# Readers vs Owner? What drives U.S. media attention on China during the Sino-US trade conflict

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**Abstract**

In the past two years, the Sino-US relation has been through a volatile period due to trade conflicts. At the same time, there is extensive heterogeneity in the coverage on China by the U.S. media, both in terms of intensity and topics. What drives media attention on China as the U.S.'s diplomatic relation with her changes? In this paper, I use President Donald Trump's tweets as indicators of diplomatic event, and I use the coverage by local daily newspapers to separate the effects from the demand (the readers') side and the supply (the owner's) side. I find that on average, a local newspaper's coverage on human rights and ideological issues of China responded to the President's tweets, and the response is driven by its owner's political leaning. The more democratic-leaning (republican-leaning) its owner is, the more a paper covered human rights and ideological issues when Sino-US relationship got better (worse). On the other hand, such pattern barely true for the coverage on the trade conflict itself. In contrast, the political preference of newspapers' readers has little consistent effect. My study sheds light on the potential concerns of media independence in the United States when it comes to coverage on foreign countries.

## 1 Introduction

Media has the potential both to drive citizens' attitudes and be dictated by their preferences. Given their potential role in shaping attitudes - in everything from welfare policy to geopolitics - it has become a first-order question of what determines media coverage. I do this for Sino-US relations, of interest in its own right and also a useful testing ground for studying what determines media coverage.

The United States and China had largely developed a cooperative relationship in the past decade until the end of 2017. In the beginning of 2018, the US and China entered a trade conflict as a result of President Donald J. Trump's diplomatic strategy. President Trump's administration allegedly accuses China of unfair trade trade practices. Several rounds of tariffs have been imposed on each other, together with a series of negotiations. President Donald J. Trump, as the major initiator and commander, announced many orders that turned the situation back and forth.

During this time, media covered China for various topics. Naturally, media reported stories or comments about Sino-US trade conflict when China was mentioned. Meanwhile, stories or elements about China's human rights, political regime and its international influence were also widely covered. While some of these coverages rised with occurence of events, say stories about China's policies related to muslim minorities, others are about pre-occurred events with little fresh elements: the Belt & Road Initiative, the Communist Party as the single ruler, the Tiananmen square protest and media environment in China. It is direct enough for readers to demand for more information on China's influence on Sino-US bilateral trade, especially when significant new events were taking place, but it is much less direct to imagine why readers would demand for more exposure on other aspects of China when there were far less updates. So why do newspapers mention these trade unrelated aspects of China during the Sino-US trade conflict? This motivates this study, which hopefully can shed light on a set of more general questions.

Does human rights coverage on newspapers respond to foreign policy? How is this media response determined by demand and supply? The existing literature has provided at least two different perspectives. On one hand, media firms build their reputation by catering to readers' preference as to maximize profits (Gentzkow and Shapiro 2006). In other words, readers' preference dictates content (Gentzkow and Shapiro 2010). On the other hand, media can be bribed by incumbent government to suppress bad signals (Besley and Prat 2006, Qian and Yanagizawa-Drott 2017) The two perspectives have natural conflicts: the demand-driven story assumes that media firms face little incentive to distort according to government's will if their profits comes only from readership, while the distortion story requires that the firms are not extensively demand-driven. In this study, I tend to reconcile the two stories under the context of the Sino-US trade conflict.

To answer this question, I conduct an event study using the variation of Sino-US relation and local media coverage on China. With diplomatic events defined by Trump's tweets, I find that a media's change of coverage in response to events is consistently determined by its owner's political stance, whereas readers' political leaning matters in some cases but not the others. Specifically, by comparing the coverage a fews days before and after a tweet that signified a better Sino-US relations was published, I find that, the more Democratic-leaning a newspaper's owner is, on average the more it increased its coverage of China's human rights issues. In contrast, little consistent evidence is found for the effect from the readers in this case. Symmetrically, when a tweet from President Trump signified a worse Sino-US relation, the more

Republican-leaning its owner is, the more a newspaper increased coverage on China's human rights issues. Meanwhile, there is little evidence that the owner's political leaning doesn't influence the coverage related to China's trade practices. This result is consistent with the intuition that republicans tend to support Trump more than democrats, and thus their formulated content is more aligned with Trump's policy than democratic ones.

This study proceeds in three steps. I first define diplomatic events. I notice that the trade conflict in 2018 to 2019 was mainly propelled by Trump (Bhandari, Bansal, and Dhillon 2019, Kwan 2020, Liu and Woo 2018). To capture POTUS's attitude towards China, Trump's twitter to infer his decisions. In case his attitude is not fully reflected in Twitter, I also complement this source by results of bilateral talks. I hired three independent United States citizens to classify President Trump's China-related tweets as positive/negative/neutral and to give a score on how informative each tweet is. Positive tweets indicate a better Sino-US relation, and symmetrically with negative and neutral. Based on their classification, an average sentiment is calculated for each day as a measure of foreign policy of that day. Days with disagreed daily sentiment scores or too insignificant to be informative are dropped. Since the comparison is done in a small window around the events, I only keep days such that no event occurred within the four-day window before the event, and the daily sentiment in the post-event window follows that of the benchmark event. I compare the difference of media coverage of topics in the post-event days with that in the pre-event days.

The main challenge of this step is the endogeneity of Trump's twitter. Some indirect evidence suggests that President Trump might be operating his twitter to boost his media exposure during the 2016 presidential election, implying a concern of reverse causality (Enli 2017). In this context, reverse causality is such that the President may publish China related tweets as a response to media coverage on China. To address the reverse causality, I test if there are pre-trends and find little evidence of existence of pre-trend. I also check if the coverage of New York Times and Wall Street Journal on China's human rights or trade practices can predict President Trump's China related tweets, since it is unlikely that he will read local newspapers. Little robust evidence is found for such a prediction. [1]

In addition to reverse causality, omitted variable bias can also be a concern. Both Trump's tweets and media's coverage could react upon people's attitude on China. However, this attitude is dynamically changing and is thus to some extent hard to capture. In attempt to circumvent this issue, I select events such that no other important event occurred in the pre-event window. I compare the post-window observations with the pre-window ones, hoping that the variation of public attitude is negligible to be observed and responded by media and President Trump. In

[1] All media outlets but Fox News have been mentioned by Trump's in his tweets about "Fake News", indicating that he is reading and probably responding to them.

case it still remains a concern, I hereby address this issue in two ways. To roughly measure this dynamic public opinion, I use pre-event Google Trend data, which provided both national level and metropolitan level searching intensity given a keyword. Including this variable also helps to study more the effect from demand. I find that a building-up demand for a Chinese human rights topics does not increase coverage for Chinese human rights issues, and including this variation doesn't vary the effect from the supply side. Additionally, motivated by Freyaldenhoven, Hansen, and Shapiro 2019, I use media coverage of Turkey's human rights issues as a placebo test. It is based on the assumption that, when people get more averse to China for a certain reason, they should get more averse to some other country with similar issues of the same reason.

The next step is to define media attention on various topics. To separate the trade-related topics and human rights issues, I define two sets of exclusive keywords to measure coverage. Given the keywords, a naive measure of media coverage of a topic is constructed by the number of reports that mention at least one of the corresponding keywords. The second measure is to divide the naive measure by the number of reports that mention China in the title or leading paragraph. These two measures capture media coverage extensively. To capture it intensively, I use weighted fraction of words mentioned in the text. [2]

Then, I define the political stance of the readers and the owner of a newspaper. Readers' political leaning is captured by fraction of voters who voted for Donald Trump in the 2016 election, and owner's political stance is captured by the fraction of donations to Republican Party/PACs/candidates made by executive leaders or firms up to 2017. With the dataset in hand, I find the effect of supply-side to be dominant in driving the change fo coverage after Trump's tweet is published, while demand side show little effect. This result is robust to controls and non-linear functional forms.

This research is highly related to a series of work by Shapiro and Gentzkow. My measure politcal stance closely follows their methodology in Gentzkow and Shapiro 2010. I replicated their exercise by neglecting the time-variation of my dataset and find similar result. Moreover, my study utilize a panel data, and results suggested a different mechanism from them. In their empirical paper Gentzkow and Shapiro 2010, they measured how republican/democratic news outlets are and found that variation in consumers' political attitudes can explain roughly 20% of the variation of media slant, while little evidence was found that the political stance of suppliers matters for slant. While they proved a demand-driven story for accumulative coverage, this paper I found an owner-driven mechanism for responsive coverage by media.

My study is also highly related to the series of work by Qian & Yanagizawa-Drott. They provided evidence on the capture of independently owned media to strategically bias human

[2] Check Appendix for the full word list.

rights commitments by foreign countries according to their diplomatic value and alliance with the United States (Qian and Yanagizawa-Drott 2017, Qian and Yanagizawa 2009a, Qian and Yanagizawa 2009b). In their discussion session, they point out that, an alternative mechanism for their result is that the biased coverage can be driven by demand, which they did not fully separate. My study will fill in this gap by disproving the demand-driven channel and confirm the supply-driven channel.

This paper also contributes to the literature from several other aspects. First, while Durante and Zhuravskaya 2018 gives an answer to how government circumvent media attention, I provide a complementary story on how media response to government according to their political allignment with government. Second, it adds to the general topic of media and polarization (Prior 2013). Finally, DellaVigna and Hermle 2017 have found evidence on the impact of ownership of media on bias on movie reviews, I provides evidence from diplomacy perspective.

The remainder of the paper is organized as follows. Section 2 provides a brief introduction on the background, including the progress of trade conflict up to now and media coverage on China issues. Section 3 describes data collection and measurement of variables. Section 4 specifies empirical strategy and 5 give results.

# 2 Background

## 2.1 Sino-US Relations and Trade Conflict

Sino-US relationship has seen huge shifts over the past decade[3]. China and the United States cooperated in a number of issues, including Korean denuclearization and global warning. Still, many issues remained unresolved, which later got amplified since 2018. According to *U.S.-China Relations Since 1949*, on the American side, problems of China "included dissatisfaction with Chinese human rights policies, with China's large trade surpluses with the United States, and with China's sales of missiles and nuclear technology to countries in the Middle East and elsewhere." On the Chinese side, "the biggest issue was continued American arms sales to Taiwan. In addition to this, China criticized American global foreign policy as one which tried to enforce American interests and did not pay enough attention to the interests of other countries." Since Xi became the Chairman & General Secretary of China in 2012, rounds of talks have ben held between top leaders of the United States and China, yet more discernible tension has also arised, such as filing to the WTO against China in 2012 and South China Sea Dispute. Among all the conflicts, the economic reason - the building up deficit of the United States against China, has became a key concern, which basically motivated the so called Sino-US

[3] *On the Trail of Xi Jinping: a new Podcast by Jane Perlez*

trade conflict (Bhandari, Bansal, and Dhillon 2019).

Under the instructions of President Donald Trump[4], on March 22, 2018, the office of United States Trade Representatives published a document that reported findings of the investigation into China's acts, policies, and practices related to technology transfer, intellectual property and innovation together with an announcement of sweeping tariffs on Chinese imports.[5] This action was then followed with a series of sanctions with retaliatory actions from China. To illustrate its progress up to the end of 2019, I borrow Liu and Woo 2018's summary of its 6 stages:

> Stage 1 (2018.3-2018.12): President Trump signed a memorandum directing the proposal of tariffs, pursuing dispute settlement in the WTO against China's discriminatory licensing practices and restricting China's investment in key technology sectors. Afterwards, multiple rounds of additional tariffs have been proposed by both sides.
>
> Stage 2 (2018.12-2019.5): President Trump and Chairman Xi met each other at G20 summit on Dec 1, 2018 and announced a temporary truce for 90 days, during which both parties will refrain from increasing tariffs or imposing new tariffs for 90 days.
>
> Stage 3 (2019.5-2019.7): President Trump hiked the additional tariff and China retaliated afterwards.
>
> Stage 4 (2019.7-2019.8): President Trump talked with Chairman Xi on the G20 Summit at the end of June and agreed to put off plans and recover high-level talks.
>
> Stage 5 (2019.8-2019.10): On Aug 1, 2019, President Trump stepped back and annouced an additional tariff.
>
> Stage 6 (2019.10-): On Oct 11, 2019, after the talk, Trump and China reached a tentative agreement.

From this timeline, one can clearly see that the dominant player is President Donald Trump. His actions often propel progress and initiate changes, whereas most of China's actions are retaliatory (Liu and Woo 2018). Thus it is essential to capture President Trump's attitude toward the trade conflict. One plausible way to achieve so is to utilize his twitter feeds. For all events mentioned above, one can see corresponding reactions from Trump's twitter.

Another significant diplomatic event between the United States and China is their involvement into North Korean denuclearization negotiation. According to the Council of Foreign

[4]See the document page 9 section B: The President instructed USTR to determine under Section 301 whether to investigate China's law, policies, practices, or actions that may be unreasonable or discriminatory and that may be harming American intellectual property rights, innovation, or technology development

[5] *Fingdings of the investigation into China's act, policies, and practices*

Relations [6], after Trump redesignates North Korea as a sponsor of terrorism in November 2017, in March 2018 Trump offered an invitation to Chairman Kim Jungon, which started the denuclearization negotiation. Trump sometimes would recognize China's positive role [7], but sometimes would devalue China's contribution and even question her motivation. [8]

## 2.2 President Trump's Twitter

To capture the earliest veers of his attitude, I gather all his tweets that mention China or Chinese leaders. There are 278 such tweets published on 158 days. When President Trump mentioned China on Twitter, it was about one of the following issues:

Trade war progress. He would announce new progress of trade negotiation or his intention for any new actions. He would also sometimes express his attitude about China, including condemning China for currency manipulation/renegotiation or expressing his satisfaction for China's willingness to cooperate.

