The War of Ideas: Institutions and Global Media Bias *

Sibo Liu[†], Alexey Makarin[‡], Jinfeng Wu[§], Dong Zhang[¶]

First Draft: December 31, 2023
This Version: January 31, 2025

Abstract

We present the first systematic analysis of how countries cover each other in the news, using a newly constructed dataset of 1.4 billion news articles issued by 55,240 distinct media sources from 176 countries between 2015 and 2022. Our findings reveal a pattern of *global media bias*, where countries with greater differences in democracy levels systematically cover each other in a more negative light, shaping both the sentiment and the topic of the news articles. This bias is particularly pronounced when authoritarian countries report on democracies, when state-controlled media is involved, or when the reporting country faces economic downturn or inflation. Our findings are confirmed by a natural experiment of regime shifts among the reporting countries. Additional analysis suggests that these ideological conflicts may have economic consequences, as reflected in the impact of cross-country media coverage on equity and loan markets.

Keywords: Institutions, Media Bias, Ideology, Geopolitics
JEL Codes: P00, F51, D74, L82

*We are grateful to Daron Acemoglu, Ruben Durante, Ruben Enikolopov, Jesse Schreger, Jesse Shapiro, and David Yang for insightful comments.

[†]School of Business, Hong Kong Baptist University (email: siboliu@hkbu.edu.hk)
[‡]MIT Sloan School of Management and CEPR (email: makarin@mit.edu)
[§]Division of Social Science, HKUST (email: jwudb@connect.ust.hk)
[¶]Division of Social Science, HKUST (email: dongzhang@ust.hk)

"Advances in information technology, satellite broadcasting, and the Internet will enable Western media networks to saturate our domestic audience with their reports and views. Countries that try to block the use of IT will lose. We have to learn to manage this relentless flood of information so that the Singapore government's point of view is not smothered by the foreign media."

—Lee Kuan Yew, From Third World to First (2000: p.196)

1 Introduction

On February 24, 2022, news of Russia's military incursion into Ukraine quickly spread across the globe, but the framing of these events differed markedly from one outlet to another. *"Russia invades Ukraine in largest European attack since WWII,"* wrote Fox News, conveying a sense of historical gravity and casting Russia as the clear aggressor. Across the Atlantic, The Guardian similarly ran the headline *"Putin invades"* and emphasized the scale of the humanitarian crisis. Meanwhile, China's state-run news agency, Xinhua, led with *"Russia-Ukraine conflicts intensify, sending shock waves across world,"* a more neutral headline that largely sidestepped explicit language of aggression. Far from being mere editorial differences, these contrasting portrayals hint at deeper forces governing how national media outlets choose to depict foreign events—a phenomenon we term *global media bias*.

Although objectivity, balance, and truthfulness are widely viewed as the pillars of journalistic ethics, a substantial body of work in economics and political science shows that media outlets often deviate from these ideals in practice. Researchers have documented pervasive ideological or partisan leanings across various democratic contexts, indicating that media bias is neither isolated nor incidental (Durante and Knight, 2012; Gentzkow and Shapiro, 2010; Groseclose and Milyo, 2005; Larcinese, Puglisi, and Snyder, 2011; Martin and Yurukoglu, 2017). Yet whether and how these biases extend beyond national borders to systematically influence cross-country reporting remain open questions. As online media consumption rises and global events unfold in real time, divergent accounts of the same incident can profoundly affect international relations, public sentiment, and even economic exchanges around the world.

This paper presents the first systematic analysis of how countries cover each other in the news, focusing on three key research questions: (i) Do systematic patterns of global media bias emerge in cross-country news coverage? (ii) What factors determine its strength and direction? (iii) Does biased international news coverage generate measurable economic consequences—for instance, by signaling deteriorating diplomatic or trade relationships?

Answering these questions is empirically challenging, for at least three reasons. First, there is a lack of standardized datasets that systematically track how media outlets in different countries report on foreign nations. Building a comprehensive dataset that includes a wide range of countries and media sources is therefore essential for identifying patterns and dynamics of media bias at the international level. Second, media landscapes vary widely across countries in terms of structure, language, and cultural context, making systematic cross-country comparisons difficult. Developing a standardized and scalable measure of media bias across countries and media outlets is therefore crucial for such empirical analysis. Third, disentangling the key drivers of media bias is a challenging task because media bias can be influenced by a multitude of factors, including but not limited to, the political leanings of individual media outlets, the cultural and political environments of the source country, and the thematic focus of the news coverage.

We address these challenges by assembling a comprehensive sample of 1.4 billion news articles published between 2015 and 2022 by 55,240 distinct media sources in 176 countries. These data come from the Global Knowledge Graph (GKG) 2.0 database of the Global Database of Events, Language, and Tone (GDELT), which offers real-time translation, emotion and theme detection in 65 languages, and rapid data extraction. Importantly, the GKG 2.0 database provides a tone measurement for each article, allowing us to generate a standardized measure of media bias from an outlet toward a foreign country. Given the tone of news coverage constitutes a form of media bias (Puglisi and Snyder, 2015), this paper regards the news coverage of a media outlet as biased if it covers another country in a systematically favorable or negative way.

After aggregating the raw article-level data at the outlet–target-country–theme–month level, we analyze the determinants of the news coverage tone. The granularity of our data allows us to control for an extensive array of fixed effects that account for time-invariant characteristics of media outlets and target countries and the effects of any changes that vary by media outlets (e.g., leadership or ownership changes), target country (e.g., foreign policy shifts), and theme. In our most rigorous model specification, we control for outlet-by-theme-by-year and target-country-by-theme-by-year fixed effects, allowing us to isolate media bias within the same media outlet for the same theme in the same year, as well as towards the same target country for the same theme within a given year.

Our findings provide compelling evidence for a geopolitically-driven global media bias. Specifically, we document a strong association between the bias displayed by a country's media outlets toward another country and the institutional distance between them, measured by the differences in the liberal democracy index from the Varieties of Democracy (V-Dem) project (Coppedge et al., 2023). In other words, when there is a sharp contrast in the level

of democracy between two countries—such as an overt dictatorship versus an established democracy—media outlets in the source country are more likely to show higher levels of bias against the target country. This relationship also holds even after controlling for other potential determinants of relationships between countries, such as common language (Melitz and Toubal, 2014), religious distance (Dow and Karunaratna, 2006), genetic distance (Spolaore and Wacziarg, 2009), geographic distance, in addition to the rich set of fixed effects.[1]

Moreover, our analysis indicates that media outlets devote more coverage to generally negative themes when reporting on institutionally distant countries. Given the breadth of international news topics and the potential limitations of theme classification, we strengthen our empirical strategy by analyzing a sample of news articles featuring national leaders. Using this refined sample, we provide evidence of a significantly stronger effect compared to the baseline results.

To further establish a causal link between media bias and institutional distance, we exploit "regime shifts"—episodes of democratic erosion—using a continuous difference-in-differences (DID) design. Our model specification includes an interaction term between the treatment variable—democratic erosion (or autocratization) in the source country—and the level of democracy in the target country. This approach allows us to estimate how democratic backsliding in the reporting country affects media bias toward highly democratic countries relative to those with lower levels of democracy. Our findings reveal that, following democratic backsliding in the source country, its media coverage of more democratic countries becomes increasingly negative relative to coverage of less democratic countries.

In our subsequent analysis, we examine how institutional distance influences media bias depending on whether the source or target country is a democracy. Our findings indicate that media bias is significantly reduced when the source country is a liberal democracy, whereas it is amplified when the target country is a liberal democracy. These results suggest that global media bias is particularly pronounced in the coverage of liberal democracies by authoritarian regimes.

