Between reality and perception: the mediating effects of mass media on public opinion toward China

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ABSTRACT
There are many conflicting theories about the relationship between media reports and public opinion, but few of them are supported by empirical work on large data sets. We use sentiment results on over 260,000 China-related articles in \textit{The New York Times} to show that events in international relations affect media sentiment which, in turn, affects public opinion. We find that sudden shifts in US-China relations are accompanied by changes in how \textit{The New York Times} covers China and that the news reporting on China leads public opinion on China by 1 year. Our work illustrates how \textit{The New York Times}, a prestigious mass media institution, propagates international relation signals to shape American views of the Chinese state and the Chinese people.

Introduction
Public opinion constrains and shapes political activity in a democratic system. American public opinion on China thus has an impact on US-China relations. Lacking personal experience or independent knowledge of China and its people, Americans’ opinions of China are heavily informed by media depictions. This paper seeks to explain how elite media may shape American attitudes on China with empirical analysis on a corpus of more than 260,000 articles from \textit{The New York Times} and a large-scale data set constructed from two cross-sectional survey series measuring the views of American public on China.
We start with the premise that Americans’ views on China are heavily shaped by media coverage. Very few non-Chinese Americans have learned much about China in school. Many non-Chinese Americans have not interacted extensively with people of Chinese descent because only 1.3% of Americans are of Chinese descent, and they are overwhelmingly concentrated in and around the major cities in America’s coasts (U.S. Census Bureau 2021). One of the only remaining vectors through which Americans can access information on or form impressions about China is media exposure. Because prestigious media tends to influence public opinion more than less-prestigious media, we will analyze articles from The New York Times, for most would agree that The New York Times, also known as the “Gray Lady,” is the most prestigious and influential newspaper in the US. The readership of The New York Times is significantly more affluent and educated than the average individual in the US. The reach of The New York Times in elite circles is hard to quantify, but if you were a fly on the wall in the coffee room of any given English-speaking social sciences department, you would probably hear its name mentioned at least a few times per day. Despite, or perhaps because of, the preponderance of The New York Times at the highest echelons of American intellectual life, there is very little academic work on this newspaper, and only a small portion of what little there is makes use of recent advances in natural language processing techniques.

Our paper aims to fill these gaps with an empirical study on how The New York Times may mold the opinions of the American public toward China. We hypothesize that national-level tensions influence media reports of foreign countries and that media coverage, in turn, influences how Americans view those countries. Following our framework for analysis summarized in Figure 1, we collect a data set for each of the three levels: a collection of key events in US-China relations, inferred sentiment of China-related articles on The New York Times, and national surveys.

![Figure 1](image-url)  
**Figure 1.** A model of how public opinion flows from the state to journalists to citizens.
Media sentiment is inferred in Huang, Cook, and Xie (2021) and segmented into eight topics in order to capture the nuance of American opinions toward China. We then use statistical techniques to examine the connections linking between the three sets of data. The empirical results agree with our hypothesis: major events in US-China relations impact reporting on China in *The New York Times*, and *The New York Times*’ coverage on China in a given year is strongly correlated with the views of the American public on China in the next year.

**Literature review**

*How news affects opinion*

There is considerable debate in the study of political communication over how the increasingly complex menu of media choices available to consumers is changing how media consumption affects the American mind (Bennett and Iyengar 2008). To name one complicating factor among many, readers (especially politically conscious individuals) usually actively select news sources whose views agree with their own (Iyengar et al. 2008; Zaller, et al. 1992). Additionally, with the advent of Twitter, traditional media respond to audience demand more strongly than ever before (Jacobs and Shapiro 2011). For now, however, our model intentionally streamlines the interplay between media and readers, and, in doing so, sidesteps those debates. We do so by focusing solely on *The New York Times*. Other authors have drawn upon data from *The New York Times* because of its perceived prestige (Wu et al. 2002), and we do so for the same reasons. There are probably a host of channels through which elite opinion percolates down to the masses below, and these may be the subject of future work. For now, our results suggest that elite media sentiment on China can predict American public opinion on China.