North Korea. He would announce the progress of denuclearization process in Twitter.

Achievements, past failure and determination to win. He sometimes said that China had been taking advantage of the United States has been robbed by China for so many years and he would turn this around. Commonly in companion with such tweets, he would also express his determination and confidence to win this trade negotiation.

Political rivals. Trump occasionally mentioned his political rivals, including Joe Bidden and other influential democrats, saying that they are unable to deal with China.

Firms or institutions like Fed, Google, General Motors. Trump mentioned them to blame for being incorperative with his actions against China.

Fake news and election. Media sometimes mentioned that China and Russia have in someway meddled in the 2016 election. In general Trump would react upon media criticism by commenting "fake news" and highlighting his achievements on trade deal with China.

Others: France, EU, NBA. These tweets are hardly related to China. China is mostly mentioned with other foreign countries.

[6] https://www.cfr.org/timeline/north-korean-nuclear-negotiations

[7] On 2018/4/27, Trump wrote on Twitter: "Please do not forget the great help that my good friend, President Xi of China, has given to the United States, particularly at the Border of North Korea. Without him it would have been a much longer, tougher, process!"

[8] On 2018/7/9 Trump wrote on Twitter: "I have confidence that Kim Jong Un will honor the contract we signed &, even more importantly, our handshake. We agreed to the denuclearization of North Korea. China, on the other hand, may be exerting negative pressure on a deal because of our posture on Chinese Trade-Hope Not!"

## 2.3 Topics of Interest in the United States about China

If one search for China in Google Trend, setting the time frame to be 2018 to 2019, one can see 8 rising related topics [9] and 25 rising related queries [10]. All of them fall into the following four categories: trade conflict, political institutions and ideology, human rights, and Chinese other diplomatic policies.

**Political Institutions** The reason why people started the discussion on Chinese political institution during this period is very likely to be the extension of term limit of Chairman Xi and the Hong Kong protest. Media would discuss Chinese political institution, commonly describing it as "communism", "authoritarian", "dictatorship", "socialism", "totalitarian" and "autocratic". For example, I see the following published on 22 newspapers during Dec 5, 2018 to Dec 11, 2018, titled *Miseducated or Stupid?*

> *"A recent Victims of Communism Memorial Foundation survey found that 51 percent of American millennials would rather live in a socialist or communist country than in a capitalist country. Only 42 percent prefer the latter. Twenty-five percent of millennials who know who Vladimir Lenin was view him favorably. Lenin was the first premier of the Union of Soviet Socialist Republics. Half of millennials have never heard of Communist Mao Zedong, who ruled China from 1949..."*

(It is also interesting to note that Dec 5, 2018 was only 4 days after Trump and Xi decided to truce. ) More broadly, even though a report doesn't focus on Chinese political system, it can still mention these terms to depict the image of China.

**Human Rights** The trigger for any discussion on human rights mainly are the issue of Uyghur re-educational camp. Even though the camp is a recent story, the discussion has been there for long. Moreover, as a general broad topic, the human rights issue has been long a focus of foreign attention on China. 2018 Human Rights report lists the human rights issues that capture western attention: human right defenders, freedom of expression, hong kong, xinjiang, tibet, freedom of religion, women's and girls' rights, disability rights, sexual orientation and

[9] The eight rising related topics are "Trade war", "China-United States trade war", "tariff", "Trade agreement", "Trade", "Muslim", "China-United States relations" and "Hong Kong"

[10] The 25 rising related queries are "china trade talks", "us china trade talks", "fortnite China"(a video game), "us china trade war", "china tariffs", "china trade news", "african swine fever china", "us china trade deal", "china trade war", "china trade deal", "winnie the pooh china", "50 lane highway in china", "china social credit", "trade war with china", "china social credit system", "lebron james china", "us china trade", "comida china cerca de mi", "china rich girlfriend", "comida china cerca","fine china lyrics", "china trade", "china muslims", "south china morning post", "chinese restaurants nearby"

gender identity, refugees and asylum seekers, key international actors and foreign policy. Many of these issues are very old ones. For example, Tiananmen Square Protest occurred in 1989. Many newspapers will publish memorial comments on its anniversary.

**Chinese Other Geopolitical Policies** Media sometimes discusses Chinese other diplomatic issues. Mostly commonly touched during the period of study were the Belt and Road initiative, conflicts and/or military force regarding the South China Sea and Chinese business in Africa. All these policies to some extent are deemed as threats imposed on the United States. In addition, western will also focus on the potential debt trap caused by the Belt and Road initiative, border issues related to South China Sea and the neo-imperialism spirit of China's policy to Africa and potential natural resource curse China could bring about.

# 3 Data

## 3.1 Identify Events

The principle of selection of events is such that it updates people's belief on the development of Sino-US relationship. For this reason, actions from the United States will be dominantly more than actions from China, the latter mostly pursuing retaliatory counterattacks. To capture U.S.'s strategies, I use President Trump's tweets and results of bilateral talks.

The selection of events is done in three steps. The first step is to determine the implication from each tweet of Trump. I notice that sometimes when Trump refers to China positively, he would write "President Xi", refering to Chairman Xi Jinping, the Chinese leader. Whenever President Trump did so, he was sending a strong signal for a better Sino-US relation, mostly either because of a smooth North Korea denuclearization progress or his intention to reach a trade deal with China. Whether mentioning "President Xi" is thus taken as a naive objective measure for a positive signal. To utilize all his tweets, I recruited three independent U.S. citizens from Boston University undergraduates to mark Trump's tweets that mentioned China as positive/negative/neutral. Positive tweets indicate a better Sino-US relation, and symmetrically with negative tweets. Neutral tweets either carry contradictory information or carry little information about Sino-US relation. Based on their classification, an average sentiment is calculated for each day as a measure of foreign policy of that day. Only days when daily score of all three undergraduates' decision agree are taken as event candidates. Among the 158 days, 91 days have been assigned with a sentiment score, with 35 positive days and 56 negative days. Other days are considered to carry ambiguous signals, since for each of them, there is at least one tester who thinks that day positive (or negative) while another tester think it negative (or positive).

The next step is to filter days. Ideally, the event should be such that the event is the only one that appearred within the window. To achieve so, one should think carefully on the choice of window length. Longer window length allows for slower media reaction upon events, but on the other hand reduces the number of potential benchmark events. After deliberation, I choose 9 days as the bindwidth, with 4 days before each event and four days after. To guarantee enough events, I also allow the post-event four-day window to contain other events, as long as their sentiment agrees with the benchmark event.

Having applied the filter, 16 positive events and 25 negative events are selected. Additionally, there are 18 days when Trump mentioned "President Xi".

## 3.2 Media Attention and Sentiment

I gather news from NewsLibrary. This database is used also by Gentzkow and Shapiro 2010, which contains around 7000 media outlets. Since the purpose of this paper is to separate demand side and supply side, I drop those papers that have national reader base, say NYT and WSJ, of which feature of readers are hard to characterize. I keep all news that mentions China or Chinese or Hong Kong or Beijing. For each report, I can view the title, first 540 letters of the article, length, source newspaper. However, due to technology contraint, I cannot observe the full text of the article and on which page it was published.

During the Sino-US trade war, the media mentions China covering various issues, which can be roughly categorized into (1) the Sino-US trade war and (2) human rights, ideology and other international influences. Very often the two topics are intertwined. A report can touch the two topics simultaneously. For example, on Dec 4th, 2018, three days after the United States and China joinly decided to truce at the G20 meeting, New York Times published a radio episode titled *What the West Got Wrong About China, Part I.* The subtitle and introduction write:

> *Many in the United States believed that captalism would never work without political freedom. Then China began to rise.*
>
> *From the very beginning, the West was certain that China would not pull off its economic experiment. That certainty came from a set of assumptions about how societies function and political freedoms emerge. But those assumptions were wrong — and China became stronger than ever.*

Apparently the episode is closely related to the truce decision made by Trump, as in the background reading it says "President Trump cast his 90-day trade war truce with President Xi Jinping of China as a victory, but his own advisers expressed caution", and the main theme is trade war progress and how to deal with China strategically in general. Yet, the wording and the image inserted (about aerospace workers wearing Long March-style uniforms in Yan'an [11], China) make the focus of this story discernibly less trade orientated. The key to disentangle media coverage of the two topics is to collect keywords and key phrases that belong to the two topics respectively and exclusively.

The selection of keywords is as follows: for topics related to the trade war, I include words/phrases that describe one of the following trade practices: i) technology transfer; ii) insufficient marketization; iii) cyber security threat. Additionally, some media has touched the issue of possible iv) election meddling, which also has been mentioned in President Trump's twitter. For topic related to China's human rights policies and international influence, I extract words from 2018 and 2019 Human Rights Report. The chapter about China discussed 12 topics, including political system and ideology of China, human rights & regional independence issue like Xinjiang, Tibet and hong kong and other policy that has international influences.

With the keywords, I measure the media attention in three ways. The naive measure is to count the number of articles that mention at least one of the keywords. In the oringinal sample, 33290 pieces of news mentioned one of human rights related keywords. Out of news that mentioned "China" in the title or leading paragraph, 10.81% mentioned human rights keywords. I further refine this measure by dividing it by the number of articles that mention "China" in the title or leading paragraph. These two captures the coverage in extensive margin.

To capture the intensive margin of media coverage, I use the weighted fraction of words/phrases mentioned over total number of words mentioned. This measure utilizes the truncated text of the title or leading paragraph, and because of the lack of full text, I assign a weight using length of words. Specifically, for each report that mentions China in the title or leading paragraph, the media attention of a word/phrase is measured by the number of its occurrence(s) times the length of the word/phrase, then divided by the total length of the analyzed text. Mathematically, $attention_{wr} = \frac{N_w \times Length_w}{TotalLength_r}$, where w denotes a word/phrase and r represents an article, and length of words/text is measured by the number of letters/digits. The reason why I multiply the number of occurrence by the length of the word/phrase can be illustrated by the following example:

[11] According to Wikipedia, Yan'an was the center of the Chinese Communist revolution from late 1935 to early 1947. Chinese communists celebrate Yan'an as the birthplace of the revolution.

> *You or your prescriber can request a medical exception to the changes in this letter. If you would like to ask for a medical exception, speak directly with your prescriber...*

The frequency of "you", "prescriber" and "medical exception" are all 2. However, "you" is a short word that can be contained in a sentence of a fixed digital length for many times. Compared with "you", "prescriber" is a longer word that can be less easily contained. Therefore, "prescriber" should be assigned a larger index than "you". Furthur, "medical exception" is a two-word phrase, which is even less likely to be contained given a fixed length. Therefore it should be assigned with the largest index. Generally speaking, for each article, the length of revealed leading text is almost fixed, and with the title, the length used for text analysis is roughly the same. How likely a word is contained in a text can be roughly measured by $\frac{TotalLength_r}{Length_w}$. The less likely a word/phrase of this length can be contained, the more weight should be given to the index.

## 3.3 Readers' Ideology

I measure the political ideology of readers by the 2016 presidential election result.

As the first step, I identify the reader base of each newspaper. I follow the methodology of Gentzkow and Shapiro. Matching the news data with Editor and Publisher Online Database, I know the location of headquarter. The metropolitan statistical area or micropolitan statistical area where the headquarter is located is identified as the reader base of the newspaper. If it is not in any metropolitan/micropolitan statistical area, then the county is taken as the reader base.

Knowing the reader base, I then measure the political stance of the average reader by the 2016 election vote share: $\frac{Voteshare_r}{Voteshare_d+Voteshare_r}-0.5$, where $Voteshare_r$ is the vote share to Donald Trump, and $Voteshare_d$ is the vote share to the Hilary Clinton. This measure is between -0.5 and 0.5, and equals to 0 when vote shares to both sides are equal. The more positive this index is, the more conservative the readers are. Exceptions are papers with names clearly conveying their political leaning, say Arkansas Democrat-Gazette (Little Rock, AR), of which index values are assigned with extreme values, i.e. either 0.5 or -0.5. This is because I expect the most readers of these papers will be only those whose political leaning is alligned with the paper.

Figure 1 shows the distribution of the readers' political leaning of newspapers. One can see several spikes, which correponds to several places where many newspapers are based at. Places with the highest number of papers are the New York-Newark-Jersey City MSA (37 dailies), Boston-Cambridge-Newton MSA (11 dailies) and Chicago-Naperville-Elgin MSA (11 dailies).

Despite the spikes, the distribution is roughly symmetric.