We further explore the role of government information control (e.g., Guriev and Treisman, 2019, 2020) in driving media bias in international reporting by documenting several patterns of heterogeneity. First, we show that media bias tends to be stronger when there is a high level of traditional media censorship and internet censorship within the source country. Second, we show that state ownership of media channels—including print and broadcast media—

[1]We also examined alternative measures of geopolitical alignment, such as the ideal point distance in United Nations General Assembly (UNGA) voting (Bailey, Strezhnev, and Voeten, 2017; Voeten, 2000, 2013). While UN voting alignment also correlates with media tone across countries, its significance disappears once we control for institutional distance and the factors mentioned above. Given this, we focus on institutional distance as our primary measure of geopolitical distance.

exacerbates media bias. Third, we present evidence that the economic performance of the source country also plays a role in shaping the global media coverage. Our findings suggest that when the source country is grappling with economic hardships, such as downturns or surging inflation rates, its global media bias is significantly heightened. These results align with information control explanation, as governments, especially authoritarian ones, are strongly motivated to manipulate information during economic challenges, aiming to manage public perception and maintain stability (e.g., Martinez, 2022).

Furthermore, we explore the economic implications of global media bias, focusing on its impact on the equity market and the syndicated loan market. We measure inter-country media bias through the average tone of news articles at the country-pair and year level. For equity market reactions, we construct a sample of US listed firms. Using detailed information on their revenue share from other countries and the media bias from those countries towards United States, we create firm-month level exposures. Firms experience immediate drops in stock price when they have significant sales exposure to a country that issues negative media coverage about the United States. To capture the banks' responses to media bias from potential borrowers' countries, we construct a lender-target country-year level sample from 2015 to 2022, utilizing a sample of global syndicated loans. Our findings reveal a positive correlation between the average tone of media coverage and both the number and value of loan deals. Additionally, we observe a negative correlation between the average tone of media coverage and borrowing costs, as measured by the spread of each syndicated loan. These results suggest that when media outlets in the source country portray a foreign country in a more negative light, banks in the source country are less inclined to provide loans to the target country or may impose additional borrowing costs for borrowers from the target country.

Finally, we analyze the relationship between global media bias and public opinion toward foreign countries. Using data from the Gallup World Poll, we investigate whether the average tone of media reporting in a source country about a target country possibly shapes the perceptions of its population toward the latter. Our analysis uncovers a statistically significant and substantively meaningful relationship: a one-standard-deviation increase in positive media tone toward a foreign country in the previous year is associated with a 7.8% increase in favorability ratings the following year. These results suggest that media narratives could play an important role in shaping public attitudes toward foreign countries.

This paper advances the existing literature in multiple ways. First, it enriches our understanding of the interplay between media and politics (for reviews, see Strömberg, 2015; Zhuravskaya, Petrova, and Enikolopov, 2020), with a particular focus on media bias. Our study represents a pioneering effort in uncovering the systematic evidence of media bias be-

tween countries at the international level, constituting a crucial addition to the prevailing empirical literature that primarily investigates ideological or partisan bias in the context of domestic politics (Durante and Knight, 2012; Gentzkow and Shapiro, 2010; Groseclose and Milyo, 2005; Larcinese, Puglisi, and Snyder, 2011; Martin and Yurukoglu, 2017; Qin, Strömberg, and Wu, 2018). While there have been a few exceptions, such as Chen and Han's (2022) who explore Western media bias towards China and finds that UK- and US-based news sites adopted a more negative tone in their reporting on China after being blocked by the Chinese government, particularly for politically sensitive topics, our research provides a more comprehensive analysis of media bias between countries across the globe. By shedding light on this understudied international dimension, our research deepens our understanding of media bias, effectively filling an empirical gap in the existing body of knowledge.

The findings of our paper closely align with a burgeoning literature on information control in non-democratic regimes (e.g., Chen and Yang, 2019; Egorov, Guriev, and Sonin, 2009; Gehlbach and Sonin, 2014; Guriev and Treisman, 2019, 2020; Martinez, 2022; Simonov and Rao, 2022).[2] Recognizing the destabilizing consequences associated with independent media and social media (Acemoglu, Hassan, and Tahoun, 2018; Enikolopov, Petrova, and Zhuravskaya, 2011; Enikolopov, Makarin, and Petrova, 2020; Guriev, Melnikov, and Zhuravskaya, 2021), authoritarian governments resort to censorship measures to restrict the free flow of information (King, Pan, and Roberts, 2013, 2017; Roberts, 2018) and leverage state ownership of media outlets to ensure alignment with their political objectives (Djankov et al., 2003; Gehlbach and Sonin, 2014; Qin, Strömberg, and Wu, 2018; You, Zhang, and Zhang, 2018). We provide evidence that the effect of institutional distance on media bias towards a specific country is more pronounced when the source country exhibits higher levels of media censorship and state ownership of media, suggesting that information control plays a crucial role in reinforcing the media bias toward a country with more democratic institutions. Furthermore, these findings, with a particular emphasis on information control, in effect contribute to our understanding of the supply-side forces that drive media bias (Anderson and McLaren, 2012; Baron, 2006; Gurun and Butler, 2012; Larcinese, Puglisi, and Snyder, 2011; Reuter and Zitzewitz, 2006).

Finally, our research sheds light on how geopolitics shapes media bias between countries. Recent studies have increasingly recognized the importance of geopolitics in affecting a range of economic outcomes such as economic growth, trade, and capital flows (e.g., Caldara and Iacoviello, 2022; Clayton, Maggiori, and Schreger, 2023; Korovkin and Makarin, 2023; Ko-

[2]We recognize that in both established and weak democracies, incumbent political parties and governments can also wield considerable influence over media coverage through financial and non-financial means (Besley and Prat, 2006; Durante and Knight, 2012; McMillan and Zoido, 2002; Qian and Yanagizawa-Drott, 2017; Tella and Franceschelli, 2011).

rovkin, Makarin, and Miyauchi, 2024, for a recent review, see Mohr and Trebesch, 2024). By highlighting the crucial role of institutional differences in shaping the way countries portray each other in the media, our findings contribute to a more nuanced understanding of the interplay between geopolitics and the global media landscape. Furthermore, as indicated by our economic impact estimates, the patterns of global media bias could itself represent a rich measure of geopolitical alliances, enriching the ongoing work in this area (Liu and Yang, 2024; Mohr and Trebesch, 2024).

2 Data

2.1 Sample

Global Media Data. The data in this study is sourced from the Global Database of Events, Language, and Tone (GDELT) (Leetaru and Schrodt, 2013). The GDELT Project consists of two main databases: the GDELT Event Database and the GDELT Global Knowledge Graph (GKG). The Event Database focuses on recording *individual events* by aggregating data from various news articles and has been applied in recent economics research (e.g., Amarasinghe, 2022, 2023). Our research investigates the media bias that arises when news articles produced in one country cover events in other countries. As such, our analysis leverages the GKG Database 2.0, which records *individual news articles* and extracts granular metadata and content, enabling a detailed analysis of their themes, contexts, and sentiments. This database offers real-time translation of news articles from 65 languages, including diverse emotions and themes with over 2,300 measures from the beginning of the GDELT project. Using advanced computer algorithms and deep learning techniques, it extracts valuable information from billions of daily published words and images. Within 15 minutes of monitoring a breaking news report worldwide, the system translates, identifies events, counts, quotes, people, organizations, locations, themes, and emotions. A detailed overview of the GKG Database 2.0 is provided in Online Appendix B, along with two representative examples from our sample in Online Appendix C.

Figure 1 provides an overview of the GKG Database 2.0, highlighting the global distribution of media outlets and the intensity of media coverage. Panel (a) illustrates the geographical distribution of media outlets included in our sample. Darker blue areas represent countries with a higher concentration of media outlets, while lighter areas indicate regions with fewer outlets. The United States stands out as the country with the highest number of media outlets, whereas many African nations have relatively few media outlets in the database. Panel (b) depicts the intensity of media coverage across the globe. Countries

that are the subject of more frequent news reporting are shaded in darker blue. Notable examples include the United States, the United Kingdom, and China, which receive extensive global media attention. In contrast, lighter-shaded regions reflect areas that are less frequently covered in news articles.

