline is set to December 5, 2004 for US newspapers and December 5, 2007 for Chinese newspapers, which were periods without significant bilateral conflicts based on the Sino-US relations. This placebo study covers the period from the September 11 attacks to the time before Barack Obama's Asian rebalance policy. If the previous analysis of the impact of the trade war on measures of US-China relations is accurate, the unity effect observed in the placebo test should be insignificant or slightly significant. The results of the placebo test are reported in **Table B.1** in Appendix B, and no significant effects are observed except for the constant term in Column (1).

Overall, my placebo-controlled study suggests that the results presented in Section 6.3 are robust to potential confounding factors. Specifically, I find that the difference in the unity effect between the treatment and control groups is primarily driven by the trade war event rather than pre-existing heterogeneous factors.

7. Robustness

In **Table C.1** in Appendix C, I present the results of my robustness tests for the main results in Section 6. Each table reports the coefficients of the t-war effect or the unity effect and their significance is based on the coefficients used in the calculations. The estimated sign of these effects and their level of significance in each robustness test are very close to the main results discussed in Section 6. Using a period of more intense conflict as the trade war event, I observe that the estimated values of the t-war effect and the unity effect tend to be higher, indicating that nationalism and government intervention in the media tend to be stronger as international conflicts escalate.

In Section 4.3, I present the LDA topic model I use to determine whether a news article should be classified as popular. As previously mentioned, K is an important parameter that we need to provide to the machine using the LDA topic model to accurately and efficiently identify the latent topics of each text document. **Figure A.1** in Appendix A presents the validation perplexity for different numbers of topics for the US and Chinese news corpora. To test the robustness of my results, I modify the news popularity dummy by increasing the number of latent topics K in the topic model to reclassify a topic for each news article, then compute a new popularity index for each new topic. I choose $K = 900$ for the US news corpus and $K = 600$ for the Chinese news corpus in this test by enhancing the model's ability to identify latent topics. **Table C.1** in Appendix C reports the results of this robustness test for the main results in Section 6.2. Under the new setting, the estimated t-war effect is as significant as in **Table 4**. Based on these results, I confirm my main conclusion on the effects of the trade war on US-China bilateral relations in the public media.

8. Conclusions

In my study, I have found evidence supporting my hypothesis that nationalism and international disputes play crucial roles in shaping bilateral relations between countries. Specifically, I have used the trade war effect and unity effect to capture the impact of nationalism and news censorship on US-China relations. My results show that the trade war has resulted in a reduction in civil and economic relations between the parties in conflict. However, news censorship can help mitigate or even conceal the nationalism generated by media sentiment, thus aiding in the repair of bilateral relations.

Based on my empirical findings, I have drawn two significant conclusions. First, excessive nationalism can hinder progress in negotiations during international conflicts, particularly if they are asymmetric, and may not always serve a government's interest. Second, in instances where one party has weaker bargaining power, suppressing unfavourable nationalism among its citizens may facilitate negotiation agreements that ultimately increase the total utility of the nation, even if some view the agreement as unfair. Overall, this chapter proposes a methodology based on textual analysis and topic modelling to quantify subjective nationalism and international relations. Such techniques are gaining popularity in the social sciences, with experts predicting a significant impact on various research fields and the management of political and economic risks.

As Shiller argues, textual analysis is poised to become a solid field in economics, owing to the increasing volume of big data generated by social media and interdisciplinary developments in fields such as psychology, neuroscience, and artificial intelligence [33]. Thus, machine learning and text analysis methodologies hold great promise for driving revolutionary results in social science and other research domains.

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Abbreviations

AI	Artificial Intelligence
CCP	Chinese Communist Party
CPU	Chinese Political Uncertainty
DID	Difference-in-Difference
LDA	Latent Dirichlet Allocation
NLP	Natural Language Processing

A. Topic selection

In the main analysis, I select 850 topics for the US news corpus and 550 topics for the Chinese news corpus. To determine if our choice of model is appropriate, I test the goodness of fit of the topic model with different numbers of latent topics K. First, I randomly choose a 20% subset of documents as our testing data and use the remaining documents as our training data to fit the LDA model for K between 50 and 1000. Then I calculate the validation perplexity of the model with the testing data as a measure of the goodness of fit. Perplexity indicates how well the model describes a set of articles, a lower value suggesting a better fit. **Figure A.1** shows the validation perplexity of the testing data for the US and Chinese news corpora. For the US news corpus, the validation perplexity stays flat after $K = 850$, and for the Chinese news corpus, the value increases after $K = 550$. Based on these observations, I choose the model for our main analysis that can best fit the data.