Scholars have adopted a broad number of differing conceptual approaches to explain the many relationships between mass media and the opinions of the American public. One group of scholars argues that media sentiment influences public opinion (Baum and Potter 2008; Iyengar and Kinder 2010) while another group instead emphasizes how the public leads the media by analyzing, for example, how the demands of news consumers warp reporting. Newspapers may gain readers by slanting their coverage of “hot-button” issues towards the established beliefs of their readers (Mullainathan and Shleifer 2005). With the advent of social media giants such as Twitter, old media outlets are more sensitive to the demands of their audiences now than ever before (Jacobs and Shapiro 2011). For their part, consumers of news generally tend to seek out the sources of news with which they most actively agree (Iyengar et al. 2008), and politically engaged readers do so more actively than the average American (Zaller et al. 1992).
Two other groups of scholars address factors beyond the media and public to explain the fluctuations in and formation of public opinion. One emphasizes the influence of the elites on the masses. Political elites may shift public sentiment directly by communicating with their constituents and the broader public (Baum and Potter 2008). Elites from abroad may also shape American opinion via American reporters, who sometimes circumvent domestic sources by instead seeking quotes and comments from foreign luminaries (Hayes and Guardino 2011). A final group of scholars focuses on how the high-level contours of public sentiment are formed through community-level and even individual-level processes. The opinions of a given individual on various topics arise from low-level personal values, many of which are shaped throughout adolescence by forces outside the control of any individual (Hatemi and McDermott 2016). Social networks, which are similarly outside individual control, also impact opinion formation (Kertzer and Zeitzoff 2017).

From the current scholarship on the topic, it is unclear whether the media shape consumers’ attitudes or if the converse is true (Baum and Potter 2008). Most of the work that does address this topic uses small sets of data to test competing theories. We offer a different contribution to this ongoing debate with large-scale analysis powered by big data. This work investigates how public views on China are related to how the news media cover China and how both are impacted by major events in US-China relations. This uniquely “big data” encompass more than a quarter million news reports on The New York Times in 50 years and additionally contains survey data in the corresponding timespan.

**How Americans view China**

Survey data reveal that Americans do not view China favorably (Xie and Jin 2021; Cao and Xu 2015; Aldrich, Lu, and Kang 2015) and are anxious about China’s growing economic and military power (Gries and Crowson 2010; Yang and Liu 2012). They also doubt that the needs of the Chinese people can be adequately served by the Chinese political system (Aldrich, Lu, and Kang 2015). Many Americans appreciate Chinese culture and respect the Chinese people while recognizing a difference between the Chinese people and the Chinese state (Gries and Crowson 2010). In one view, Americans may paradoxically dislike the Chinese state precisely because they like the Chinese people so much. A 2011 survey of impressions of China on social media found that respondents viewed China as economically successful and culturally rich but politically repressive (Xiang 2013). The stereotype content model (Fiske et al. 2002) decomposes common stereotypes into two dimensions: “competence” and
“warmth.” In this model, Chinese people are usually stereotyped as high in competence but low in warmth (Lin et al. 2005). In order to capture some of the nuance in American opinions toward China, we segment media sentiment into eight topics and predict which of these topic-specific sentiment measures are most correlated with public opinion of China. We ask how The New York Times’ reporting on China may impact the opinions of ordinary Americans toward China.

The New York Times

The New York Times is famously known as the “Newspaper of Record.” The paper, famous but firmly local until the 1940s, rose to national prominence through a series of calculated business decisions (Schwarz 2012, 198). It is the nation’s preeminent news source and has been for a number of decades. This makes it an ideal source of media sentiment writ large.

The paper may have attained eminent prestige and broad, nation-wide distribution by the 1990s, but its secretive board of managing directors chose to expand further. By 2000, the paper was delivered to homes in more than 200 American cites, siphoning upper-class readers away from local newspapers in the process (George and Waldfogel 2006). Former Times editor Max Frankel remarked in the 1990s that “our kind of educated, curious, and affluent readers could be found not only in Manhattan, Scarsdale, and Southampton but also in Grosse Point, Atlanta, Dallas, and San Jose” (Frankel 2000, 509). The paper raked in an impressive US$140 million in operating profit in 2019 (Arbel 2020), but the cultural impact of The New York Times far outstrips its financial footprint.