We further depict the bilateral reporting relations of the database in Figure 2. Panel (a) presents a heat map visualizing the intensity of news coverage between countries. For simplicity, we focus on the top 50 countries ranked by the total number of news articles published by their media outlets. The Y-axis represents the source country (the country of origin for the news article), and the X-axis represents the target country (the country being reported on). The color gradient indicates the volume of news articles from source countries covering events or issues in target countries. Panel (b) shows a network figure where the size of each node corresponds to the total number of news articles published by that country's media outlets. The thickness of the edges reflects the volume of news coverage exchanged between countries.. Blue nodes represent democratic countries, while red nodes represent non-democratic countries. Together, Figures 1 and 2 demonstrate the comprehensive nature of the database, enhancing its credibility as a reliable resource for studying global media dynamics.

Countries of Origin for Media Outlets. A challenging task we faced was accurately identifying the source country of each media outlet. To address this challenge, we adopted a multi-step approach. First, we leveraged a comprehensive Wikipedia list of 187 news agencies by country to classify major outlets. Second, we analyzed domain suffixes (TLDs) to determine country affiliation, though this method was limited by the frequent use of generic domains (.com, .net, .org). For outlets not identified through these methods, we employed OpenAI's ChatGPT-4o model to determine the country of origin. To evaluate its accuracy, we manually coded the country of origin for a random sample of 1,000 outlets and compared it to ChatGPT-4o's classifications. The ChatGPT-4o model achieved an impressive 94% accuracy rate in this validation exercise. A more detailed discussion of this process is provided in Online Appendix B, while Online Appendix D lists the major media outlets identified. Finally, by combining the source country of each media outlet with the target country of its reporting, we merged the GDELT data with other country-level datasets containing political and economic indicators.

Themes. To classify the news articles into different themes, we rely on the World Bank Group (WBG) Topical Taxonomy, which has been integrated into the GDELT GKG 2.0. The WBG Topical Taxonomy comprises a broad spectrum of level-1 themes, including economic growth, poverty, trade, social development, education, health, environment, energy, public sector management, gender, violence, and more. To provide a more granular classi-

fication, each level-1 theme is further divided into sub-themes. In our research, we utilize 24 level-1 themes from the WBG Topical Taxonomy as reported in the GKG 2.0 database. Figure 3 present the distribution of the themes. Themes with highest number of news articles include "Public Sector Management", "Health Nutrition and Population", and "Fragility Conflict and Violence". Themes such as "Climate Change", "Macroeconomic and Structural Policies", and "Public Private Partnerships" are among ones with the lowest number of news articles. Although there are more news articles falling into certain themes, the distribution of news counts by themes are relatively disperse, providing suitable conditions for empirical investigations.

Sample construction. The sample used in our main analysis was constructed through the following steps. To begin with, we obtained the raw data for the years 2015 to 2022 from the GKG 2.0 database, which is accessible on the official GDELT website. This yielded a substantial collection of approximately 1.4 billion news articles. After processing the detailed information of all news articles, we retained only those news articles that reported on one single country and had unique URLs. Next, we aggregated the data at the level of media outlet by reported country by theme by month. At this level, we calculated the average tone of news coverage. Each news article was categorized into one of the 24 themes defined by the World Bank Group Topical Taxonomy. Hence, in our final sample (outlet by reported country by theme by month), the tone in each observation corresponds to the average tone of news coverage by a media outlet when reporting on a specific country during a given month and for a specific theme. The final sample at the media outlet, theme, and month level consists of 81,036,750 observations with 55,240 media outlets across 176 source countries reporting on issues related to 177 target countries between 2015 and 2022. The sample construction process is detailed in Online Appendix B.

We construct our sample at the media outlet-target country-theme-month level for two reasons. First, as detailed below, we aggregate the sentiment measure of the news articles at this level to make estimation possible. The sample at the article level, in contrast, contains huge amount of observations, preventing efficient econometric estimation. Second, to gain identification, this sample allows econometric models considering granular fixed effects for our research purposes. Importantly, by including Target Country $\times$ Theme $\times$ Year fixed effects, we examine the variation of the bias within a given target country on a theme in the same year. In addition, we could remove the trends at the media outlet level to further isolate the effect.

2.2 Measuring Media Bias

Media bias can take on multiple forms, one of which is the "tone" and "sentiment" in news coverage (Puglisi and Snyder, 2015). In this paper, we primarily focus on the tone that one country's media outlets use to report on another country. We consider a media outlet biased if its news coverage reports another country in a systematically favorable or negative manner.

In the GKG 2.0 database, the tone of a news article is computed using three key metrics: Positive Score, Negative Score, and Tone. Specifically, $Positive\ Score_q$ is the percentage of all words in the article that carry a positive emotional connotation for a given news article q. It is calculated based on the total number of words in the article and the number of words with a positive connotation:

$$\text{Positive Score}_q = \left(\frac{\text{Number of positive words}_q}{\text{Total number of words}_q} \right) \times 100 \tag{1}$$

where q index the news article. In contrast, the $Negative\ Score_q$ is the percentage of all words in the article that carry a negative emotional connotation. It is calculated based on the total number of words in the article and the number of words with a negative connotation:

$$\text{Negative Score}_q = \left(\frac{\text{Number of negative words}_q}{\text{Total number of words}_q} \right) \times 100 \tag{2}$$

The $Tone_q$ is an aggregate measure representing the article's overall sentiment, derived from the difference between the Positive Score and the Negative Score:

$$\text{Tone}_q = \text{Positive Score}_q - \text{Negative Score}_q \tag{3}$$

Accordingly, the tone of a news article in GKG 2.0 database is quantified as a score ranging from -100 (extremely negative) to +100 (extremely positive), with common values falling between -10 and +10, and 0 indicating a neutral tone.

To confirm the external validity of the tone measures provided in the GKG 2.0 database, we randomly select 100 thousands news articles from our sample and retrieve the tone measures. Using the article URLs provided, we download the original content of each news article from the internet and create several tone measures of our own using standard sentiment dictionaries. We consider AFINN lexicon (Nielsen, 2011), lexicon from Bing Liu and collaborators (Hu and Liu, 2004), and Loughran-McDonald lexicon (Loughran and McDonald, 2011).

In Figure A1 of the Online Appendix, we compare the tone measures we constructed

against the measures provided in GKG 2.0 database and we identify significant Pearson correlations between those two types of measures in a range between 0.52 and 0.60. The tone measure provided in GKG 2.0 database is most correlated with AFINN lexicon (Nielsen, 2011) with a Pearson correlation coefficient of 0.6. The results here indicate the measures provided in GKG 2.0 database are informative and valid.[3] Tone measures provided in GKG 2.0 convey sentiment information similar to common algorithms as in the literature. GKG 2.0 database also provides alternative tone measures based on Lexicoder Sentiment Dictionary (LSD) and SentiWordNet 3.0 (SWN). We later in this study show that our results are highly robust to those two alternative measures.

We aggregate the tone measure at the media outlet, theme, and month level to facilitate analysis using the baseline sample.

$$\text{Tone}_{i,j,s,m} = \frac{\sum_{q \in \Omega_{i,j,s,m}} \text{Tone}_q}{\text{N}_{i,j,s,m}} \tag{4}$$

where $\text{Tone}_{i,j,s,m}$ is the average tone for news articles issued by a media outlet i covering issues in theme s occurring in country j in month m.

The summary statistics of the baseline sample is presented in Panel A of Table 1. The mean and the median of the tone measure is -1.925 and -1.673, respectively. The sentiment variable demonstrates a large variation with a standard deviation of 3.754. The tone is negative on average as the percentage of negative words are relatively higher than that of the positive words.

Panel (a) of Figure 4 shows the density of the tone measure, while the densities for positive tone and negative tone are reported in Panel (b), suggesting a relatively normal statistical property of the tone measures. Panel (c) shows the mean and 95% confidence intervals over time. As the baseline sample is at a highly granular level, the tone demonstrate large cross-sectional variation and does not show a clear intertemporal pattern. Panel (d) of Figure 4 of displays the tone trend in news articles published by Russian and Ukrainian media. It is evident that Ukrainian media sentiment towards Russia experienced a sharp decline following the Russia-Ukraine war in early 2022, whereas Russian media sentiment witnessed only a modest decrease during the same period.[4] This illustrative example provides reassurance that article tone serves as a sensible measure and that the sample of articles selected for this

[3] As discussed in GKG 2.0 database, the GDELT team cleaned the original content of the news articles by excluding texts from the website not related to the news itself. As we do not access to their internal algorithm, for research purposes, we stick to the text directly downloaded from the website for variable construction. This practice inevitably introduces noise.