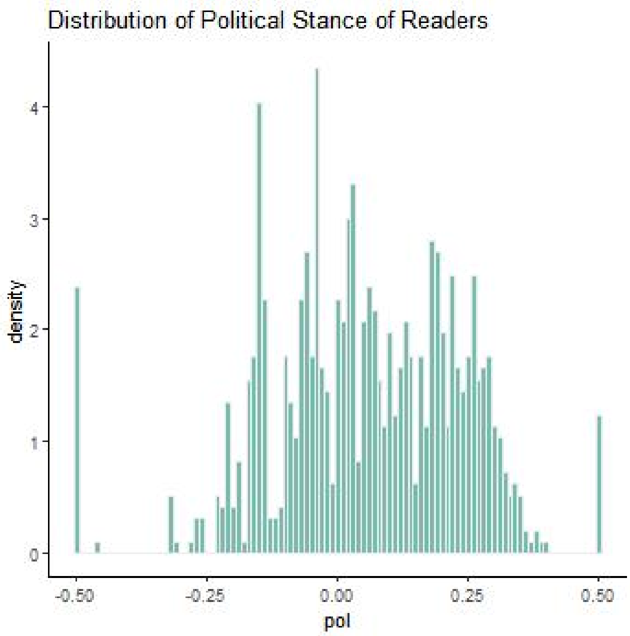


Figure 1: Distribution of Readers' Political Leaning

This measure may be interpreted in multiple ways. Most directly, it can be interpreted as how much the readers support Trump. Besides, this measure is also very much related to how much readers support the trade policy. Using CCES 2018 individual level data, the correlation between political leaning towards Republican and support to President Trump's trade policy is as high as 0.894. In addition, it can also be interpreted as how much they view China as a rivalry. The more conservative one is, the more likely that he/she is against China. Analyzing CCES 2017 data, I found that among those who voted for Trump 28.2% consider China as an enemy, whereas 17.9% of those voted for Hilary consider China as a rival. Unfortunately, I cannot disentangle all these interpretations using CCES data, as the data is a survey data without a large enough sample size, such that one cannot get enough sample observations at msa/county level. Nevertheless, this measure summarizes to some extent a set of aggregated preference of local readers of a paper.

## 3.4 Owners' Ideology

I adopt the measure from Gentzkow and Shapiro to proxy owner's political contribution. Specifically, I calculate the share of political donations going to republican candidates or PACs or the Republican party directly for three categories: i) those from executives at firms that own multiple US newspapers ii) those from executives at independent newspapers and iii) corporate contributions by newspaper firms but not PACs. Only contributions made by 2018 are used to calculate this measure.

To measure political stance of company leaders, I first collect information on all members of the executive team of each company. Executive positions include CEO (and all other chief officers, e.g. chief financial officer, chief revenue officer, chief product officer...), president, executive vice president, chairman, vice chairman, board of directors, owner, founder, publisher and general manager. This information is mostly provided by the Editor&Publisher database. To make up the missing observations and keep the existing observations updated, I also collect data from company's official website and Wikipedia.

The next step is to collect political contribution data for each person. This information was extracted from FEC, opensecret.org and followthemoney.org. Given a name, these three sources can not only return records of contribution under this name, but also occupation and employer of that person when the contribution is made, if the information is not missing. This helps to determine if a record belongs to a target person. To make sure that I do not miss any historical record, I collect one's biographical data via linkedin. Still, whenever I cannot pin down if a record belongs to a specific person, the record will be discarded.

This measure captures owner's ideology. Some may question that the political contribution doesn't measure ideology, but can be opposite. If someone is ideologically liberal, then he/she could tend to contribute the conservative, since if the conservative wins, the contribution might buy him/her some influence of the policy, if possible, to swerve the policy towards the bliss point of liberal more. While corporate PACs donate money mainly out of pratical reasons, corporate elites are more willing to direct funds to non-incumbents and competitive races, and favor far less candidates in position of power. Meanwhile, contributions from individuals significantly respond to change of ideology (Barber 2016, Bonica 2016). Additionally, in my sample, the amount of contributions given to a single campaign individual in a year ranges from \$25 to \$5,000 , and the amount to a Party/PAC ranges from \$75 to \$28,360. Meanwhile, take the 2016 election cycle as an example, the total amount of money received by those winner individuals who raised the least is \$78,278 for House candidate and \$3,797,124 for Senate. The amount a PAC/party raised is billion-level. Since compared with the total amount raise, political contribution from an individual is very limited, I doubt with this amount, one can impose any influence after the vendor comes to power.

For a political contribution made by a firm, I collect data by searching entity's name in opensecret.org or followthemoney. Compared with that of the executive team, observations under firms' name are less, and are more subject to the above concern. Sometimes the company's contribution can be huge enough to constitude a significant part of vendor's received amount. Moreover, for big firms, contributions are likely to be made on both sides. For this reason, I drop contributions made by company PACs so that in my sample, most corporate donations range from $42 to $45,000.

As the final step, I matched the newspaper with its owner. The merge is based on Editor&Publisher database, with adjustment of recent merges and acquisitions made during 2018 and 2019. (Therefore the ownership for some newspapers is time-varying). There are 165 firms checked. The smallest owns one daily, and the largest owns 142 dailies in our sample. The measure is then normalized to 0 for those with equal contributions to both sides and those with no donation records. The distribution of political stance of the panel data is given by figure 2.

Shown in the graph, around half of the dailies are marked as non-political (0). A few newspapers have political contribution clustered around 0, in the range of [-0.2, 0.1]. Among the remaining half, republican and democratic are roughly equally splitted. Based on this continous measure, I also generate a discrete measure for political stance: Middle ones are those between [-0.2, 0.1], those greater than 0.1 are marked as conservative, and those below -0.2 are marked as liberal.

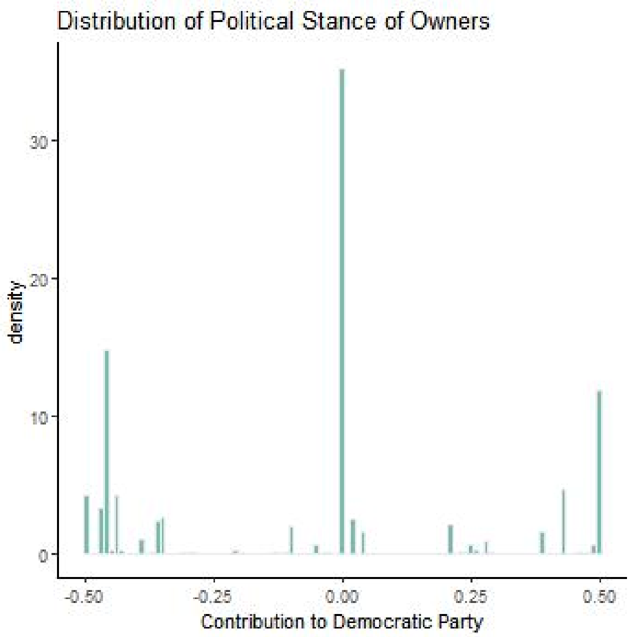


Figure 2: Distribution of Owner's Political Leaning

Figure 3 shows how readers' stance and owner's are related. The two variables are significantly positively correlated, with correlation being 0.1734. This could be explained by the tendency to acquire papers serving left-wing (right-wing) readers by left-wing (right-wing) owners. Still the correlation is so high that there is still variation to explore.

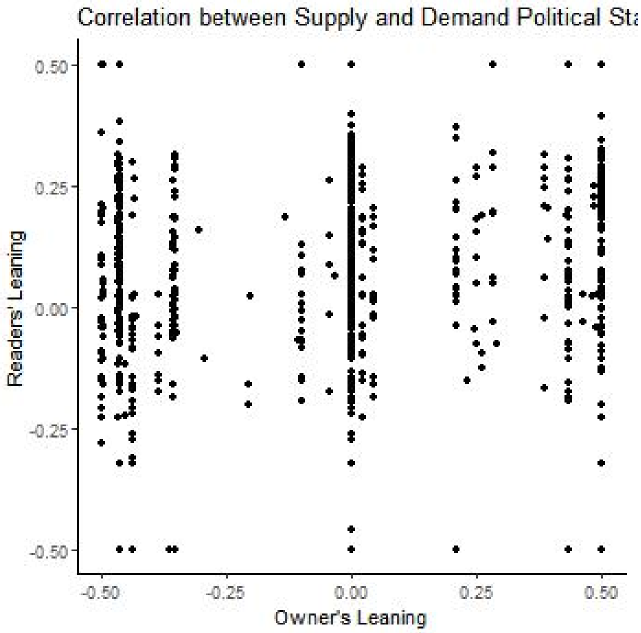


Figure 3: Distribution of Owner's Political Leaning

## 3.5 Demand for Topics

Besides the political stance, per capita income and other static aspects of readers, news content might react to some dynamic feature of readers. For example, there might be some local episode occurred related to human rights issue before a trade event, which built up the following peaked coverage on this human rights issue and mentioned China simultaneously. To capture the dynamic feature of demand, I explore the Google trends data, which measures how intensively a word/phrase has been searched in some certain area under a certain time frame. For each subtopic, I use a subset of corresponding keywords that give the highest searching intensity. I collect the google trends data for 210 metropolitan areas from 2018 to 2019.

Apparently a major concern of this index is that, it captures an equilibrium searching quantity that depends on both supply and demand for information. Actually, one can hardly disentangle demand and supply of information. Intuitively, people receive some information first and then begin to be interested in topics related, which in the next round boost supply. Simply speaking, the pattern is rather a supply-demand-supply-demand... chain. If this pattern is true, then the google trend before the event can serve as a proxy of demand.

The strategy is as follows: given a newspaper and a benchmark event, I define whether the readers of the newspaper have an increasing demand for some topic before the benchmark event. To implement this categorization, I fit a linear trend with Google trend seaching volumn data 7 days before a benchmark event. If the coefficient is significantly positive at $\alpha = 0.1$, then I define this newspaper-event window as experiencing an increasing demand before hand. Linear model fits the trend poorly for sure, but it at least tells whether the trend is in general increasing or decreasing. To complement this linear model, another method I adopt is to estimate if during a week before the benchmark event, the searching volumn is significantly (at $\alpha = 0.1$) more than the week before last week. They roughly give the same cateogorization.

Figure 4 illustrate the searching quantity for China's human rights issues around days when Trump's twitter mentioned "President Xi". Within the 15 day window before day 0 when the tweet is posted, the trend doesn't significantly increase, but the 7-day pre-event window seemingly exhibits a weak boosts of seaching intensity. This justifies the use of pre-event 7 day window to construct the index above.

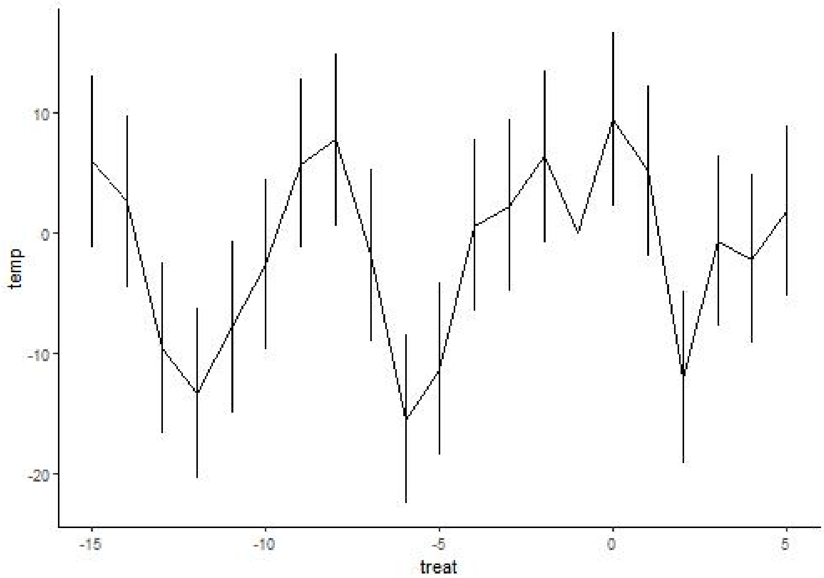


Figure 4: How Google Search For China's Human Rights Issue

Since the Google trend data serves as a complement for static voting pattern of the average reader, I present how Google trend varies with readers' political leaning in Figure 5. The reaction of conservative and liberal metropolitans are on average largely overlapped.

# 4 Empirical Strategy

## 4.1 Event Study Setup

I apply event study to estimate the effect of Trump's tweets. The assumption behind is that, to local news media, President Trump's attitudes and trade policies towards China are exogeneous. The analysis is performed on a panel dataset, with cross sectional variable being newspaper-event, and time variable as day. The dataset contains around 75% of all the circulating dailies

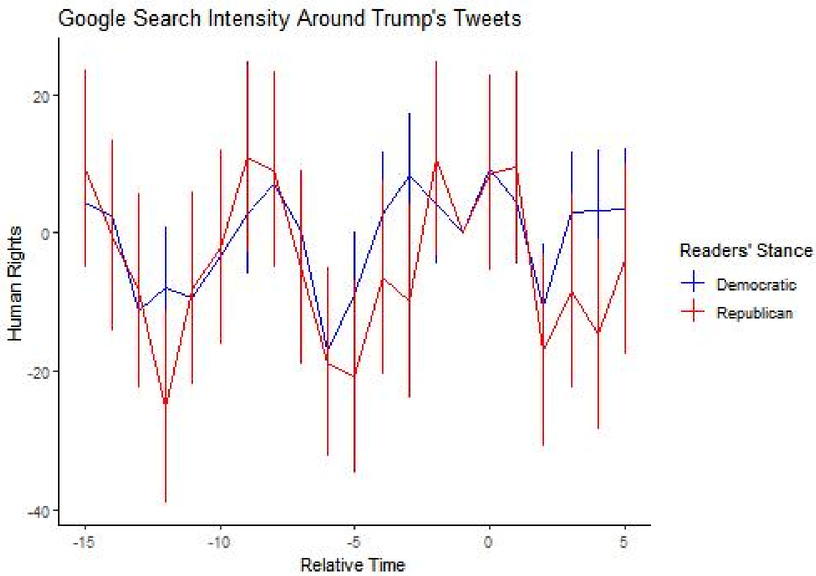


Figure 5: How Google Search For China's Human Rights Issue

in the United States. [12].