Though its influence is difficult to quantify, almost all available evidence indicates that The New York Times is the most impactful newspaper in the United States by a significant margin. The paper’s readership represents an elite subset of the public. The New York Times media kit boasts that “the New York Times delivers world-class journalism to the world’s most influential audiences,” that the paper “delivers an audience of readers who shape society,” and that “the NYT Weekday ranks #1 with Opinion Leaders, reaching 57% of this elite group” (The New York Times Company 2018). Daniel Schwarz interviewed many editors of The New York Times and noted that they reflected the pretensions of their audience and often spoke with “slightly arrogant elitism” (Schwarz 2012, 198). Subscribers to The New York Times print edition are reported to have a median household income of US$191,000, three times as high as the US median household income of US$63,179 (Rothbaum and Edwards 2019). Digital subscribers have a lower but still impressive median income of US$96,000.

There are other sources of data that we could have employed, but we focus on newspaper data and, more specifically, *The New York Times* for a number of reasons. We ignore Twitter in this work for the simple reason that Twitter did not exist for the vast majority of the years covered in our international relations and public opinion data. While we address Twitter data in further work, Twitter is irrelevant in any historical context. Television exposure may also influence American conceptions of China, and some scholars of political communication have used television news to great effect (Iyengar and Kinder 2010). Because we treat the sentiment of *The New York Times* toward China as a proxy for the sentiment of all media sources toward China, adding television data would not provide much new information.

Daniel Schwarz, a professor of English at Cornell University, remarks that “for much of the twentieth century, *The New York Times* was a repository of America’s historical memories and cultural contexts” and that it “has had and still has immense social, political, and economic influence on America and the world” (Schwarz 2012, 81). The New York Times, in short, is both a particular paper with its own interests and, by virtue of its importance, a general container for American cultural shifts. The paper’s reputation makes it a valid proxy for the sentiment of all American media towards China and an important target for analysis in its own right.

**Media bias**

Many Americans think that media outlets are biased but expect unbiasedness. The peculiarly American expectation of press neutrality stems from a postwar golden age of even-handed reporting (Baum and Groeling 2013). Most American newspapers before the 1900s were fiercely partisan.
and openly received funding from political parties (Baum and Groeling 2013). Newspapers became independent as costs of printing and information-gathering declined, and, by the 1920s, they had become significantly more fact-based (Gentzkow, Glaeser, and Goldin 2004). Whether or not The New York Times is biased, however, is beside the point for our analyses, as long as the particular biases affecting how The New York Times views China are stable over the analyzed timespan.

If The New York Times has a particular bent to how it reports on China, establishing the origins of this bias is not trivial. There are many competing theories for how news coverage of foreign countries might be affected by, for example, international relations and the goals of the state, but few of them seem to have been written with East Asia in mind. Some theories suggest that the US news media serve as unwitting “shills” for the US military and intelligence agencies. This theory was famously expounded by Herman and Chomsky in their book Manufacturing Consent (Herman et al. 1988). The conspicuous lack of China-related cases in Chomsky and Herman’s work suggests that China has been of secondary or tertiary importance to American news media for the majority of our sample. China has been foregrounded in the American mind only in the wake of a select few events, including but not limited to President Richard Nixon’s visit to Beijing in 1972. This means that coverage of China in The New York Times may have been less biased than that of front-line culture war issues or foreign conflicts during the period being studied and that we can assume its bias toward China is likely to be stable over the time period of our sample. Also, because China has not consistently been a first-line culture war issue, there may not be as much heterogeneity between different news outlets regarding China for the years in our data. This further motivates treating The New York Times as a proxy for the American media in general in regards to sentiment on China.