[4] These patterns are in line with the asymmetric reactions to the 2014 phase of the conflict (Korovkin and Makarin, 2023). See also Abramenko, Korovkin, and Makarin (2024) for the shifts in the language of social media content within Ukraine.

study is reasonable.

2.3 Institutional Distance

To capture the institutional framework of a country, we employ the liberal democracy index from the Varieties of Democracy (V-Dem) project (Coppedge et al., 2023). Each indicator within the V-Dem dataset is assessed by at least five country experts who independently rate the indicators (Pemstein et al., 2022). The liberal democracy index provides an assessment of the extent to which a country adheres to the principles of liberal democracy, including the rule of law, checks and balances, and civil liberties. This index operates on a scale from 0 to 1, with higher values indicating a high degree of liberal democracy.

Let *Liberal Democracy Index*$_{A,t}$ and *Liberal Democracy Index*$_{B,t}$ represent the liberal democracy index of country A and country B in year t, respectively. The institutional distance between country A and country B, *Institutional Distance*$_{A,B,t}$, can be calculated using the following equation:

$$\text{Institutional Distance}_{A,B,t} = \left|\text{Liberal Democracy Index}_{A,t} - \text{Liberal Democracy Index}_{B,t}\right| \tag{5}$$

The variable *Institutional Distance*$_{A,B,t}$ constitutes our main independent variable of interest. We thus show the summary statistics of this variable in Panel B of Table 1 and explore the statistical properties in Figure 5. As shown in Panel (a) of Figure 5, the institutional distance between two countries is quite disperse. There are more countries pairs having smaller distance and the number of country pairs decreases gradually with the distance. However, as suggested in Panel (b), most of countries pairs do not demonstrate changes in institutional distance over time. The large variation as evidenced in Panel (a) is mainly due to cross-sectional differences across country pairs. There are a handful of countries that experience regime shifts, leading to changes in institutional distances between countries. We consider those cases as natural experiments and utilize this small sample for analysis in Section 3.3.

Additionally, we construct alternative measures of institutional distance by using the electoral democracy index from the V-dem project and the Polity2 score from Marshall, Gurr, and Jaggers (2019). The electoral democracy index primarily captures the core principles of electoral or representative democracy, focusing on the extent to which political leaders are elected through comprehensive voting rights in free and fair elections, as well as the degree to which freedoms of association and expression are safeguarded. In comparison, the liberal democracy index takes into account additional dimensions of democracy, such as civil liberties and checks and balances, making it a more comprehensive assessment of political

institutions. It is also important to note, however, that the Polity2 score, while commonly employed, is only updated until the year 2018. In robustness checks, we verify that the results are robust to these two alternative measures of democracy.

2.4 Other Data

We retrieve datasets from the following sources to construct variables that fall into three categories: (a) country-pair and year level, (b) country-year level, and (c) firm-related variables.

Country-pair and year level variables. For the robustness checks, we control for a set of variables to take into account alternative explanations. We use ideal point distances in UNGA voting as an indicator to measure the extent to which countries share common or divergent foreign policy interests and preferences (Bailey, Strezhnev, and Voeten, 2017; Voeten, 2000, 2013). The UN voting data is obtained from United Nations General Assembly Voting Data on Harvard Dataverse (Voeten, Strezhnev, and Bailey, 2023). To account for linguistic similarity, we use the Common Official Language (COL) indicator (Melitz and Toubal, 2014), sourced from the Centre d'Études Prospectives et d'Informations Internationales (CEPII). Additionally, we use a measure of religious distance developed by Dow and Karunaratna (2006). This composite measure combines three 5-point scale items into a single factor. The first item is the distance between the two closest major religions for each pair of countries. The second and third items measure the incidence of one country's major religion(s) in other countries. These three items are then collapsed into a unified factor score. Moreover, we calculate the geographic distance between countries using the geodesic distance between their capital cities, relying on a dataset compiled by researchers affiliated with CEPII. Finally, genetic distance between countries is measured by the distance to "the most recent common ancestors of two populations, or, equivalently, of their degree of genealogical relatedness" (Spolaore and Wacziarg, 2009, p.481). Summary statistics of these variables are presented in Panel B of Table 1.

Country-year level variables. To investigate the effect heterogeneity, we use the source country's monthly GDP growth rate measured with night light data from the VIIRS-DNB dataset and inflation data taken from the World Development Indicators (WDI) database. To measure the extent of government control over the media in the source country, our analysis uses indicators of media censorship and state media ownership derived from the V-Dem database (Coppedge et al., 2023). Media censorship indicators include "government censorship effort" and "internet censorship effort", whereas media state ownership indicators include "state-owned print media" and "state-owned broadcast media." It is important to

note that the first two indicators, "government censorship effort" and "internet censorship effort", assign higher values to indicate lower levels of censorship in the V-Dem database. To avoid potential confusion, we choose to rename these two indicators as "traditional media freedom" and "internet freedom," respectively. Summary statistics of these variables are presented in Panel C of Table 1.

Firm related variables. To gain insights into the economic costs of global media bias, we investigate how the equity market and the loan market respond to the intensified media biases between countries. On the one hand, the rich data from financial markets enables the construction of nuanced exposures for empirical investigations. On the other hand, financial markets would incorporate relevant information quickly. The effect of media bias if exists would be identified in a clean fashion. For the analysis on the equity market, we retrieve the data from the Center for Research in Security Prices (CRSP), Compustat, and Factset Revere database. For the analysis on the syndicated loan market banking loans between countries, we rely on the DealScan database, which serves as a comprehensive source of information on the global syndicated loan market. This database provides detailed data on loan terms and conditions, covenants, pricing, and the institutions participating in syndicated loan deals. Details of the variables and empirical designs will be discussed in section 4 when used.

3 Empirical Strategy and Results

3.1 Institutional Distance and Global Media Bias

We visualize clear contrasts in media sentiment among key nations in Figure 6. Panel (a) indicates that U.S. media consistently portrays Russia more negatively than U.K. or China. Conversely, Panel (c) reveals that Russian media regularly presents the U.S. in a negative light. Both American and Russian media saw a downturn in tone regarding China during the pandemic outbreak in 2020. Notably, Chinese outlets initially reported evenly on the U.S., U.K., and Russia, but from 2018, the tone grew distinctly more negative towards the U.S. while warming towards Russia.[5]

Baseline results. We construct the baseline sample at the media outlet-by-target country-by-theme-by-month level. To examine the relationship between media bias and institutional distance, we estimate the following baseline model:

$$\text{Tone}_{i,j,s,m} = \beta \, \text{Institutional Distance}_{c,j,t} + \theta_{j,s,t} + \delta_{i,s,t} + \epsilon_{i,j,s,m} \tag{6}$$

[5]Our findings hold consistent even after adjusting for theme effects in the tone measure, indicating that the observed patterns are not merely a result of varying theme distributions among the countries.

where $Tone_{i,j,s,m}$ is the average tone of media outlet i from country c when reporting country j for theme s during month m. As defined in Section 2.3, Institutional Distance$_{c,j,t}$ is the institutional distance between country c and country j in year t. $\theta_{j,s,t}$ denotes target country $\times$ theme $\times$ year fixed effects; $\delta_{i,s,t}$ denotes outlet $\times$ theme $\times$ year fixed effects; $\epsilon_{i,j,s,m}$ is an idiosyncratic error term. The standard errors are clustered at the country-pair level.