The methodology can be summarized into the following econometric specification:

$$Coverage_{ijt} = \alpha_{ij} + \beta_1 Relation_{jt} + \beta_2 Relation_{jt} \times ReaderRepub_i + \beta_3 Relation_{jt} \times OwnerRepub_i + controls_{it} + u_{it}$$

where i represents newspaper, j indicates event and t represents day. $Relation_t$ is a discrete variable that indicates Sino-US relation change. $Relation_t = 0$ for all pre-event observations, and $Relation_t = 1$ if the observation is after a positive event, and $Relation_t = -1$ if the observation is after a negative event. $ReaderRepub_i$ and $OwnerRepub_i$ are measures for how republican the owner and readers are.

All $\beta$s should be interpreted as causal effects. For local newspapers, the publication of President Trump's tweets, captured by $Relation_{jt}$ is largely exogenous. Thus $\beta_1$ is the effect of Trump's tweets on coverage of China on non-political local papers. Also, since $OwnerRepub_i$ and $ReaderRepub_i$ are measured using pre-2018 data,$\beta_1$, $\beta_2$ and $\beta_3$, should all be interpreted as causal effects.

## 4.2 Endogeneity Issues

The assumption for this event study is that Trump's twitter is exogenous to local newspapers. This assumption can be vulnerable to reverse causality and omitted variable bias. In this con-

[12] As a reference, up to 2018, there are 1279 dailies in total in the United States, according to Statista: https://www.statista.com/statistics/183408/number-of-us-daily-newspapers-since-1975/

text, President Trump may notice reports criticizing China's trade policies or human rights in the media and then respond by publishing corresponding tweets (Durante and Zhuravskaya 2018, Enli 2017). Also, Trump's tweets can be influenced by other factors, such as people's increasing demand for anti-China sentiment, which also drive local newspaper's coverage.

To address the reverse causality issue, I first check if the local newspapers blamed China's trade or human rights policies before the events. A test of pre-trend is performed by checking if media coverage on human rights and trade practices can predict Trump's negative tweets. Table 1 shows that no evidence on the media's prediction power.

| | (1)<br>Event | (2)<br>Event | (3)<br>Event | (4)<br>Event | (5)<br>Event | (6)<br>Event | (7)<br>Event |
|---|---|---|---|---|---|---|---|
| Event | | | | | | | |
| HumanRights(Cov) Lag(1) | 0.000717<br>(0.000851) | | | | | | |
| China(Cov) Lag(1) | | -0.0000799<br>(0.000582) | | | | | |
| HumanRights(Frac) Lag(1) | | | 0.000102<br>(0.000105) | | | | |
| HumanRights(Text) Lag(1) | | | | 0.00160<br>(0.00166) | | | |
| UnfairTrade(Cov) Lag(1) | | | | | -0.00172<br>(0.00151) | | |
| UnfairTrade(Frac) Lag(1) | | | | | | -0.000379<br>(0.000289) | |
| UnfairTrade(Text) Lag(1) | | | | | | | 0.000903<br>(0.00547) |
| cluster | Day | Day | Day | Day | Day | Day | Day |
| fixed effects | N | N | N | N | N | N | N |
| drop large papers | Y | Y | Y | Y | Y | Y | Y |
| controls | Y | Y | Y | Y | Y | Y | Y |
| N obs | 175790 | 175771 | 175798 | 175795 | 175807 | 175810 | 175796 |

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

Table 1: Can Media Predict Tweets?
A logit regression is performed, with the dependent variable being an indicator of event occurence. Regressors are lagged observation on media coverage on local newspapers.

While President Trump is unlikely to read local newspapers and then respond, it is confirmed that he will read papers like New York Times and Wall Street Journal and publish twitter in response. [13] I thus further confirm the absence of reverse causality by checking if the coverage of NYT and WSJ hiked before selected events. Figure 6 and Figure 7 show that neither papers could significantly predict these events. A Granger causality test is performed in addition to the graphical representation. For all Trump's tweets that mentioned China, one-day lagged coverage on human rights issues from Fox News and New York Times can predict events with p-value being 0.07. However, among the events I selected, one can not reject the

[13] One of Trump's tweets says "Do you notice the Fake News Mainstream Media never likes covering the great and record setting economic news, but rather talks about anything negative or that can be turned into the negative. The Russian Collusion Hoax is dead, except as it pertains to the Dems. Public gets it!"

hypothesis that coverage of these papers can't predict events.

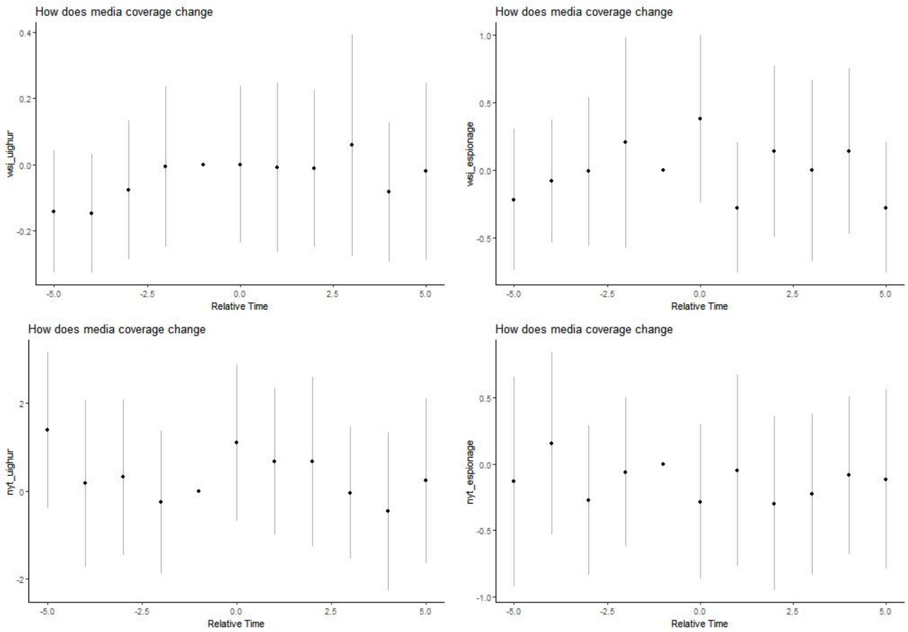


Figure 6: How NYT/WSJ Respond Upon Trump's Positive Tweets

Note: The dependent variable is the number of negative articles that mention "Uighur" or "espionage" by NYT and WSJ

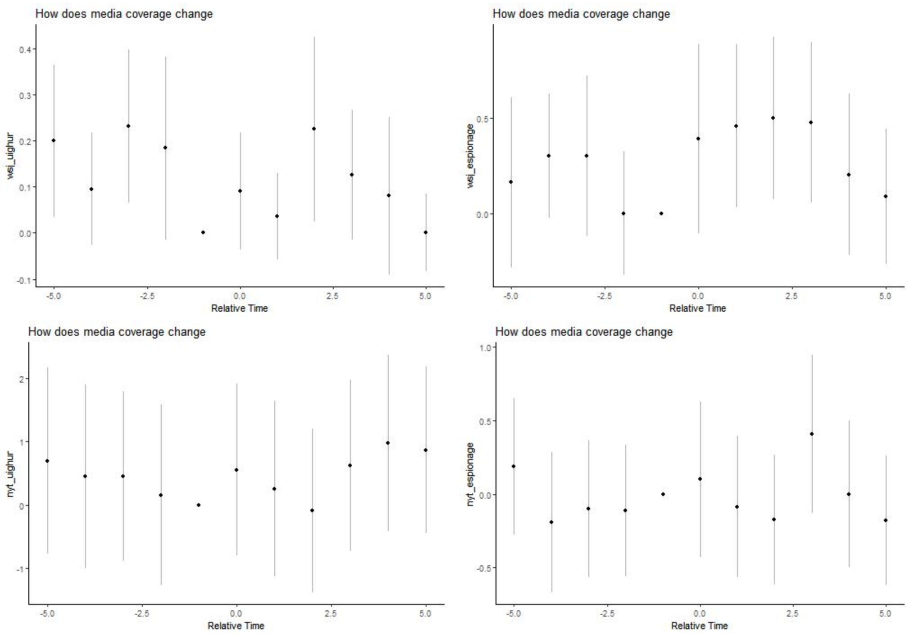


Figure 7: How NYT/WSJ Respond Upon Trump's Negative Tweets

Note: The dependent variable is the number of negative articles that mention "Uighur" or "espionage" by NYT and WSJ

The other potential concern is omitted variable bias. The most direct mechanism is that President Trump may observe a change in public anger on China, which is a weighted average of local change in anti-China sentiment. The change in public opinion on China could also be observed by local papers, upon which they adjust their coverage. The bias is of the same direction as my prediction. Unfortunately, the daily demand is hard to capture. Notice that President Trump should only respond upon a national trend. That being said, if daily fixed effects are included, then the trend has been eliminated. I also run the following equation as a baseline specification.

$$Coverage_{ijt} = \\ \alpha_{ij} + \gamma_t + \beta_2 Relation_{jt} \times ReaderRepub_i + \beta_3 Relation_{jt} \times OwnerRepub_i + controls_{it} + u_{it}$$

I attempt to solve this problem in two ways. First, I intend to measure this dynamic demand by lagged Google trend data. Second, I use a placebo test to illustrate that the result is unlikely be driven by daily demand. Please refer to section 6.1 for more details.

# 5 Empirical Result

## 5.1 Total coverage

Do readers' and owner's preference influence total coverage? I regress the daily coverage of topics on readers and owners political leaning, neglecting the time-varying Sino-US relationship. This serves a replication of Shapiro & Gentzkow's cross-sectional exercise (Gentzkow and Shapiro 2010) using this new dataset.

Table 2 lists the effects on total coverage of China's human rights (Columns 1 to 3) and trade concerns (Columns 4 to 6). Alligned with Shapiro & Gentzkow, readers' political preference explains much more than owner's, both in terms of magnitude and significance. The more conservative readers are, the less a paper covered China's human rights policies and trade concerns. Table 11 demostrates that this result is robust to different measures of owner's leaning and adding state fixed effects and daily fixed effects.

The effect from readers' leaning to total coverage could be interpreted by the difference in opinion on China's economic threat and human rights abuses. Regarding China's threat on the United States, according to Cooperative Congressional Election Study 2017, slightly more percentage of Clinton's supporters believe that China has imposed major threat on national security (71.8% vs 75.7%) and economics (80.5% vs 84.5%) of the United States, and substantially more think that China meddled U.S. election (43.7% vs 78.2%). As for China's human rights policy, among those who think President Trump a very good president, 51.4% think China's human rights issues very serious, and around 17.4% consider as not too serious or not a problem at all, whereas among those who are extremely unsatisfied with President Trump, corresponding ratios are 54.7% and 10.6%. In general President Trump's supporters deem China's human rights issues or threat to the United States less a problem. The total coverage appears to cater to readers' attitude towards China.

| | (1) HumanRights(Cov) | (2) HumanRights(Frac) | (3) HumanRights(Text) | (4) UnfairTrade(Cov) | (5) UnfairTrade(Frac) | (6) UnfairTrade(Text) |
|---|---|---|---|---|---|---|
| Owner Republican | -0.0180 | -1.781 | 0.0582 | 0.0562 | 0.114 | 0.0195 |
| | (0.653) | (4.701) | (0.0678) | (0.0597) | (0.270) | (0.0125) |
| Readers Republican | -5.875*** | -32.30*** | -0.471** | -0.548** | -2.254** | -0.0916** |
| | (2.128) | (11.43) | (0.184) | (0.260) | (0.939) | (0.0460) |
| cluster | Market | Market | Market | Market | Market | Market |
| drop large papers | N | N | N | N | N | N |
| controls | Y | Y | Y | Y | Y | Y |
| N obs | 670403 | 670403 | 670403 | 670403 | 670403 | 670403 |
| F stat | 4.403 | 4.402 | 4.363 | 4.473 | 5.029 | 3.262 |
| adj. R2 | 0.00523 | 0.00292 | 0.000867 | 0.000735 | 0.000429 | 0.000300 |

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

Table 2: Total Media Coverage

These results can help substantiate the measure of readers' political leaning. To repeat the major concern of this measure, while when market has one monopoly daily newspaper, firms should cater to the median reader to maximize fraction of readers. However, competition can segment the market so that the average reader of the entire market might not be a good proxy for its real reader base. Table 3 illustrates how demand and supply sides effects varies with market competition, measured by the number of competitive dailies within local markets. For all measures, higher competition tends to offset the effect from average reader. However, the magnitude is small such that the number of dailies should be at least 4 to completely offset the effect of median reader's preference. As a reference, 84.9% of the 966 dailies have less then 5 competitors. Also, the effect has little significance either. That all being said, median reader still captures a significant part of readers' feature.