The New York Times may have a bias to how it covers certain events, and it may also have a bias to what it covers and, more specifically, what international events it covers. Because Americans do not care much about news from abroad (Graber 1988), and because foreign news requires expensive international bureaus to cover adequately (Gans 2004), only a small subset of international news makes it way to the pages of The New York Times. As one might expect, then, the international news that does receive coverage in American papers tends to be “relevant to Americans or American interests” (Gans 2004, 37). A corollary to this, supported by limited evidence, is that the American media tend to cover international events less during American election cycles (Wells and King 1994). The Chomskyan view similarly argues that newspapers cover whatever international events that the US state tell them to cover (Herman and
Chomsky 1994). Whether the view of Gans or Chomsky is true, it stands to reason that *The New York Times* will cover most major events in US-China relations.

We are not the first team to study *The New York Times* nor the first team to study how *The New York Times* views China. Other authors have used autoregression models to predict public opinion with time series data (Blood and Phillips 1995). One team find with autoregression that public sentiment predicts economic performance (Wu et al. 2002). Peng (2004) characterizes changes in coverage of China through four distinct color-coded phases: communist “Red China” from 1949 to 1979; the economically promising image of “Green China” from 1979 to 1989; a “Dark China” from 1989 to 1992; and the prosperous but oppressive “Grey China” from 1992 to the present. Peng (2004) finds that the volume of China-related reporting has increased over time, but the paper has consistently portrayed China in a bad light. Very little existent work leverages natural language processing models to analyze news articles at scale. A rare exception may be found in Atalay et al. (2018), which analyzes a collection of leading newspapers, including *The New York Times* and *The Wall Street Journal*, to inspect trends in the number of help wanted classifieds that mention information technologies.

**Data**

Following Figure 1, we hypothesize that shifts in US-China relations affect reporting on China in *The New York Times* and that the reporting, in turn, affects American public opinion on China. This implies a hierarchy where sentiment flows from state to media then to citizen, and we have collated one data set for each of these actors to yield a total of three data sets. We discuss each data set in sequence, beginning with the state-level data and ending with public opinion data.

**Major milestones in international relations**

We have collected a database of 42 events in US-China relations from two online sources: the Council on Foreign Relations and History.com that summarize the key moments in the relationship between US and China. We believe these two sources, a reputable public policy tank and a commercial website, together provide a complete list that covers most influential events in US-China relations. Each event was dated and manually labeled for how it might have affected *The New York Times*’ reporting on China across the eight topic domains (see Supplementary Material for more details). For example, in October 2001, China supported the US-led War on Terror, an action that infamously proceeded with the backing of the editorial board of
The New York Times (New York Times Editorial Board 2004). We suspect that this may have influenced The New York Times to be more favorably-disposed toward China in its subsequent reporting on China in some topic domains. To ensure that events were coded without personal bias, two coders annotated the events independently of each other. The few disagreements between coders were resolved with group discussions.

**Media sentiment on The New York Times**

We use article-level sentiment on The New York Times inferred and released by Huang, Cook, and Xie (2021) to quantify media sentiment. Those results label 267,907 articles in The New York Times from January 1970 to December 2019 as expressing positive, neutral, or negative sentiment in each of the eight topic domains: “ideology, government & administration, democracy, economic development, marketization, welfare & well-being, globalization, and culture” (Huang, Cook, and Xie 2021). Overall media sentiment in each topic was then represented as the yearly difference between the proportions of positive articles and negative news reports. This yields a time series that is comparable to events in US-China relations and yearly public opinion data.

**Public opinion surveys**

To measure American public opinion toward China, we combine two nationwide public surveys: the General Social Survey (GSS) and Pew Research Center Spring Global Attitudes Survey (Smith et al. 2018; Pew 2019). The surveys asked American respondents how favorable their opinions of China were every year from 1974 to 1994 (GSS) and then from 2005 to 2018 (Pew). In each year, we measure yearly public attitude by subtracting the percentage of respondents who responded “unfavorable” from the percentage of respondents who responded “favorable” in the surveys. The measurement, therefore, ranges logically from a minimum of −100% to a maximum of 100%.