Panel A of Table 2 presents the results of estimating the effects of institutional distance on the monthly average tone of news articles about the target country, as produced by the media outlets in the source country. Throughout columns (1)–(3), we control for target country $\times$ theme $\times$ year fixed effects to estimate the effect on media bias towards the same target country for the same theme and in the same year. In column (1), we further control for outlet fixed effects to take into account time-invariant characteristics of outlets. In column (2), we add outlet $\times$ year fixed effects to take into account the effects of any changes that vary by media outlets (e.g., leadership or ownership changes). Column (3) presents the results of our most rigorous model specification (Equation 6), which includes outlet $\times$ theme $\times$ year fixed effects and target country $\times$ theme $\times$ year fixed effects. We essentially estimate the effect of institutional distance on media bias within the same media outlet for the same theme in the same year.

The estimated coefficients across columns (1)–(3) remain remarkably stable and statistically significant at the 1% level. The coefficient presented in column (3) indicates that a one standard deviation increase in Institutional Distance is associated with a 0.058 decrease in the average media tone between two countries, which corresponds to 1.55% of the standard deviation of the dependent variable. The magnitude of this media bias is exacerbated under specific conditions, as demonstrated by the heterogeneity tests that follow.

Overall, the findings reveal a robust negative association between the average monthly tone of media outlets from the source country towards the target country and the institutional distance between the two countries. In other words, when there is a notable contrast between the news source country and the reported country in terms of degree of democracy, media outlets in the source country tend to systematically portray the target country in a negative light.

Negative sentiments often play a crucial role in propaganda, particularly when it comes to depicting adversarial countries. Specifically, negative sentiments against a common 'enemy' can strengthen in-group solidarity and national identity (e.g., Weiss, 2014). By defining an out-group, propaganda can reinforce the boundaries of the in-group, making internal conflicts seem less significant in comparison. As a supporting evidence, we separate the tone variable into positive tone and negative tone. The results in Online Appendix Table A2 suggest negative sentiments are more sensitive to institutional distance. One standard

deviation decrease in institutional distance leads to more negative sentiments by 1.64% of the standard deviation.

Panel B of Table 2 examines how UN voting ideal point distance (Bailey, Strezhnev, and Voeten, 2017; Voeten, 2000, 2013) affects monthly average media tone. The results suggest that as the voting distance between two countries increases, media outlets in the source country adopt a more negative tone in their coverage of the target country.

In Panel C, we add a set of measures that capture bilateral country similarities. Specifically, we control for language similarity (Melitz and Toubal, 2014), religious distance (Dow and Karunaratna, 2006), genetic distance (Spolaore and Wacziarg, 2009), and geographic distance, alongside institutional distance and UN voting ideal point distance. The variation of these variables are at the country pair and year level. The effect of institutional distance remains statistically significant and the estimated coefficients decrease only slightly despite these controls, whereas the coefficients of UN voting distance become statistically insignificant. Given these findings, our subsequent analysis focuses on the relationship between institutional distance and news coverage.

Robustness. We conduct an extensive battery of robustness checks. First, we examine whether our results are sensitive to alternative model specifications. We introduce controls for country-pair fixed effects and country-pair $\times$ theme fixed effects, respectively. The results are presented in columns (1) and (2) of Online Appendix Table A3. By including country-pair fixed effects, we remove any time-invariant confounders at the country-pair level, including most of the variation in the control variables considered above. As institutional quality tends to persist over time, the inclusion of country-pair fixed effects absorbs substantial variation of the independent variable of interest. While the magnitude of the effect declines under these more demanding model specifications, the results remain robust. Additionally, in columns (3)–(5) of Online Appendix Table A3, we control for year-month fixed effects, allowing us to estimate the effect of institutional distance on news coverage pertaining to the same target country, theme, and month.

Second, the findings are robust to alternative standard error clusters, as shown in Online Appendix Table A4. In the baseline estimation, we cluster the standard errors at the country-pair level. We additionally show that coefficients are consistently significant if we use clusters at media outlet, or source country level. Following (Petersen, 2008), we also employ two-way clustering methods. We obtain robust results when standard errors are clustered at (pair, year), (outlet, year), or (source country, year) levels. Reassuringly, the results hold up under any of the alternative model specifications or clustering methods considered.

Third, we consider alternative measures in our baseline estimation. Online Appendix Table A5 presents results based on two alternative measures with Lexicoder Sentiment

Dictionary (LSD) and SentiWordNet 3.0 (SWN) provided in GDELT GKG 2.0 database. Tone(LSD) is measured with the difference between positive word frequency and negative word frequency used by media outlets. Tone (SWN) is measured with the difference between the positive values and negative values of news. The baseline results are insensitive to any of these alternative measures. Online Appendix Table A6 demonstrates that the findings remain fairly robust to two alternative measures of institutional distance constructed based on the V-dem electoral democracy index and the Polity2 score. Importantly, the effect size, relative to the standard deviation of the outcome variable, is quite similar across all measures.

We also leverage fine-grained sentiment measures from the GDELT database, which employs the WordNet-Affect (WNA) lexicon for sentiment classification (Strapparava and Valitutti, 2004). This lexicon provides comprehensive emotional and affective annotations for words and phrases, enabling us to capture nuanced emotional content and sentiment variations in news text. For each article, we calculate WNA sentiment scores as the proportion of words associated with specific emotional categories, then aggregate these measures at the outlet-target country-theme-month level. Figure 7 displays the effects of institutional distance on a range of subtle sentiment measures as categorized by the WordNet-Affect lexicon (the detailed results are reported in Online Appendix Table A7). Our analysis clearly shows that greater institutional distance is associated with an increase in negative sentiments, including "fear," "sadness," and "anxiety," while it correlates with a significant decrease in positive sentiments such as "liking" and "love." These findings indicate a clear emotional pattern in media coverage that varies with institutional differences between countries.[6]

Fourth, we conduct additional tests using alternative samples. We report the results based on the tone variable winsorized at 0.5%, 1%, and 5%, respectively, in Online Appendix Table A8. News articles that are issued by US media outlets or cover US related issues account for a large proportion of the sample. We presents in Online Appendix Table A9 the robustness check to the baseline estimation by removing observations related to the United States. Online Appendix Figure A3 also suggests that our findings are less likely to be driven by a small fraction of the sample. Panel (a) shows the t-values for the coefficient of interest in the sample excluding one of top 100 country-pair in terms of the number of observations. Panel (b) shows the results based on sample randomly excluding 5% of the observations once a time.

Fifth, we additionally control for economic interdependence and conflicts between the source and target countries. In Online Appendix Table A11, we include controls for the source country's trade dependence (column (1)) and trade balance (column (2) with the

[6]The validity of our WNA sentiment measures is further corroborated through Pearson correlation analysis with our tone measures (see Online Appendix Figure A4).

target country, as well as a dummy variable indicating whether the source country was sanctioned by the target country (column (3)). Nevertheless, none of these control variables are statistically significant, and the estimated effect of Institutional Distance remains robust and largely unaffected.

Lastly, we replicate the baseline result presented in Table 2 by utilizing a sample constructed from the GDELT Event 2.0 database. In Online Appendix B, we also provide a comprehensive discussion on why we favored the GKG 2.0 over the Event 2.0 database. The results obtained from the GDELT Event 2.0 sample are reported in Table A12. Different from the baseline models, we include Event Type fixed effects instead of Theme fixed effects in this part of analysis because the GDELT 2.0 database does not provide theme classifications for news articles. Nevertheless, the significance and magnitude of the coefficients remain consistent with our baseline findings. This suggests that our conclusions are robust to variations in sample construction and theme classification methods.

Dynamics. Furthermore, we explore the dynamic effects of institutional distance. We modify our baseline model (Equation (6)) and interact institutional distance with a linear time trend. As shown in columns (1) and (2) of Table 3, institutional distance has an increasing effect on the media sentiment over time. The effect grows annually by 12% (=0.023/0.191 as in column (2)) relatively to the baseline benchmark. We further estimate the following model to assess the dynamic effect of institutional distance:

$$\begin{aligned} \text{Tone}_{i,j,s,m} = & \sum_{t=2015}^{2022} \beta_t (\text{D}_t \times \text{Institutional Distance}_{c,j,t}) \\ & + \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m} \end{aligned} \tag{7}$$

where D_t is the indicator set to one for the year t and zero otherwise. Other model specification follows the convention in Equation (6). Essentially, this model estimates the effect of $\text{Institutional Distance}_{c,j,t}$ by year separately. Figure 8 graphically represents the coefficients associated with the interaction terms (β_t). As time unfolds, the impact of institutional distance on media bias becomes increasingly negative, a pattern consistent with the evidence based on linear trend interaction as in columns (1) and (2) of Table 3. Notably, the effect bottomed out in the year 2021, followed by a slight rebound in 2022. This trend underscores the increasing relevance of the contrast in political systems between the source country and the target country in shaping global media bias. It implies that as the difference in political systems between the two countries become more prominent, it exerts a more significant influence on the formation and intensification of biases within the global media landscape.