Similarly, this could also shed light on how well lagged Google Trend data can predict coverage. Listed in Table 4, only the coverage of "China" shows comprehensive result: lagged Google trend data can predict future coverage, and the effect fades as the number of lags increases. Meanwhile, the coefficient of lagged searching intensities for coverage of the two topics are negative, which are rather counter-intuitive. Moreover, the coefficient of trade related coverage is even negatively significant. There are at least two reasons behind this phenomenon. One is measurement error of this Google Trend data. Compared with the keyword "China",

| | (1) HumanRights(Cov) | (2) HumanRights(Frac) | (3) HumanRights(Text) | (4) UnfairTrade(Cov) | (5) UnfairTrade(Frac) | (6) UnfairTrade(Text) |
|---|---|---|---|---|---|---|
| Owner Republican | 0.120 | 0.187 | 0.0430 | 0.0717 | 0.189 | 0.0260* |
| | (0.653) | (4.637) | (0.0689) | (0.0691) | (0.297) | (0.0135) |
| Readers Republican | -7.414*** | -43.69*** | -0.558*** | -0.712** | -2.924** | -0.124** |
| | (2.337) | (12.55) | (0.200) | (0.330) | (1.152) | (0.0554) |
| NumDailies X Readers Republican | 1.379 | 10.40 | 0.0727 | 0.147 | 0.604 | 0.0297* |
| | (0.967) | (6.496) | (0.107) | (0.101) | (0.422) | (0.0176) |
| NumDailies X Owner Republican | -0.0976 | -1.288 | 0.00818 | -0.0109 | -0.0513 | -0.00418 |
| | (0.229) | (1.887) | (0.0267) | (0.0194) | (0.0850) | (0.00565) |
| cluster | Market | Market | Market | Market | Market | Market |
| drop large papers | N | N | N | N | N | N |
| controls | Y | Y | Y | Y | Y | Y |
| N obs | 670403 | 670403 | 670403 | 670403 | 670403 | 670403 |
| F stat | 6.092 | 7.395 | 4.864 | 4.469 | 5.412 | 3.829 |
| adj. R2 | 0.00590 | 0.00352 | 0.000909 | 0.000851 | 0.000494 | 0.000364 |

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

Table 3: Total Media Coverage and Local Competition

keywords like "cyber espionage" and "communism" has far less searching intensity, so relative measurement error could be greater. The other is that, while the total coverage of China's trade practices and human rights issues are highly influenced by readers' preference, in-time coverage is not responsive to local dynamic demand at all. If the latter is true, then the omitted variable bias is not a threat to the causality inference.

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) | (5) UnfairTrade(Cov) | (6) UnfairTrade(Frac) | (7) UnfairTrade(Text) |
|---|---|---|---|---|---|---|---|
| Owner Republican | -0.104 | -1.207 | -2.512 | 0.104 | 0.0505 | 0.0947 | 0.0257 |
| | (1.099) | (1.941) | (7.897) | (0.119) | (0.0906) | (0.426) | (0.0197) |
| Readers Republican | -7.427 | -13.44* | -34.22 | -0.313 | -0.432 | -1.811 | -0.0880 |
| | (4.782) | (7.498) | (26.01) | (0.384) | (0.277) | (1.177) | (0.0663) |
| Lag(1) GoogleTrend | -0.961 | 13.06* | -5.369 | -0.112 | -0.343 | -1.953 | -0.141** |
| | (0.770) | (7.191) | (4.862) | (0.109) | (0.532) | (2.770) | (0.0597) |
| Lag(2) GoogleTrend | -0.676 | 11.47* | -3.527 | -0.0365 | -1.338*** | -6.684*** | -0.189*** |
| | (0.732) | (6.805) | (4.372) | (0.0973) | (0.382) | (1.570) | (0.0462) |
| Lag(3) GoogleTrend | -0.936 | 9.335 | -5.964 | 0.0620 | -1.917*** | -9.733*** | -0.379*** |
| | (0.955) | (7.437) | (6.959) | (0.0792) | (0.357) | (2.062) | (0.0846) |
| cluster | Metro | Metro | Metro | Metro | Metro | Metro | Metro |
| fixed effects | | | | | | | |
| drop large papers | N | N | N | N | N | N | N |
| controls | Y | Y | Y | Y | Y | Y | Y |
| N obs | 352410 | 352410 | 352410 | 352410 | 352410 | 352410 | 352410 |
| F stat | 1.068 | 2.354 | 1.050 | 1.029 | 15.08 | 16.52 | 12.42 |
| adj. R2 | 0.00297 | 0.00760 | 0.00118 | 0.000536 | 0.000499 | 0.000300 | 0.000212 |

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

Table 4: Total Media Coverage and Google Trend

## 5.2 Tweets Mentioning "President Xi"

The series of events I use to analyze are the tweets that mentioned "President Xi".[14]

[14] The days include: 2018-03-10, 2018-04-10, 2018-04-27, 2018-05-08, 2018-05-13, 2018-08-29, 2018-11-01, 2018-12-03,2018-12-29, 2019-01-31, 2019-02-24, 2019-05-10, 2019-06-18, 2019-06-28, 2019-08-01, 2019-08-14, 2019-08-23, 2019-10-31

Figure 8 shows how the number of reports that mention Chinese human rights and ideology of different owner's stance reacted upon Trump's tweeting "President Xi". Horizontal axis shows relative day around the event, where 0 is the time when an event occurred. As shown, after Trump tweeted President Xi, newspapers with democratic owner significantly increased their coverage about Chinese human rights issues and ideology. Papers with republican or middle owner didn't respond to these events. Noticeably, the jump of coverage started on the day when events took place, not before the event started. This to some extent reduces the concern of reverse causality.

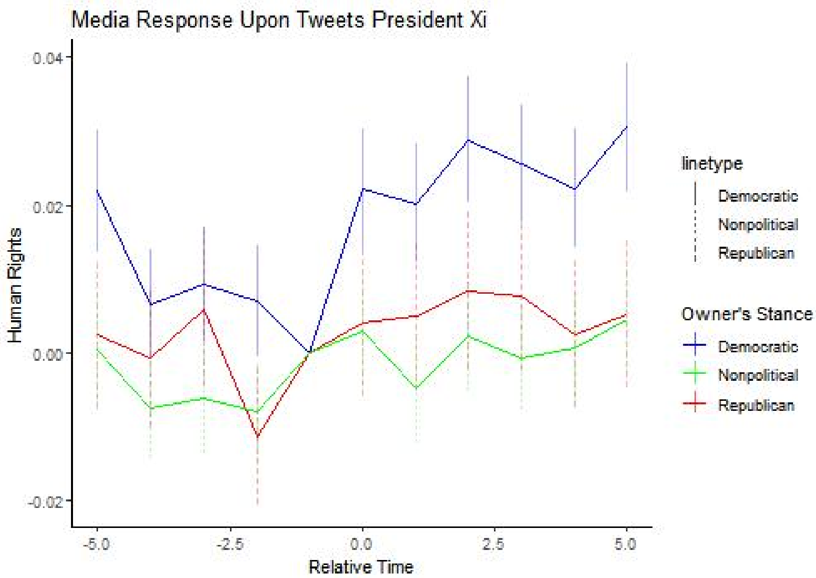


Figure 8: Media Reaction After Mentioning "President Xi" - Human Rights Coverage

Note: The dependent variable is the number of negative articles that mentioned human rights issue/political institution and ideology/other geopolitical policies. Horizontal axis shows relative time around an event. 0 is the day when an event took place. The day before an event is taken as reference.

The negative coverage related to the "unfair trade practices" does not show obvious heterogeneity across owner's political stance, as shown in Figure 9. To a limited extent, newspapers with a republican owner are slightly more responsive to President's tweets. On a day when President Trump tweeted "President Xi", coverage on trade practices on average increased drastically, and then it fell below the democratic/middle ones.

Do newspapers report more China's human rights issues because they pay more attention on China in general? Figure 10 shows the heterogeneous response of the number of reports mentioning China: the pattern is not the same as the coverage of Chinese human rights issue, thus the heterogeneous reaction of biased coverage is not driven by differential attention to China. For some papers, there is a noticeable spike one or two days before an event. This is because some tweets were published at bilateral meetings, and some media would report

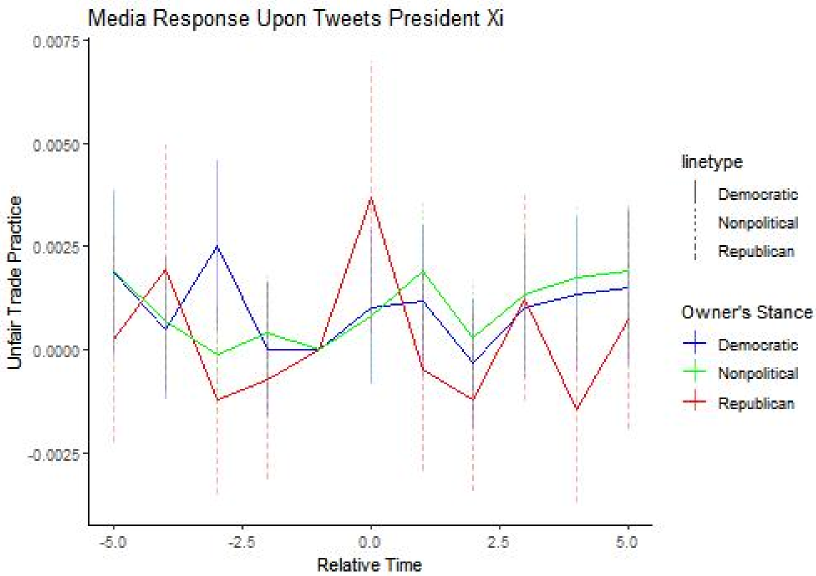


Figure 9: Media Reaction After Mentioning "President Xi" - Trade Practice Coverage

Note: The dependent variable is the number of articles that mentioned trade-conflict-related topics. Horizontal axis shows relative time around an event. 0 is the day when an event took place. The day before an event is taken as reference.

more on the "forthcoming" meetings before they started. While the coverage of China's human rights and trade practices does not exhibit pre-trend, the raised reports on China beforehand are reporting facts about meetings.

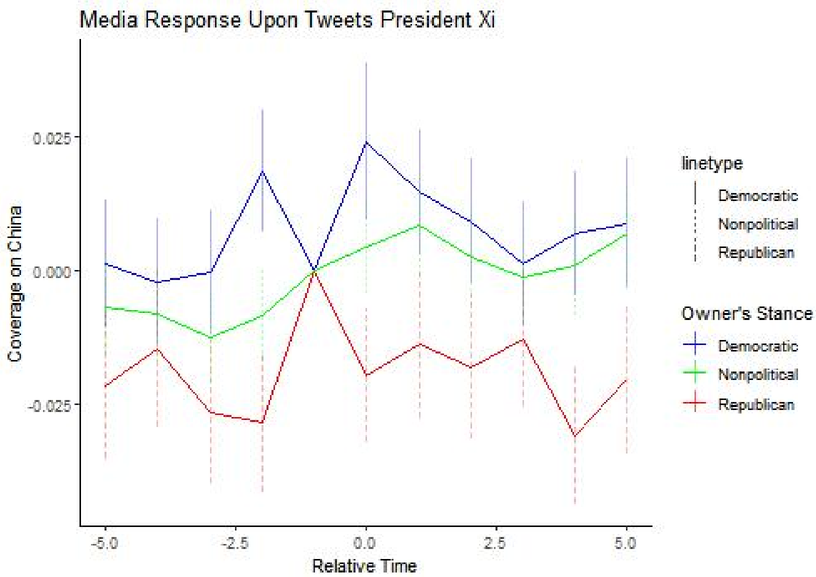


Figure 10: Media Reaction After Mentioning "President Xi"

Note: The dependent variable is the number of articles that mentioned China in the title or leading paragraph, regardless of the sentiment.

Table 5 summarizes the pattern shown in Figure 8. The regression model is Equation 4.1 and controls include per capita income level and whether the local market has more than one daily. The dependent variable is measured using the naive way: counting the number of articles mentioning China's human rights issues or ideology. Since the events used are positive, *Relation* takes either 0 or 1. I also add the coverage of China as control so as to rule out the effect from general attention. Regarding the change of coverage on China's human rights issue following President Trump mentioning "President Xi", the effect from political stance of readers and owner are of the same direction and roughly comparable magnitude. Column (1) implies that, compared with middle ones, papers of democratic ownership delivered much more after a positive event, while republican delivers slightly more. The more democratic its owner is, the more a paper covers China's human rights stories. (Column (2)). Similarly, the more democratic its average reader is, the more a paper on average delivered China's human rights issues after a positive event. While the coefficient of reader's leaning is not significant, that of owner's leaning is consistently significantly negative. This contradicts the prediction of Shapiro and Gentzkow that readers' preference should overwhelm owner's preference in determining media content. Column (3) and (4) show that this result barely changes after adding daily fixed effects. This pattern is robust to all measures of human rights coverage and different model specifications. (See Appendix Table 12 and Table 16 )

In Table 5, Column 1, the marginal effect of owner's stance is around 1.334, which should be interpreted as: compared with a middle newspaper, a democratic paper would increase the number of reports that mention China's human rights issues after Trump tweeted "President Xi" by roughly 0.01334. To set a reference, the average number of articles covered per day per paper is 0.0538. To address the potential concern of sparcity, among the 966 dailies, 858 have at least one report about human rights during the 18 events windows, and 748 papers have nonzero post-tweet response. Even though the magnitude is relatively small, sparcity is not that troublesome here.