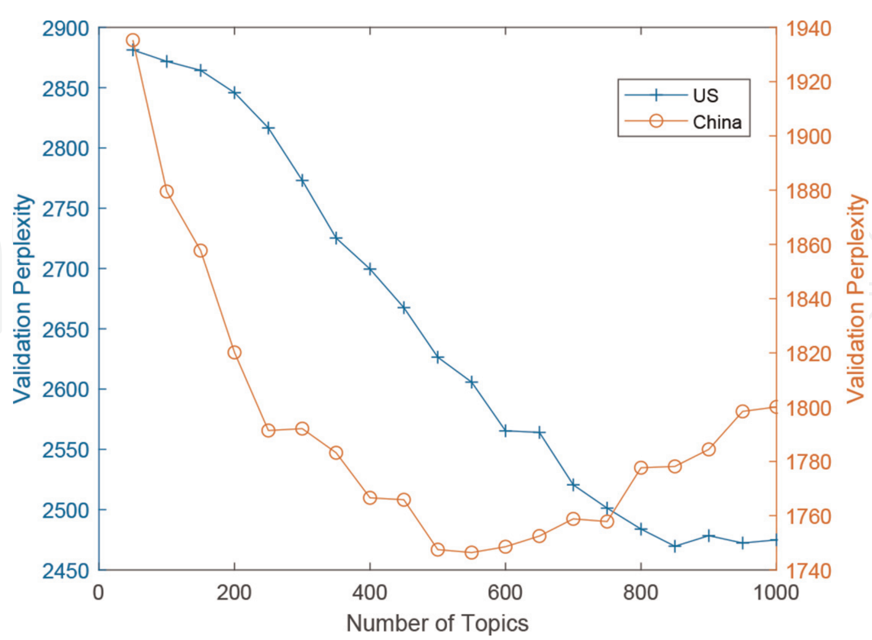

Figure A.1.
Validation perplexity of testing data for different topics. Note: *This figure indicates the validation perplexity of 20% random selected documents for testing. Typically when the number of topics increase, the accuracy of the model enhances, and the model with the lowest perplexity is generally considered the "best". These data show that the goodness-of-fit of the topic model reaches the apex around $K = 850$ for English documents and $K = 550$ for Chinese documents.*

B. Placebo estimates on news sentiment

Main regressors	US (1)	China (2)
D(T − war) × Consistency	−0.0041	0.016
	[.004]	[.016]
Consistency	−0.0022	−0.048
	[.015]	[.094]
Constant	0.44***	−0.027
	[0.015]	[0.065]
Observations	6484	8722
Source FE	Yes	Yes
Pre-war avg	0.44	−0.064
Unity effect	−0.8	−20.5

*Notes. This table replicate the estimation procedure for the **Table 7** under the placebo-controlled study setting. I set the observation window of the US newspaper from January 2002 to December 2006 and choose December 5, 2004 as the date of a placebo event. For Chinese newspaper, I set the data from January 2005 to December 2010 and set December 5, 2007 as the placebo date. Cluster-robust standard errors in parentheses. Coefficients are labelled based on significance (* p < .1, ** p < .05, ***p < .01). The unity effect for the US region reports the estimated coefficient $\hat{\theta}_1$ (see details in Section 6.3) times 0.9 (approximate mean value to distinguish inconsistent and consistent news in **Figure 5a**, and for Chinese newspaper the value is 0.8 corresponds to **Figure 5b**), and divided by pre-placebo average media sentiment. The significant stars of the unity effect correspond to the significance level of the parameter $\hat{\theta}_1$ that I estimated.*

Table B.1.
Placebo estimates for news sentiment.

C. Robustness for nationalism

Main regressors	US (1)	China (2)
D(T-war)	−0.037***	0.054***
	[.002]	[.009]
CPU Index	−0.000084***	0.000014***
	[.000]	[.000]
$\text{MarketReturn}_{t-1}$	0.30***	0.39**
	[.098]	[.164]
D(Popular)	−0.0078***	0.0065**
	[.001]	[.003]
D(Unpopular)	0.0010	0.0018
	[.002]	[.008]
Constant	0.43***	−0.053***
	[.002]	[.009]

Main regressors	US (1)	China (2)
Observations	42,133	81,964
Source FE	Yes	Yes
Pre-war avg	0.42	−0.034
T-war effect	−8.9***	−159.5***

*Notes. This table denotes the robustness test for news articles with the top 35% most popular topics. The corresponding baseline results are presented in **Table 4**. In this test I modify the number of latent topic in the Topic model from 850 to 900 for the US news and from 550 to 600 for the Chinese news as plotted in **Figure A.1**. Cluster-robust standard errors in parentheses. Coefficients are labelled based on significance (*p < .1, **p < .05, ***p < .01).*

Table C.1.
Robustness results for the effects of the trade war.

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