Effects by Theme. A pertinent question arises as to whether media bias is confined

solely to political topics, which are commonly believed to be the most sensitive to institutional differences. To demonstrate the effect of institutional distance by media theme, we estimate the following model:

$$\begin{aligned}\text{Tone}_{i,j,s,m} = &\sum_{s\in\Omega^s} \beta_s(\text{W}_s \times \text{Institutional Distance}_{c,j,t}) \\ &+ \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m}\end{aligned} \tag{8}$$

where W_s is the indicator set to one for the theme s and zero otherwise. Other model specification follows the convention in Equation (6). We plot the estimated the coefficients of β_s in Figure 9 and report the results in Online Appendix Table A13. Themes that are related to political topics are among ones with the strongest effects due to institutional distance including "Public Private Partnerships" and "Public Sector Management". However, the media bias extends beyond those political topics and encompasses a variety of social and economic issues, such as "Social Protection and Labor," "Gender," "Financial Sector Development," "Economic Growth," and "Trade."

Biased Theme Selection. Media bias can manifest through selective theme coverage, where media outlets choose to report topics that typically carry negative connotations. For instance, a Chinese media outlet may tend to emphasize governmental failures in handling natural disasters when covering the United States. To examine this pattern empirically, we employ the following model:

$$\begin{aligned}\text{Theme Share}_{c,j,s,t} = &\beta\text{Institutional Distance}_{c,j,t} \times \overline{\text{Theme Tone}} \\ &+ \gamma\text{Institutional Distance}_{c,j,t} \\ &+ \delta_{j,s} + \theta_c + \alpha_t + \epsilon_{c,j,s,t}\end{aligned} \tag{9}$$

where $\text{Theme Share}_{c,j,s,t}$ is the share of news in theme s scaled by total number of news articles by source country c covering target country j in year t. In some specifications, we use a binary variable as the dependent variable to indicate whether news on theme s concerning target country j was reported by source country c in year t. It is worth noting that given the constraints of computing power, we aggregate our data at the source country-target country-theme-year level. $\overline{\text{Theme Tone}}$ is the average tone of theme s and can be measured in the following two ways. The first approach calculates the average theme tone with the average tone of all news articles covering theme s. This is expressed by the following equation:

$$\overline{\text{Theme Tone}}_s = \frac{1}{I}\sum_{i=1}^{I} \text{Tone}_s \tag{10}$$

The other approach calculates the average tone for a specific target country j, theme$s$, and year t by averaging across tones of all related news articles. This is represented by the following equation:

$$\overline{\text{Theme Tone}}_{j,s,t} = \frac{1}{I}\sum_{i=1}^{I} \text{Tone}_{j,s,t} \tag{11}$$

We expect the estimated coefficient β to be negative. This negative coefficient would suggest that media outlets in a source country increase their coverage of inherently negative themes when reporting on countries with greater institutional differences from their own. For instance, when a theme typically carries negative connotations (i.e., has a negative average tone), the effect of institutional distance on the theme's share in total news coverage becomes more pronounced.

Using two distinct measures of average tone for theme s, columns (1) and (2) of Table 4 demonstrate that the interaction effect between institutional distance and theme tone is negative and statistically significant. Columns (3) and (4) corroborate these findings using a binary dependent variable. These results collectively indicate that as institutional distance increases between source and target countries, media outlets tend to cover negative themes. In column (5), we focus on news articles covering the theme of "violence," one of the most consistently negative themes in our dataset. The results reveal that institutional distance has a positive and significant effect on the proportion of violence-related coverage. This pattern provides additional supporting evidence that media outlets devote more coverage to negative themes when reporting on institutionally distant countries.

Biased News Coverage on National Leaders. Our baseline model addresses the diverse nature of international media coverage through target country by theme by year fixed effects, allowing us to estimate the effect of institutional distance on media bias toward the same target country within the same theme and time period. However, recognizing both the breadth of international news topics and potential limitations in theme classification, we sharpen our identification strategy by examining a sample of news articles focusing on national leaders. National leaders are the most visible embodiments of their countries' political institutions. If institutional differences between countries indeed drive media bias, such effects should manifest most clearly in how media outlets cover foreign leaders.

Using a sample of news articles on national leaders (see detailed sample construction in Online Appendix B.2), we present our findings in Table 5. Our analysis employs increasingly

granular fixed effects specifications. In column (1), we control for outlet fixed effects, leader fixed effects, year fixed effects, allowing us to identify media bias in the coverage of the same leaders while controlling for time-invariant outlet characteristics and common temporal effects. In column (2), we introduce outlet × year and leader × year fixed effects to estimate media bias toward the same leaders within the same year while accounting for annual changes in outlet-specific characteristics. In column (3), we employ our most demanding specification with outlet × year-month and leader × year-month fixed effects, allowing us to identify media bias by comparing how different outlets cover identical leaders within the same month, while controlling for outlet-specific monthly changes. The results reveal strong and stable coefficients across columns (1)–(3). Most notably, the magnitude of the effect in column (2) is equivalent to 3.52 times that estimated in our baseline model (column (3) of Panel A in Table 2), suggesting that a one-standard-deviation increase in institutional distance corresponds to a 6.1% standard deviation decrease in the monthly average tone. This result highlights a substantially stronger effect when focusing on national leader coverage.

3.2 How Democracy Shapes Media Bias

In this section, we explore the heterogeneous effects of institutional distance depending whether the source country is a liberal democracy or not. We include an interaction term of institutional distance and a dummy variable indicating whether the source country is a liberal democracy in the baseline model. Other model specifications follow the convention in Equation (6).

$$\begin{aligned}\text{Tone}_{i,j,s,m} = {} & \beta \text{Institutional Distance}_{c,j,t} \\ & + \lambda \text{Institutional Distance}_{c,j,t} \times \text{Liberal Democracy Indicator}_{c,t}^{\text{Source Country}} \\ & + \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m}\end{aligned} \tag{12}$$

where $\text{Liberal Democracy Indicator}_{c,t}^{\text{Source Country}}$ is an indicator variable that equals one when the source country is a liberal democracy in year t. According to the Regimes of the World (RoW) measure from the V-Dem dataset, a country is classified as either a "liberal democracy" or not for a given year.

Likewise, we use the following model specification to study the heterogeneous effects of institutional distance when the target country is the liberal democracy.

$$\begin{aligned}\text{Tone}_{i,j,s,m} = {} & \beta \text{Institutional Distance}_{c,j,t} \\ & + \lambda \text{Institutional Distance}_{c,j,t} \times \text{Liberal Democracy Indicator}_{j,t}^{\text{Target Country}} \\ & + \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m}\end{aligned} \tag{13}$$

where Liberal Democracy Indicator$_{j,t}^{\text{Target Country}}$ is an indicator variable that equals one when the target country is a liberal democracy in year t.

In columns (1)–(2) of Table 6, this enables us to examine the differential effects of institutional instance depending on whether the source country is a liberal democracy. Column (1) controls for outlet × theme × year fixed effects and target country × year fixed effects. Column (2) uses the most rigorous model specification as in column (5) in Table 2 and controls for outlet × theme × year fixed effects and target country × theme × year fixed effects. The results in columns (1)–(2) demonstrate that when the source country is a liberal democracy, the effect of institutional distance on media bias is largely mitigated. Conversely, the effect is more pronounced among non-democratic countries. In column (2), the estimated coefficient of institutional distance is -0.387 and the estimated coefficient of the interaction term is 0.246. Comparing with the standalone coefficient (-0.260 as shown in column (3) in Panel A of Table 2), the effect on media bias for democratic source countries decreases by 45.8% to -0.141. For non-democratic source countries, one standard deviation increase in institutional distance leads to a 0.086 decrease in the monthly average tone (= 0.387 × 0.223), which corresponds to 2.3% of one standard deviation in the monthly average tone.