I repeat the exercise on the coverage of "unfair trade practices" of China, using the naive measure. Table 6 shows the results. The sign of readers' effect is still negative, but the owner's effect is positive insignificant. This is also confirmed by the Figure 9.

To summarize the findings in this section, owner's ideology, measured by its political contribution made to parties/candidates, can affect coverage of China's human rights issues. There are more than one explanation for this stylish fact. The most intuitive one is that, the newspaper owner may formulate the news content according to its own political alliance with President Trump's foreign policy. A left-leaning firm, compared with a middle one, tends to disagree with

|  | (1) HumanRights(Cov) | (2) HumanRights(Cov) | (3) HumanRights(Cov) | (4) HumanRights(Cov) |
|---|---|---|---|---|
| Relation | 0.714 | 1.324** |  |  |
|  | (0.548) | (0.554) |  |  |
| Owner Dem × Relation | 1.334*** |  | 1.334*** |  |
|  | (0.308) |  | (0.308) |  |
| Owner Rep × Relation | 0.369 |  | 0.369 |  |
|  | (0.278) |  | (0.279) |  |
| Relation × Readers Republican | -1.213 | -1.114 | -1.213 | -1.113 |
|  | (0.841) | (0.852) | (0.841) | (0.853) |
| Relation × Owner Republican |  | -1.303*** |  | -1.303*** |
|  |  | (0.384) |  | (0.384) |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event&Day | Newspaper-Event&Day |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 156491 | 156491 | 156491 | 156491 |
| F stat | 35.17 | 40.86 | 8.298 | 8.221 |
| adj. R2 | 0.0557 | 0.0556 | 0.0597 | 0.0596 |

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

Table 5: Media Reaction After Mentioning "President Xi"

|  | (1) UnfairTrade(Cov) | (2) UnfairTrade(Cov) | (3) UnfairTrade(Cov) | (4) UnfairTrade(Cov) |
|---|---|---|---|---|
| Relation | 0.156 | 0.115 |  |  |
|  | (0.131) | (0.126) |  |  |
| Owner Dem × Relation | -0.0848 |  | -0.0847 |  |
|  | (0.0549) |  | (0.0549) |  |
| Owner Rep × Relation | -0.0301 |  | -0.0299 |  |
|  | (0.0747) |  | (0.0747) |  |
| Relation × Readers Republican | -0.0519 | -0.0492 | -0.0515 | -0.0488 |
|  | (0.187) | (0.188) | (0.187) | (0.189) |
| Relation × Owner Republican |  | 0.0335 |  | 0.0336 |
|  |  | (0.0745) |  | (0.0746) |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event&Day | Newspaper-Event&Day |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 156491 | 156491 | 156491 | 156491 |
| F stat | 9.179 | 10.45 | 3.276 | 3.290 |
| adj. R2 | 0.0286 | 0.0286 | 0.0303 | 0.0303 |

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

Table 6: Media Reaction After Mentioning "President Xi"

Trump's policy. This disagreement is reflected in the operation of coverage on China's human rights issues but not trade practices. Interestingly, the readers' preference is not reflected in the same way as owner's taste. While the political stance of owner makes a difference in media coverage on China, that of the median reader doesn't play a significant role. This contradicts the profix-maximizing intuition.

Unfortunately, to check whether President Trump's tweets mentioned "President Xi" only helps in selecting roughly positive tweets. There are three days when POTUS mentioned "Chairman Xi" and "Xi Jinping" directly in his Twitter, implying a less friendly gesture. However the days are too few to perform analysis with. In the next section, I presents results for both positive and negative events, based on the judgement of sentiment according to voting-age native United States citizens.

## 5.3 Coverage of Human Rights

Instead of using tweets mentioning "President Xi", hereby all tweets that mentioned China contribute to the calculation of President Trump's attitude towards China. There are 14 days with positive attitude [15] and 19 with negative attitude [16].

On 8 of the 14 positive days did President Trump mention "President Xi". First of all, all 34 tweets except for two that mentioned "President Xi" are marked as positive (26) or at least ambiguous/neutral (6). [17] Among the 18 days taken as benchmark events in the previous section, 11 days are marked as positive, 4 days are neutral and 3 days are marked as negative. The disparity comes from the following two sources. First, their judgement on POTUS's attitude towards China is based on all tweets published on the day, not only those that mentioned "President Xi". If too many negative tweets were published on one day, sentiment of that day can be hardly overturned by a single tweet with "President Xi". Second, as shown in footnote, not all tweets with "President Xi" are deemed positive by testers. Finally, not all tweets mentioning "President Xi" are selected, even though they are judged as positive. This is because, after taking into account all the tweets, there are many more days taken as candidates events. After applying the filter of events so that the pre-event window is clear, some events are ruled out. For instance, Mar 10th, 2018 is excluded because there is a positive event arised on Mar 7th, 2018.

Figure 11 shows how coverage changes upon positive events using two different measures. Following a positive event, democratic-leaning papers reported marginally more number of reports that mentioned human rights keywords than middle and republican ones; republican papers include less words in the first paragraph. Table 13 in the Appendix summarizes this pattern.

When it comes to negative days, the response is reversed. As Figure 12 illustrates, now it is the republican papers that delivered more on a negative day, compared with middle and

[15] Days are 2018-03-07, 2018-04-27, 2018-05-08, 2018-05-13, 2018-11-01, 2018-12-01, 2018-12-29, 2019-01-31, 2019-02-17, 2019-02-24, 2019-04-04, 2019-06-18, 2019-09-12, 2019-10-11

[16] Days are 2018-04-16, 2018-07-09, 2018-07-20, 2018-07-25, 2018-08-04, 2018-08-20, 2018-09-18, 2018-09-26, 2019-01-21, 2019-04-15, 2019-05-05, 2019-06-01, 2019-06-11, 2019-07-11, 2019-08-01, 2019-08-13, 2019-09-03, 2019-09-30, 2019-10-06

[17] The tweet published on Aug 23rd, 2019 mentioning "President Xi" is marked negative. In this tweet, President Trump wrote "President Xi said [fentanyl] would stop - it didn't". The other negative tweet mentioned "President Xi" is published on March 13rd, 2018. He wrote "I say openly to President Xi & all of my many friends in China that China will be hurt very badly if you don't make a deal because companies will be forced to leave China for other countries. Too expensive to buy in China. You had a great deal, almost completed, & you backed out!"

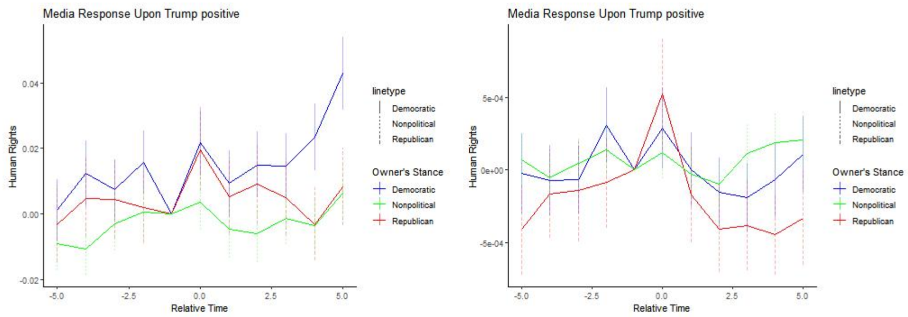


Figure 11: Media Reaction After Positive Events

Graphs are ploted using two measures for human rights coverage and trade pratices: 1) counting number of reports that mention keywords in the complete text 2) fraction of digits that are keywords.

democratic papers. Table 14 in Appendix provides statistical confirmation on this.

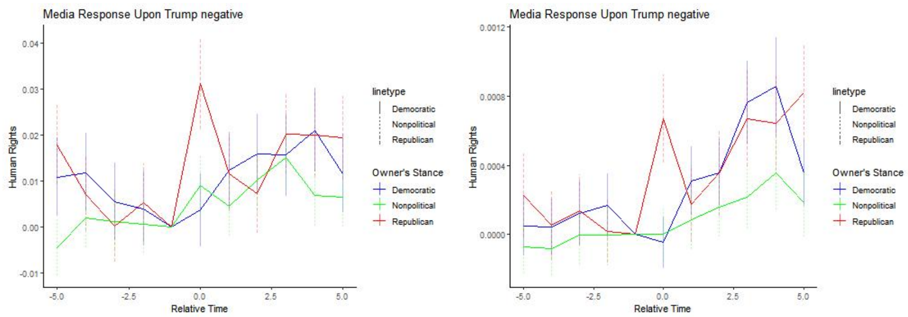


Figure 12: Media Response Upon Predicted Talks: Negative Tweets

Graphs one to three use measures for human rights coverage: 1) counting number of reports that mention keywords in the complete text, 2) fraction of digits that are keywords.

I hereby combine the two sets of events to estimate Equation 4.1. Results are listed in Table 7. When Sino-US relationship got better, the more republican its owner is, the less a paper reported on China's human rights issues; when Sino-US relationship got worse, the more republican its owner is, the more human rights issues of China would be covered. This pattern applies to all measures (Column 3 and 4) of human rights coverage and cannot be interpreted as heterogeneous attention on China (Column 2). On the other hand, the effect of readers' political preference is not consistently significant. Interestingly, the effect of readers preference is in different direction, suggesting that even though readers' preference plays a role, the mechanism behind is different from that of owner's leaning. Table 15 in Appendix records the results using discrete measure of owner's stance.

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | 0.508 | -0.105 | 1.791 | -0.0384 |
| | (0.594) | (0.836) | (4.053) | (0.147) |
| Relation × Owner Republican | -0.685*** | -0.466 | -5.325** | -0.132* |
| | (0.261) | (0.411) | (2.087) | (0.0721) |
| Relation × Readers Republican | 1.023* | 2.486*** | 5.506 | 0.308** |
| | (0.610) | (0.925) | (4.467) | (0.154) |
| China(Cov) | 0.215*** | | | |
| | (0.0114) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 286901 | 286901 | 286901 | 286901 |
| F stat | 62.36 | 14.07 | 1.674 | 11.04 |
| adj. R2 | 0.0778 | 0.000445 | 0.0000235 | 0.000305 |

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

Table 7: Media Reaction on Sino-US relation

## 5.4 Coverage of Trade Practice

The owner's political leaning can carry many personal traits or opinions. There are in general two types of traits or opinions: owner's thoughts on President Trump and owner's thought on China. In the context of trade conflict, the owner's influence might come from their opinion on China's trade practices. However, different studies give different correlation implication between political leaning and opinion on China's impact on U.S. economy. According to the Cooperative Congressional Election Study 2017, slightly more percentage of Clinton's supporters believe that China has imposed major threat on and economics (71.8% vs 75.7%). Meanwhile, by 2017 Global Attitude Survey by Pew Research Center, more of President Trump's supporters believes that the the U.S. deficit with China, U.S. debt held by China and jobloss due to China are much more serious problems than Clinton's supporters do.

Suppose it is the republican-leaning owners that deem China more as a serious threat to U.S. economics than middle and democratic-leaning owners. One explanation for the pattern of coverage of human rights is that it is driven by owner's antipathy to China for its trade practices. When China complies as trade negotiation went well, discussion of human rights is reduced, and vice versa. If so, then the coverage of China's "unfair" trade practices should react in the same way, if not more.

This turns out to be not the case, as shown in Figure 13 and Figure 14. Republican papers on average increased the coverage of trade practices on the day when an event occurred, regardless of the nature of the event. In contrast, democratic and middle papers are far less responsive upon POTUS's tweets.

Table 8 further confirms that the pattern of trade related coverage doesn't coincide with the pattern of human rights coverage. This difference to some extent sheds light on what trait

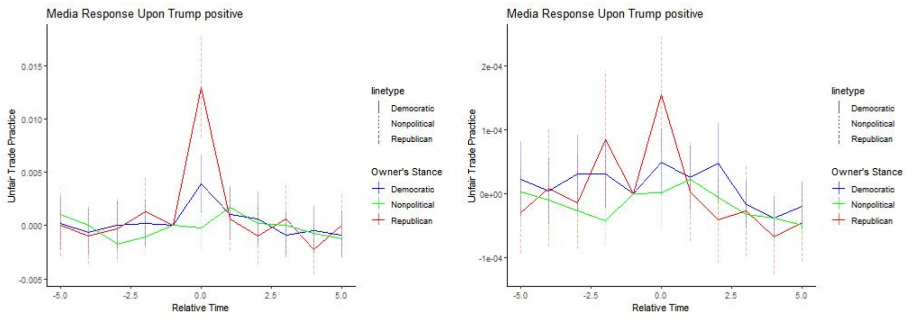


Figure 13: Media Response Upon Predicted Talks: Positive Tweets

Graphs one to three use measures for human rights coverage: 1) counting number of reports that mention keywords in the complete text, 2) fraction of digits that are keywords.