**Results**

Following Figure 1, we begin with a descriptive discussion of how sentiment toward China changes in our corpus of articles from The New York Times. We follow this with a discussion of how international events affect coverage of China in The New York Times and an analysis of how that coverage is correlated with fluctuations in American public opinion on China. Our results empirically support the hypothesis that public opinion begins with the state and is then shaped by the media.
Milestones in international relations shape media sentiment

There are innumerable potential factors that may have contributed to the changes in media sentiment toward China in *The New York Times*. Here, we consider a selection of discrete events that represent major inflection points in the changing relationship between the US and China. We hypothesize that major perturbations in US-China relations will correspond to changes in media sentiment and that media sentiment will change the most in specific topic domains related to the events in question. For example, if China expresses a desire to open its massive domestic markets to international speculation, we would expect to see more positive articles on globalization.

In the following section, we analyze how media sentiment corresponds to major events in US-China relations. We have collated a library of 42 key events in US-China relations, and we identify 19 times that a positive international relations event was mirrored by a correspondingly positive change in media sentiment (Figure 2). Some events provoked long-term changes in the sentiment toward China in *The New York Times*. 

![Figure 2. International relations events affecting media sentiment. The lines demonstrate how media sentiment toward China respond to US-China relations milestone events with long-term positive (solid orange), long-term negative (solid blue), short-term positive (dash orange), or short-term negative (dash blue) impact. We report the changed media sentiment in any of the eight topics from 2 years before the event to 3 years afterwards. Media sentiment (y-axis) is shown as relative changes from its level 720 days before the event. Fourteen positive and 15 negative events witness long-term changes of media sentiments that deviate from the baseline (720 days before) over 5% in 3 years. In contrast, 5 positive and 18 negative events brought short-term impacts on media sentiment.](image-url)
Times where others produced only short-term variation. Fourteen positive events prompted enduring upward shifts in media sentiment, some of which even reversed previously stable sentiment trends in a given topic domain. For example, before the iconic event that gave rise to the term ping-pong diplomacy in April 1971, The New York Times reported very negatively on China’s ideology and government and administration. After this event, however, The New York Times changed its tune on those two topics, and the percentage of positive articles on ideology and government and administration increased for a few years. Events that prompted a positive shift in coverage triggered, on average, an increase in positive sentiment of 5% in a particular topic over 3 years relative to the baseline of sentiment in said topic 2 years before the event.

The remaining five positive events are associated with transient changes in media sentiment. Such events push sentiment in a particular topic to a peak of 2.5% more positive within 1 year. Sentiment then promptly returns to the level it maintained before the events. For example, President Bill Clinton’s visit to China in 1998 spurred sentiment on China’s marketization to rise to a peak, but sentiment on marketization returned to its 1995 baseline level shortly after Clinton’s visit.

Similarly, 15 events provoked long-term negative changes that resulted in a gradual 7% decrease in sentiment on average over 3 years, and 18 events prompted short-term dips in sentiment. The above evidence supports the hypothesis that significant shifts in US-China relations are mirrored by corresponding shifts in media sentiment. We see that opinion formation begins with international events and then moves to the American media.

**Media sentiment predicts public opinion**

To explore how public opinion percolates from the media to the public, we run a non-negative linear regression to predict public opinion based on media sentiment from preceding years.

Because there is inertia to public opinion, which means that a broadly-held public opinion does not change suddenly, we assume that it may require some time for media sentiment to affect public opinion. We consequently inspect lagged media sentiment as the candidate predictors in our statistical models for public attitudes toward China. We represent negative sentiment with negative numbers to allow the estimated coefficients of our model to be non-negative. We hypothesize that negative media sentiment leads to negative public opinion.