We next visualize the contrast in the effect of institutional distance on media bias. We first adjust the tone measure by considering the two main sets of fixed effects considered in our baseline analysis (Outlet × Year, Target Country × Theme × Year) and retrieve the residual. The sample is split by Liberal Democracy Indicator$_{c,t}^{\text{Source Country}}$ and we draw the adjusted tone measure against the institutional distance in two separate bin scatter plots. Panel (a) and Panel (b) of Figure 10 present the effect of institutional distance for democratic reporting country and non-democratic reporting country, respectively. In Panel (a), the slope of the relationship between institutional distance and media tone is downward and becomes steeper when distance is greater than 0.5, while in Panel (b), the relationship is mainly flat.

Columns (3)–(4) of Table 6 test whether the effect on media bias varies when the target country is a liberal democracy. The results suggest that when the target country is a liberal democracy. The results in column (4) show that the estimated effect of institutional distance on media bias becomes stronger from -0.260 to -0.466 when a liberal democracy is the subject of news coverage, indicating an amplified effect. In sharp contrast, for non-democratic countries, the effect is marginally significant with a coefficient of -0.106. In Panel (c) and (d) of Figure 10, we visualize the difference of the effect on democratic target countries and non-democratic target countries. As shown in Panel (d), when target country is democratic, the effect of institutional distance is more visible as evidenced by the steeper slope of the relationship. Therefore, media bias is not only a function of the source country's political system but is also deeply influenced by the democratic status of the target country.

3.3 Democratic Erosion as Natural Experiments

We exploit episodes of democratic erosion in the source country to provide further evidence that the institutional distance between the source country and the target country plays a critical role in shaping global media bias. Drawing on the Regimes of the World (RoW) measure from the V-Dem dataset, we define episodes of democratic erosion as instances where a country experiences a downward shift in the degree of democracy: moving from a liberal democracy to an electoral democracy, or descending from an electoral democracy to an electoral autocracy, or falling from an electoral autocracy to a closed autocracy. To account for potential signs of democratic backsliding prior to explicit changes in regime type, we leverage the Episodes of Regime Transformation (ERT) dataset (Maerz et al., 2023) to identify the source countries in which the onset of democratic erosion initiated prior to 2016, which marks the starting year of our sample. This yields a total of 17 episodes of democratic erosion in our analysis. In addition, to focus on episodes of democratic erosion, we also exclude source countries that underwent democratic transitions during the sample period. The summary of the treatment countries is presented in Table A14.

If institutional distance indeed is a driving force of media bias, we would expect that following a country's democratic backsliding, which leads to an increased institutional distance from democratic countries, the media outlets within that country would exhibit a tendency to report on democratic countries in a more negative light. In order to test this observable implication, we employ a continuous Difference-in-Differences (DID) design to estimate the effect of the target country's levels of democracy on the media bias of source countries after experiencing democratic erosion. The model is specified as follows:

$$\begin{aligned} \text{Tone}_{i,j,s,m} =& \beta \text{Erosion}_{c,t} \times \text{Liberal Democracy Index}_{j,t}^{\text{Target Country}} \\ &+ \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m} \end{aligned} \tag{14}$$

where $Erosion_{c,t}$ is an indicator variable that equals to one for the years following the occurrence of democratic erosion in country c. Liberal Democracy $\text{Index}_{j,t}^{\text{Target Country}}$ represents the degree of democracy in the target country j in year t. β captures the change in media bias toward countries with higher levels of democracy (relative to those with lower levels of democracy) after the democratic erosion of the source country.

We further explore the dynamic effects, using the following model specification:

$$\begin{aligned} \text{Tone}_{i,j,s,m} =& \sum_{\substack{\tau=-4 \\ \tau \neq -1}}^{4} \beta_\tau (\text{Erosion}_{c,\tau} \times \text{Liberal Democracy Index}_{j,\tau}^{\text{Target Country}}) \\ &+ \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m} \end{aligned} \tag{15}$$

where $\text{Erosion}_{c,\tau}$ a set of five dummy variables that equal 1 if τ periods have passed since the democratic erosion in the source country c. $\tau = -1$ is the omitted baseline period. We estimate this equation using both OLS and the Sun and Abraham (2021) estimator.

Table A15 of the Online Appendix illustrates the estimation results of Equation (14). As suggested by column (4), democratic erosion results in a 0.089 decrease in media tone toward democratic countries compared to non-democratic countries, which corresponds to 2.38% of the standard deviation of the outcome variable (3.747 as in Table 1). The dynamic coefficients of Equation (15) are visualized in Figure A2 and reported in Online Appendix Table A16. The estimated coefficients of the interaction term of the target country's levels of democracy and event-year dummies steadily become negative, larger in magnitude, and statistically significant following the episodes of democratic erosion. Importantly, there are no clear signs of pre-existing trends. Overall, the results further lend credence to the importance of institutional distance in accounting for global media bias.

3.4 Information Control

In their efforts to maintain regime stability, governments — particularly those of an authoritarian nature — frequently employ a variety of information control strategies aimed at manipulating the flow of information (Guriev and Treisman, 2019, 2020). These strategies include the employment of censorship to silence dissenting voices and shape the narrative and tone of media coverage and online discussions (King, Pan, and Roberts, 2013, 2017; Roberts, 2018). Authoritarian governments also actively promote state-owned media to ensure its dominance across various information channels, including print media, television stations, and social media platforms (Gehlbach and Sonin, 2014). As a result, in authoritarian countries, the media landscape tends to be characterized by higher levels of state ownership (Djankov et al., 2003). Government-controlled media outlets typically prioritize political objectives over profitability (Qin, Strömberg, and Wu, 2018; You, Zhang, and Zhang, 2018), as their operations are not driven by business success but by the mandate to serve governmental agendas.

In this section, we allow the effect of institutional distance to vary across countries with different levels of information control.

$$\begin{aligned}\text{Tone}_{i,j,s,m} = \alpha\text{Institutional Distance}_{c,j,t} + \beta\text{Institutional Distance}_{c,j,t} \times \text{Z}_{c,t} \\ + \delta_{i,s,t} + \theta_{j,s,t} + \epsilon_{i,j,s,m}\end{aligned} \tag{16}$$

where $Z_{c,t}$ indicates the levels of information control in the source country c in year t. We use different indicators to capture the levels of information control as detailed below.

In Panel A of Table 7, we study whether the effect of institutional distance on media bias depends on media freedom in the source country. In columns (1) and (2), we introduce the interaction term between institutional distance and a measure of traditional media freedom (TV, radio, magazines, and newspapers). The results are largely similar to those for internet freedom. Therefore, we can conclude that both internet and traditional media censorship amplify the effect of institutional distance on media bias. When media are subject to censorship, institutional distance has a robust and statistically significant negative effect on the tone of news coverage. In contrast, with media freedom, the effect of institutional distance on media bias is significantly attenuated.

In columns (3) and (4) of Panel A, we include the interaction term between institutional distance and a measure of internet freedom into our baseline model. The coefficients on institutional distance, which indicate the effect of institutional distance without internet freedom (representing extreme internet censorship), are negative and statistically significant, whereas the coefficients on the interaction term between institutional distance and internet freedom, which indicate the difference in effects with and without internet freedom, are positive and statistically significant.