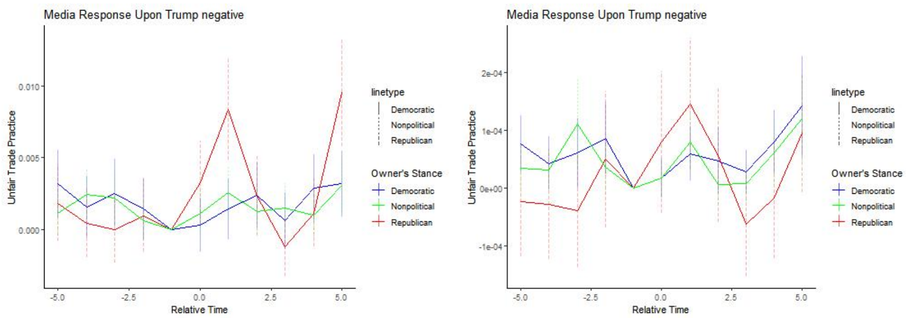


Figure 14: Media Response Upon Predicted Talks: Negative Tweets

Graphs one to three use measures for human rights coverage: 1) counting number of reports that mention keywords in the complete text, 2) fraction of digits that are keywords.

behind political stance that drives the change of human rights coverage. Figure 15 shows what keywords are frequently mentioned when China is mentioned in the title or leading paragraph. Aparently "trade", "tariff", "President Trump", "billion" are highly mentioned, indicating that China is mostly discussed for its involvement in trade conflict. However, when human rights/ideology is mentioned, keywords related to trade become noticeably rarer, shown in Figure 16. Notice that, the word cloud is plotted without excluding those reports that mention both human rights and trade practices. "President Trump" becomes the hottest word here. This implies that, the human rights coverage are unlikely to be responding to trade per se, but instead, President Trump. This may explain why the coverage responsiveness are different regarding human rights topics and trade related topics, even though the keywords are selected such that the sentiment of the two coverage are both rather negative/neutral.

| | (1) UnfairTrade(Cov) | (2) UnfairTrade(Frac) | (3) UnfairTrade(Text) |
|---|---|---|---|
| Relation | 0.0965 | 0.142 | 0.0329 |
| | (0.0948) | (0.436) | (0.0283) |
| Relation × Owner Republican | -0.0775 | -0.592 | -0.0259 |
| | (0.0735) | (0.399) | (0.0244) |
| Relation × Readers Republican | -0.0373 | 0.740 | -0.0277 |
| | (0.163) | (0.791) | (0.0590) |
| China(Cov) | 0.0371*** | | |
| | (0.00272) | | |
| cluster | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N |
| controls | Y | Y | Y |
| N obs | 286901 | 286901 | 286901 |
| F stat | 33.17 | 2.969 | 1.202 |
| adj. R2 | 0.0331 | 0.0000415 | 0.0000186 |

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

Table 8: Media Reaction on Sino-US relation

# 6 Robustness Check and Extensions

## 6.1 Dynamic Demand

In this section, I further include an indicator variable that capture if daily demand for human rights topics increases before event and check if it predicts the change of coverage in response to events. Econometrically, I include $Relation_{jt} \times IncreasingTrend_j$ in the model. The coefficient represents how the pre-event building up demand contributes to the post-event increase/decrease of coverage.

This exercise completes the logic in two ways. First, it complements the static feature of readers' political stance. Suppose newspapers owners can observe dynamics of local demand and respond to it, and suppose they tend to acquire papers of which the dynamic trend is correlated with their own political stance, then the coefficient $\beta_3$ could actually reflects the effect from demand, but not supply. Second, it helps to address the omitted variable bias concern. Omitted variable bias concern rises if President Trump's twitter is strategically manipulated to cater to public opinion on China, which also should affect media coverage. By giving a rough measure of this public opinion, I partially solve the omitted variable bias issue.

Table 9 shows the results. Pre-existing building up Google trend will increase the coverage of China, but not the coverage of China's human rights issues. This is consistent with Table 4 that lagged Google trend predicts coverage of China but not human rights issues. At the same time, including this variable reduces the power of owner's preference a bit, but the main result still remains.

Nevertheless, the validity of these two implications highly depends on the accuracy of this measure. This is not a perfect measure, which are subject to at least two drawbacks. First,

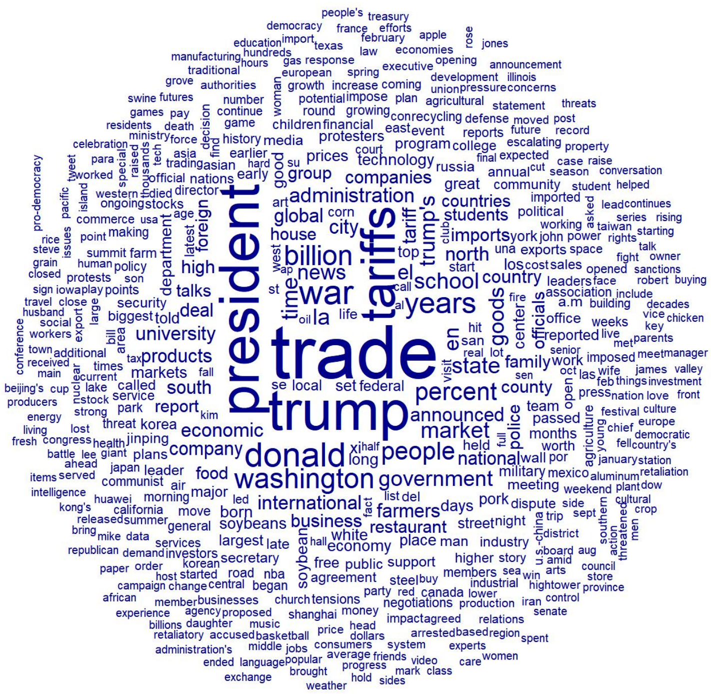


Figure 15: Words mentioned when China is covered

| | (1)<br>HumanRights(Cov) | (2)<br>China(Cov) | (3)<br>HumanRights(Frac) | (4)<br>HumanRights(Text) |
|---|---|---|---|---|
| Relation | 0.481 | 0.179 | -1.443 | -0.0938 |
| | (1.436) | (1.197) | (6.950) | (0.316) |
| Relation × Owner Republican | -0.906** | 0.138 | -7.075** | -0.148 |
| | (0.445) | (0.635) | (3.320) | (0.118) |
| Relation × Readers Republican | 1.868 | 1.777 | 12.89 | 0.106 |
| | (1.297) | (1.479) | (8.935) | (0.328) |
| Event=1 × IncreasingTrend=1 | -0.220 | 0.712 | -2.241 | 0.00741 |
| | (0.788) | (0.687) | (7.463) | (0.108) |
| cluster | Metro | Metro | Metro | Metro |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 151470 | 151470 | 151470 | 151470 |
| F stat | 35.85 | 6.768 | 2.089 | 7.055 |
| adj. R2 | 0.0723 | 0.000445 | 0.0000870 | 0.000415 |

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

Table 9: Media Reaction on Sino-US relation

Google Trend is a variable not only reflect demand, but also supply. Second, when searching intensity is too low, zero is assigned. Beside this test, a placebo test using the coverage of Turkey human rights issues is performed.

## 6.2 Turkish Human Rights Issues

Another nation of which human rights concerns attract much attention of the United States media is Turkey. In terms of diplomatic relationship with the United States, China and Turkey

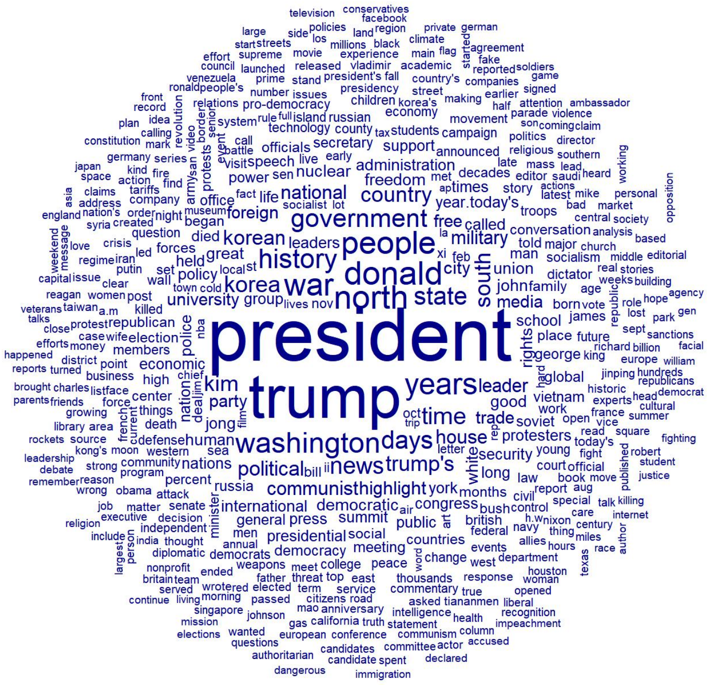


Figure 16: Words mentioned when China's human rights issues covered

are independent enough so that the coverage of Turkey should not be driven by Sino-US relationship, let alone coverage of its human rights issues. This provides a "placebo" environment to test my methodology.

To perform the test, I first eliminate events of which the windows overlap with US-Turkey related events. The US-Turkey related events include dates when President Trump mentioned "Turkey" or "Erdogan" on Twitter and other relevant incidences. Out of the 33 events, 9 are dropped, leaving 11 positive events and 13 negative events. [18]

Table 10 shows the result. The first three columns show the human rights coverage about China, and the last column shows that of Turkey. Dropping events and newspapers according to Turkish coverage roughly preserves the responsive pattern of media coverage on China's human rights issues. In contrast, column (4) shows that neither readers' or owner's preference affect the response of Turkey coverage following Sino-US events. The nonpolitical papers serving middle readers do adjust their coverage of Turkish human rights issues according to Sino-US relation. In respond to Sino-US relation, the sign of China's human rights coverage is positive whereas that of Turkey's is negative. Editorials might drop Turkey coverage to spare room for China coverage.

[18] Deleted events include 2018-04-16, 2018-07-20, 2018-07-25, 2018-08-20, 2018-11-01, 2018-12-29, 2018-09-18. These are days when President Trump had conversations with Turkey President Erdogan, Gulen movement took place, the disappearance of Washington Post journalist Jamal Khashoggi and the trade sanction on Turkey.

| | (1) HumanRights(Cov) | (2) HumanRights(Frac) | (3) HumanRights(Text) | (4) HumanRights(Turkey) |
|---|---|---|---|---|
| Relation | 1.224 | 10.27 | 0.0218 | -0.306* |
| | (0.924) | (6.596) | (0.378) | (0.169) |
| Relation × Owner Republican | -0.742 | -6.025 | -0.399*** | 0.0525 |
| | (0.513) | (4.025) | (0.152) | (0.119) |
| Relation × Readers Republican | 0.0722 | -1.892 | 0.556 | 0.164 |
| | (1.176) | (8.534) | (0.346) | (0.271) |
| China(Cov) | 0.220*** | | | |
| | (0.0115) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 84888 | 84888 | 84888 | 84888 |
| F stat | 74.79 | 0.935 | 8.636 | 1.837 |
| adj. R2 | 0.0769 | 0.00000354 | 0.000606 | 0.0000237 |

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

Table 10: Media Reaction on Sino-US Relation

The placebo test sheds light on the omitted variable bias issue. The idea largely follows Freyaldenhoven, Hansen, and Shapiro 2019, which tackles endogenous policies for event study methodology. In this study, suppose the demand is actually driven by unobserved public anger against China. To decompose the anger, there are probably three reasons behind: 1) trade policy, 2) human rights policy, 3) international influence. Since the coverage is mainly on 2) and 3), it should be responding to anti-China sentiment for reason 2) and 3). Intuitively, when readers become more anti-China for her human rights policy, then they should become more anti-Turkey for the same reason as well, given no related news released for both nations. For this reason, if the dynamic-demand-driven story is true, one should expect the coverage of Turkey human rights to share the same responsive pattern. The finding rejects this demand-driven channel.

# 7 Conclusion

In this paper, I check whether diplomatic policies will induce media coverage of human rights and how this response varies with owner's and readers' political stance. I found that, the local newspaper respond to Trump's tweets about China to adjust their attention on Chinese human rights/ideology/international influence issues. The more democratic-leaning (republican-leaning) its owner is, the more a paper delivered when Sino-US relationship got better (worse). Meanwhile, neither readers' political leaning nor readers' dynamic demand could explain this change of coverage. Meanwhile, this pattern only show up in the coverage of human rights, but not "unfair trade practices". Several robustness checks have been performed to guarantee the causal interpretation.

Several relevant questions still remain unsolved. First, what exactly is reflected by owner's political stance that drives the heterogeneous coverage still remains unclear. I partially address this question by comparing the pattern of human rights coverage and trade practice coverage, implying that the driving force should be owner's alliance with President Trump, but not their attitude towards China's role on trade and in general U.S. economics. Despite this indirect evidence, one may still raise many other traits that can undermine the validity of this statement. More direct evidence is needed to fully identify the really influential owner's trait. Nevertheless, this ambiguity does not downgrade my contribution, as it still confirms and role of owner's preference, which should not play a role morally and economically according to the conventional model.