We run a greedy search to select the best media sentiment features that explain the largest possible fraction of the variance of public opinion, i.e., $r^2$. We select from a total of 144 candidate features, including the average daily volume of articles, the fraction of positive articles, and the
fraction of negative articles in each topic in the same year and in each of the previous 5 years. Table 1 reports linear models with a varying number of features. Model 1 attempts to regress the dependent variable, yearly public opinion, on every single feature. It selects a feature $v_0$ that best explains the dependent variable, i.e., the maximal $r^2$. Model 2 regresses the yearly public opinion on $v_0$ and every remaining feature, and selects a second feature $v_1$ such that $\{v_0, v_1\}$ together maximize the explained variance $r^2$ of the dependent variable. To reduce the overfitting risk, we seek a sparse solution that includes no more than one feature in each topic. Therefore $v_1$ is chosen from all topics except the topic of $v_0$. Model 3 continues the search to scan remaining features except those in the topics of $v_0$ and $v_1$, and selects a feature $v_2$ such that $\{v_0, v_1, v_2\}$ maximizes the explained variance. Model 4 is parallel to Model 3, finding a substitute feature $v'_2$ outside the topics of $\{v_0, v_1, v_2\}$ such that $\{v_0, v_1, v'_2\}$ together maximally explain the dependent variable. This parallel model shows how the performance changes on topic selection. Model 5, based on Model 3, continues to seek a fourth feature $v_3$ from a used topic such that $\{v_0, v_1, v_2, v_3\}$ best explain the dependent variable. Model 6 is parallel to Model 5, finding a substitute feature $v'_3$ outside the topics of $\{v_0, v_1, v_2, v_3\}$ such that $\{v_0, v_1, v_2, v'_3\}$ maximizes the explained variance.

The greedy search ensures a sub-optimal combination of features (Nemhauser, Wolsey, and Fisher 1978), which empirically ends up with $\{v_0, v_1, v_2, v_3\}$ in topics “Culture,” “Democracy,” “Economic development,” and “Ideology” respectively. Substitute features are $v'_2$ in “Marketization” and $v'_3$ in “Globalization”. The parallel models show that the selection of the third and fourth topics does not largely change the performance when we fix the first two topics (Table 1).

Adding features unsurprisingly leads to better fitting up to a saturation point after two features. Balancing fitting accuracy and structural complexity, the automatic selection process settles on the first two selected features: $F_{\text{culture}, t-4, \text{positive}}$ the fraction of positive articles on culture in year $t-4$, and $F_{\text{democracy}, t-1, \text{negative}}$ the fraction of negative articles on democracy in year $t-1$ (Model 2 in Table 1). The lag $t-4$ means that media sentiment on culture affects public opinion after 4 years. This long lag is difficult to interpret intuitively but is commonly observed in practical optimization tasks. The evaluation function, which is the explained variance in our analysis, is relatively flat around the (local) maximum, and the desired parameter configuration with the best balance of goodness-of-fit and interpretability is therefore outperformed by a neighbor with slightly more goodness-of-fit but significantly worse interpretability. This holds for our work. In our case, substituting the positive article fraction on culture in year $t-4$ with the fraction in year $t-1$ ($F_{\text{culture}, t-1, \text{positive}}$)
Table 1. Candidate models regressing public opinion on media sentiment.

<table>
<thead>
<tr>
<th>Topic</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Culture</td>
<td>1.90 (0.53)</td>
<td>1.66 (0.49)*</td>
<td>0.94 (0.47)</td>
<td>1.10 (0.45)*</td>
<td>0.52 (0.46)</td>
<td>0.64 (0.46)</td>
</tr>
<tr>
<td>Democracy</td>
<td>0.81 (0.33)</td>
<td>1.11 (0.30)*</td>
<td>1.26 (0.32)*</td>
<td>1.03 (0.27)**</td>
<td>1.31 (0.29)**</td>
<td></td>
</tr>
<tr>
<td>Economic dev.</td>
<td>3.20 (0.95)*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>7.82 (2.38)*</td>
</tr>
<tr>
<td>Marketization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.29 (0.53)*</td>
</tr>
<tr>
<td>Ideology</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.66 (0.78)</td>
</tr>
<tr>
<td>Globalization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>−0.98 (0.28)</td>
<td>−0.51 (0.32)</td>
<td>0.13 (0.33)</td>
<td>0.11 (0.33)</td>
<td>0.59 (0.35)</td>
<td>−1.21 (0.70)</td>
</tr>
<tr>
<td>Explained variance ($r^2$)</td>
<td>33.2%</td>
<td>45.8%</td>
<td>63.1%</td>
<td>62.7%</td>
<td>70.7%</td>
<td>69.2%</td>
</tr>
</tbody>
</table>

Sample size ($N$) = 28 (years).