Another unsolved issue is the reason why owner's preference could be reflected in the coverage. Two most direct mechanisms are cost reduction and imposing political influence. Under the cost reduction mechanism, firms operate with many subsidiaries may distribute the same report regardless of what the readers' preference is, especially during a short window after an event takes place. The reasons they do so are simply that it is inexpensive to generate articles that are alligned with owner's political leaning, and it is costly to tailer articles to cater to each individual market. In reality, many papers do dismiss local editorial boards after merging and acquisition, and thus it lacks entities to adjust content according to local readers. Under the political influence mechanism, the firms may formulate stories to impose their political influence, leaving profitability less a concern. Historically, the Hearst company used biased coverage to support the war between Spain and the United States. Nowdays, media firm owers sometimes will design the ownership structure such that even though they hold relatively small share of stocks, they enjoy substantially high voting power, implying that being lucrative is not the only goal for running a newspaper for an owner. In this paper, I do not intend to separate the two mechanisms, but will do in future projects.

Finally, coming back to the initial motivation, my paper stands in the middle of Shapiro and Gentzkow's readership-driven story and Qian and Yanagizawa-Drott's media capture story. My results obviously cannot be accommodated in the Shapiro & Gentzkow's framework, but neither do they imply the latter to be true. I have no direct evidence on bribes given to media, neither do I know if the owner does so unconsciously (out of cost-reducing motive) or consciously for his/her own goods (out of political-influence motive). This should be at least partially addressed if the above question is answered.

| | (1) HumanRights(Cov) | (2) HumanRights(Frac) | (3) HumanRights(Text) | (4) UnfairTrade(Cov) | (5) UnfairTrade(Frac) | (6) UnfairTrade(Text) |
|---|---|---|---|---|---|---|
| Owner Dem | 1.144* | 10.31*** | 0.0748 | 0.0659 | 0.309 | 0.00828 |
| | (0.614) | (3.686) | (0.0631) | (0.0518) | (0.230) | (0.00947) |
| Owner Rep | 1.105* | 9.592** | 0.133* | 0.112 | 0.459 | 0.0190 |
| | (0.663) | (4.172) | (0.0807) | (0.0698) | (0.298) | (0.0116) |
| Readers Republican | -4.193** | -25.77** | -0.322** | -0.297** | -1.352** | -0.0639** |
| | (1.862) | (10.53) | (0.144) | (0.127) | (0.552) | (0.0299) |
| cluster | Market | Market | Market | Market | Market | Market |
| fixed effects | State&Day | State&Day | State&Day | State&Day | State&Day | State&Day |
| drop large papers | N | N | N | N | N | N |
| controls | Y | Y | Y | Y | Y | Y |
| N obs | 670403 | 670403 | 670403 | 670403 | 670403 | 670403 |
| F stat | . | . | . | . | . | . |
| adj. R2 | 0.0262 | 0.0175 | 0.0124 | 0.0103 | 0.00624 | 0.00547 |

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

| | (1) HumanRights(Cov) | (2) HumanRights(Frac) | (3) HumanRights(Text) | (4) UnfairTrade(Cov) | (5) UnfairTrade(Frac) | (6) UnfairTrade(Text) |
|---|---|---|---|---|---|---|
| Owner Republican | -0.447 | -3.963 | 0.0350 | 0.00132 | -0.0437 | 0.00466 |
| | (0.656) | (4.623) | (0.0698) | (0.0550) | (0.253) | (0.0107) |
| Readers Republican | -4.053** | -24.60** | -0.310** | -0.283** | -1.292** | -0.0618** |
| | (1.878) | (10.61) | (0.146) | (0.128) | (0.556) | (0.0301) |
| cluster | Market | Market | Market | Market | Market | Market |
| fixed effects | State&Day | State&Day | State&Day | State&Day | State&Day | State&Day |
| drop large papers | N | N | N | N | N | N |
| controls | Y | Y | Y | Y | Y | Y |
| N obs | 670403 | 670403 | 670403 | 670403 | 670403 | 670403 |
| F stat | . | . | . | . | . | . |
| adj. R2 | 0.0258 | 0.0169 | 0.0123 | 0.0103 | 0.00621 | 0.00545 |

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

Table 11: Total Coverage, Readers and Owner

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | 1.324** | -0.646 | 10.17** | 0.154 |
| | (0.554) | (0.910) | (4.088) | (0.149) |
| Relation × Owner Republican | -1.303*** | -0.647 | -10.23*** | -0.314*** |
| | (0.384) | (0.475) | (3.133) | (0.110) |
| Relation × Readers Republican | -1.114 | -1.874* | -7.598 | -0.112 |
| | (0.852) | (1.053) | (6.443) | (0.224) |
| China(Cov) | 0.176*** | | | |
| | (0.0132) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 156491 | 156491 | 156491 | 156491 |
| F stat | 40.86 | 4.039 | 21.11 | 3.199 |
| adj. R2 | 0.0556 | 0.000264 | 0.000771 | 0.0000739 |

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

Table 12: Media Reaction After Mentioning "President Xi"

# A Tables

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | 1.362** | 0.409 | 8.537* | 0.0745 |
| | (0.687) | (0.733) | (4.430) | (0.171) |
| Relation × Owner Republican | -0.636 | -0.0313 | -5.470 | -0.155 |
| | (0.445) | (0.539) | (3.584) | (0.109) |
| Relation × Readers Republican | -0.0512 | 0.903 | -2.316 | 0.537*** |
| | (0.857) | (1.060) | (7.107) | (0.205) |
| China(Cov) | 0.229*** | | | |
| | (0.0190) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 121715 | 121715 | 121715 | 121715 |
| F stat | 27.65 | 0.818 | 4.928 | 4.365 |
| adj. R2 | 0.0826 | -0.000000538 | 0.000181 | 0.000151 |

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

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | 0.844 | 1.211 | 3.013 | 0.165 |
| | (0.726) | (0.738) | (4.722) | (0.169) |
| Owner Dem × Relation | 0.925** | -1.039** | 9.463*** | -0.0565 |
| | (0.362) | (0.429) | (2.867) | (0.0829) |
| Owner Rep × Relation | 0.515 | -1.176*** | 5.872** | -0.192** |
| | (0.325) | (0.384) | (2.646) | (0.0884) |
| Relation × Readers Republican | -0.136 | 1.004 | -3.121 | 0.545*** |
| | (0.838) | (1.034) | (6.874) | (0.203) |
| China(Cov) | 0.229*** | | | |
| | (0.0190) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 121715 | 121715 | 121715 | 121715 |
| F stat | 23.76 | 3.287 | 5.168 | 4.188 |
| adj. R2 | 0.0827 | 0.0000783 | 0.000282 | 0.000164 |

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

Table 13: Media Reaction After Positive Tweets

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | 0.132 | 0.484 | 3.180 | 0.122 |
| | (0.755) | (1.296) | (5.954) | (0.155) |
| Relation × Owner Republican | 0.730** | 0.787 | 5.218* | 0.116 |
| | (0.339) | (0.538) | (2.787) | (0.0994) |
| Relation × Readers Republican | -1.844 | -3.653*** | -11.27 | -0.139 |
| | (1.160) | (1.371) | (8.166) | (0.191) |
| China(Cov) | 0.204*** | | | |
| | (0.00995) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 165186 | 165186 | 165186 | 165186 |
| F stat | 93.79 | 21.28 | 4.815 | 20.08 |
| adj. R2 | 0.0745 | 0.00107 | 0.000199 | 0.000661 |

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

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | -0.0764 | -0.239 | 1.551 | -0.0680 |
| | (0.720) | (1.166) | (5.679) | (0.148) |
| Owner Dem × Relation | -0.0958 | 0.545 | -0.365 | 0.185** |
| | (0.311) | (0.498) | (2.445) | (0.0722) |
| Owner Rep × Relation | 0.661** | 1.444*** | 4.795** | 0.337*** |
| | (0.330) | (0.519) | (2.361) | (0.0832) |
| Relation × Readers Republican | -1.893* | -3.773*** | -11.57 | -0.170 |
| | (1.147) | (1.359) | (8.076) | (0.188) |
| China(Cov) | 0.204*** | | | |
| | (0.00996) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 165186 | 165186 | 165186 | 165186 |
| F stat | 80.88 | 20.49 | 4.888 | 19.45 |
| adj. R2 | 0.0746 | 0.00114 | 0.000204 | 0.000768 |

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

Table 14: Media Reaction After Negative Tweets

| | (1) HumanRights(Cov) | (2) China(Cov) | (3) HumanRights(Frac) | (4) HumanRights(Text) |
|---|---|---|---|---|
| Relation | 0.408 | 0.652 | 0.385 | 0.109 |
| | (0.576) | (0.738) | (3.987) | (0.137) |
| Owner Dem × Relation | 0.444** | -0.755** | 4.225** | -0.131** |
| | (0.219) | (0.367) | (1.780) | (0.0545) |
| Owner Rep × Relation | -0.160 | -1.330*** | -0.269 | -0.276*** |
| | (0.228) | (0.362) | (1.645) | (0.0646) |
| Relation × Readers Republican | 1.015* | 2.598*** | 5.337 | 0.329** |
| | (0.603) | (0.906) | (4.414) | (0.151) |
| China(Cov) | 0.215*** | | | |
| | (0.0114) | | | |
| cluster | Market | Market | Market | Market |
| fixed effects | Newspaper-Event | Newspaper-Event | Newspaper-Event | Newspaper-Event |
| drop large papers | N | N | N | N |
| controls | Y | Y | Y | Y |
| N obs | 286901 | 286901 | 286901 | 286901 |
| F stat | 54.61 | 16.41 | 1.509 | 13.55 |
| adj. R2 | 0.0778 | 0.000518 | 0.0000292 | 0.000369 |

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

Table 15: Media Reaction on Sino-US relation

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | HumanRights(Cov) | HumanRights(Cov) | HumanRights(Cov) | HumanRights(Cov) | HumanRights(Cov) | HumanRights(Cov) | HumanRights(Cov) | HumanRights(Cov) |
| main | | | | | | | | |
| After=1 | 1.020*** | 1.255* | 1.242** | 1.242* | | | 1.796*** | 0.566 |
| | (0.289) | (0.654) | (0.564) | (0.660) | | | (0.632) | (0.599) |
| Owner Democratic | -1.015*** | -1.147*** | | | | | -0.296 | -1.741*** |
| | (0.353) | (0.344) | | | | | (0.472) | (0.454) |
| After=1 × Owner Democratic | 1.358*** | 1.403*** | 1.404*** | 1.404*** | 1.404*** | 1.269** | 1.319** | 1.139** |
| | (0.520) | (0.510) | (0.391) | (0.513) | (0.513) | (0.498) | (0.510) | (0.478) |
| Readers Democratic | 8.247*** | 4.040*** | | | | | | |
| | (0.737) | (0.783) | | | | | | |
| After=1 × Readers Democratic | 0.741 | 0.962 | 0.954 | 0.954 | 0.952 | 0.522 | 2.602*** | -0.852 |
| | (1.048) | (1.023) | (0.770) | (1.032) | (1.033) | (0.879) | (0.965) | (0.812) |
| China(Cov) | | | | | | | | 0.185*** |
| | | | | | | | | (0.0135) |
| cluster | Day | Day | Newspaper | Day | Day | Day | Day | Day |
| fixed effects | | | Newspaper | Newspaper | Newspaper&Day | Newspaper&Day | Headquarter | Headquarter |
| drop large papers | N | N | N | N | N | Y | N | Y |
| controls | | Y | Y | Y | Y | Y | Y | Y |
| N obs | 161322 | 161295 | 161295 | 161295 | 161295 | 159980 | 161294 | 159979 |
| F stat | 19.08 | 31.88 | . | . | . | . | . | . |
| adj. R2 | 0.00695 | 0.00834 | 0.0971 | 0.0971 | 0.101 | 0.0692 | 0.0539 | 0.103 |

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

Table 16: Media Reaction After Trump Tweeted "President Xi"

Note: The dependent variable is the number of articles that mention human rights or political system aspects of China, times 100. The percinc is the per capital income (kdollar). The key regressors are the political stance of readers and owner, both measured continously. Outlier observations have been dropped for all columns, abandoning no more than 100 observations. By "drop large papers", I meant to drop the newspapers that covered China's human rights issue way more than others, specifically, those with total coverage more than 250 pieces. The last column uses poisson specification, others use linear specification.

## B Keywords

**Ideology** I include words that media normally use to describe China's political ideology and political regime, such as "communism", "authoritarian", "dictator", "soviet", "autocratic", "totalitarian", "socialism". Some media would also mention Chairman Xi together with "Mao Zedong", "Orwell", "term limit". Other phrases such as "red china", "red army", "pro-democracy", "fascism", "red guard" are also included.

**Human Rights Activists** I include words related to Tiananmen Square protest in 1989, such as "tank man". I also include names from "Chinese Human Rights Defenders" webpage [19]. Besides, "nobel peace", "activists missing", and "human rights" are also included.

**Freedom of Expression and Religion** Words or phrases related to three aspects are included: i) media censorship ii) surveillance system and social score system iii) Chinese Christians. For instance, "big brother", "great firewall", "destroy bible" are included.

**Tibet, Xinjiang and Hong Kong** I include "Dalai", "Tibet free", "Uighur", "reeducation camp" and "pro-democracy".

**Key International Actors and Foreign Policy** I include words used to describe two policies of China: i) the Belt & Road Initiative and ii) South China Sea. Words included are "imperialism", "debt trap".

**Trade Practices** Synonyms of i) intellectual property transfer, ii) cyber hacking and iii) currency manipulation are included. Morever, other factors that are deemed by the United States as threats are also included. Two examples are "Chinese anti-satellite weapon" and "Confucius Institute"

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