* $p < 0.05$, ** $p < 0.01$.

We linearly regress public opinion on media sentiments of a varying number of topics, and use greedy search to find the most important topics. The goodness-of-fit is measured by $r^2$, the variance of the dependent variable (yearly public opinion) explained by the features. Model 1 finds a single feature that linearly explains the largest fraction 33.2% of the variance of the dependent variable. Model 2 finds an additional feature to join Model 1 that together maximize the explained variance, subject to a sparse condition that selected features must be from different topics to reduce the overfitting risk. Models 3 and 5 continue the greedy search and add one feature from unused topics at a time, with marginal increase on the explained variance $r^2$. Models 4 and 6 inspect alternative choices on the third and fourth features, showing that the performance is not sensitive to this selection when the first two topics are fixed. Each column displays a model with coefficients of involved variables.
provides a more transparent model with slightly less goodness-of-fit (44.2%):

\[ \mu_t = -0.385 + 1.92F_{\text{culture}, t-1, \text{positive}} + 1.47F_{\text{democracy}, t-1, \text{negative}}, \]

(1)

where \( \mu_t \in [-1, 1] \) is the predicted public opinion in year \( t \). Their linear combination explains 44.1% of the variance of public opinion as a time series (Figure 3).

Overall, we find that The New York Times’ reporting on China’s culture and democracy in one year holds predictive power for the American public’s views toward China in the next. Although this finding emerges from an automated model-fitting process, we are not surprised because these two aspects of Chinese society have historically been highly salient in the American media. The New York Times has been consistent in relaying strong sentiments in these two domains to its readers and almost never discusses Chinese culture negatively or Chinese democracy positively. As discussed in the earlier section, however, political events have caused some temporal variation in sentiment in these two domains. Considering the large volume of articles published on these two topics and the event-contingent changes in the tones in which they are covered,
it is not surprising that articles on culture and democracy contribute the most predictive power in explaining the public’s overall judgements about China.

**Discussion**

In this study, we use *The New York Times* to quantitatively analyze how American elite media acts as a bridge between major events in US-China relations and public attitudes toward China. The results of our analysis reveal that media sentiment has closely tracked milestone events in US-China relations and, in turn, that changes in media sentiment on China’s culture and democracy in one year are strongly associated with corresponding fluctuations in American public opinion in the following year. This suggests that public opinion begins with the state, is transmitted through news media, and ends with the citizen. It may be too simplistic, but not necessarily incorrect, to say that domestic politics in China affect reporting on China abroad, which in turn affects public opinion on China in other countries.

The analysis in this study is not causal but instead suggests a causal story. A number of possible extensions remain for further research to improve this story. Firstly, though randomized experiments are impractical for international events and media reports, future work may use causal inference techniques to further strengthen the understanding of the causal chain that connects international events to public attitudes toward China through media coverage. Secondly, we conduct our analysis under a simplified framework that ignores the possibility of state-level actors influencing public opinion directly. The possibility of opinion transmission occurring outside of the confines of the media’s postwar stranglehold on public opinion was not high before the advent of the information age, but it is hard to discount this entirely after the rise of blogs in the 2000s and social media in the 2010s. It is not unusual for politicians (such as high-level US government officials or US legislators) to become influential on social media. Indeed, former president Donald Trump was well known for his anti-China Twitter posts during his presidency. Such posts could have directly altered public attitudes toward China.

Thirdly, the specific nature of the links between elite media sentiment and public opinion might vary for controversial social issues. For example, we observe that *The New York Times* reports on globalization in almost uncritically positive tones, but the 2016 election of Donald J. Trump as president reveals that not all Americans view globalization so favorably.

Fourthly, we plan to expand our analysis to more data sources, such as left- and right-leaning and regional newspapers, and to social media
platforms like Twitter. Data from these new sources may help further our understanding of the diffusion of media sentiment.

Finally, this analysis was begun in a climate of trade tensions between China and the US and concluded in a climate of great hostility between the two countries due to COVID-19. The exogenous nature of the global pandemic might bring new evidence to bear on the relationships between state, media, and public opinion.

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**Data availability statement**


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