In Panel B, we investigate the heterogeneous effects based on the media ownership in the source country. Columns (1) and (2) reveal negative and statistically significant coefficients for the interaction term between institutional distance and a measure of state ownership of print media. Similarly, in columns (3) and (4), the coefficients on the interaction term between institutional distance and a measure of state ownership of broadcast media are also negative and statistically significant. In Online Appendix Table A17, we introduce an interaction term between institutional distance and a dummy variable indicating the ownership status of the media outlet, whether state-owned or not. To identify state-owned media outlets, we harness the ChatGPT-4o API. The results reveal that while the estimated effect of institutional distance on media bias for non-state media outlets is -0.23, the estimated coefficient of the interaction term is approximately -0.29, representing an additional increase in the magnitude of media bias for state-owned media outlets. Taken together, we provide suggestive evidence that state ownership of media can further amplify the impact of institutional distance on media bias.

Our findings thus far indicate that in cases where the source country is an authoritarian regime with strict control over the media, democracies often become the targets of biased reporting. Authoritarian regimes strategically deploy state media to project their governance as superior while casting democracies unfavorably, thereby reinforcing domestic support for authoritarianism. During the COVID-19 pandemic, for example, Chinese state media criticized the United States for its pandemic response, highlighting the US govern-

ment's mismanagement and lack of accountability, while praising China's capacity for rapid social mobilization (Fu, 2023; Xia, Huang, and Zhang, 2022).[7] This stark contrast in media narratives likely enhances Chinese citizens' satisfaction with their government in comparison to the instability in democracies (Huang, 2015). Moreover, authoritarian regimes frequently deflect criticism by attributing internal issues to external factors, as exemplified by Syrian state media framing the Arab Spring uprisings as foreign plots (Blaydes et al., 2021). Such anti-foreign messaging stirs nationalistic feelings, fostering a unifying "rally-round-the-flag" effect, which has long been an effective tool to garner popular support (Weiss, 2014). Therefore, biased reporting targeting democracies serves as a strategic tool for authoritarian governments to shore up popular support and maintain the authoritarian rule.

3.5 Economic Distress

We next examine whether the impact of institutional distance between the source country and the target country on media bias becomes more pronounced during periods of economic hardship in the source country. Martinez (2022) shows that autocracies engage in more severe information manipulation, most notably inflating GDP growth figures, when the domestic economy is performing poorly. Rozenas and Stukal (2019) provide evidence suggesting that during periods of economic downturn, Russia's state-controlled television often attributes the blame for bad economic news to external factors such as the foreign economy or foreign governments.

In Table 8, we explore heterogeneous effects based on source countries' economic growth. Since official GDP statistics may be subject to misreporting or manipulation (e.g., Martinez, 2022), particularly in less developed or non-democratic countries, we employ an alternative measure of economic activity using satellite nightlight data (Henderson, Storeygard, and Weil, 2012). Specifically, our analysis employs the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) dataset, which is aggregated at the country-month level throughout our sample period.

In columns (1) and (2), we include an interaction term between institutional distance and the monthly growth of the source country's nightlight. The coefficients of the interaction term are positive, suggesting that a higher economic growth rate in the source country may mitigate the impact of institutional distance on media bias, whereas a lower GDP growth rate appears to magnify this effect. Consider that, as our results indicates, when an

[7] See also: Global Times. March 6, 2020. "China Outperforms the United States in Public Health," https://oversea.huanqiu.com/article/9CaKrnKpKEV?bsh_bid=5488851275 (accessed December 31, 2023); Global Times. April 9, 2020. "The US Has Dragged Down the Fight Against the Epidemic, and It Has Also Dimmed the Prospects of the World," https://opinion.huanqiu.com/article/3xlaqBQqzYD (accessed December 31, 2023).

authoritarian country experiences an economic slowdown, its media outlets are more likely to cover democratic countries in a more negative manner.

In columns (3) and (4), we investigate the effect heterogeneity by the source country's inflation rate. In model specifications, we interact institutional distance and the source country's annual inflation rate (lagged). We find that the estimated coefficients of the interaction term are negative and statistically significant. The results indicate that as the inflation rate in the source country increases, the effect of institutional distance on media bias is expected to become more pronounced.

3.6 Domestic Turmoil

In addition to economic challenges, we further investigate domestic instability prompts authoritarian regimes to strategically manipulate media narratives by portraying paint democratic countries in a negative light. Following Amarasinghe (2022), we construct an index of domestic turmoil based on all domestic events where the target is the government and the associated sentiment on the Goldstein scale (Goldstein, 1992) from the GDELT Event Database 2.0. This index measures people's resentment towards their government by calculating the proportion of events with negative sentiment scores among all events targeted at the government.

In columns (1) and (2) of Table 9, we analyze the entire sample and find that the intensity of domestic turmoil is associated with more negative sentiment in the news coverage towards foreign countries in general. However, the effect of institutional distance does not change depending on domestic turmoil. In Column (3), we focus on non-democratic regimes as the source countries. Here, the interaction between institutional distance and the turmoil index is both negative and statistically significant, suggesting that when authoritarian regimes experience domestic turmoil, their media outlets are more likely to portray countries negatively, especially those with greater institutional distance, namely liberal democracies. In contrast, column (4) shows that this pattern is absent when examining media coverage originating from liberal democracies.

3.7 Alliances in Ideological Warfare

The current findings establish that media outlets tend to publish more positive news articles about countries with which they have a smaller institutional distance. In this subsection, we adopt a fresh perspective to investigate how countries form alliances through their media narratives—an important consideration in the context of the ideological struggles underpinning political and economic alliances. Our empirical analysis reveals this pattern and offers

estimations for subsequent economic evaluations.

To this end, we start with the tone variable used in our baseline estimation. We aggregate the tone measure at the desirable level:

$$\underset{j\neq c}{\text{Tone}_{c,j,s,t}} = \frac{\sum_{i,j,s,m\in\Omega_{c,j,s,t}} \text{Tone}_{i,j,s,m}}{\text{N}_{c,j,s,t}} \tag{17}$$

where $Tone_{i,j,s,m}$ is the average tone of media outlet i from country c when reporting country j for theme s during month m. We thus construct the tone measure at the reporting country c, target country j, theme s and year t level. For our research purpose, we aim to gauge the co-movement in media coverage between country A and country B, relying on their tone measures toward themes in countries besides each other. Formally, for country A in year t, we have the tone measure $\underset{j\neq A,B}{\text{Tone}_{A,j,s,t}}$ that capture the media sentiment towards theme s in country j, where we exclude any news from country A or B. For country B, we have the similar tone measure, $\underset{j\neq A,B}{\text{Tone}_{B,j,s,t}}$. With $\underset{j\neq A,B}{\text{Tone}_{A,j,s,t}}$ and $\underset{j\neq A,B}{\text{Tone}_{B,j,s,t}}$ in year t, we are able to compare how they cover the same theme s in a country j. For any pairs of A and B in year t, we construct the Pearson correlation coefficient as follows.

$$\rho_{A,B,t} = \frac{\text{Cov}(\text{Tone}_{A,j,s,t}, \text{Tone}_{B,j,s,t})_{j\neq A,B}}{\sigma_{A,t}\sigma_{B,t}} \tag{18}$$

where the numerator is the covariance between $\text{Tone}_{A,j,s,t}$ and $\text{Tone}_{B,j,s,t}$. $\sigma_{A,t}$ and $\sigma_{B,t}$ are standard deviation of $\text{Tone}_{A,j,s,t}$ and $\text{Tone}_{B,j,s,t}$, respectively, for the year t.

We adjust $\rho_{A,B,t}$ by considering fixed effects for the source country, target country, and year, and then extract the residual, $\rho'_{A,B,t}$. In Panel (a) of Figure 12, we plot the relationship between $\rho'_{A,B,t}$ and institutional distance. The evident negative relationship suggests that countries with distinct institutions are less likely to form alliances and cover issues in other countries in a synchronized manner. The country-pair structure of $\rho_{A,B,t}$ enables us to conduct a network analysis. To depict the relative positions of countries in terms of media tone synchronicity, we construct a network graph in Panel (b) using the data from 2022. In this graph, countries serve as nodes. A link is established between two countries if their correlation coefficient in 2022 falls within the top 10% percentile. Blue nodes represent democratic countries, while red nodes represent non-democratic countries. The size of each node corresponds to the volume of news articles reported by media outlets from that country. Democratic countries are predominantly situated at the center of the graph, centered around the United States, and encircled by non-democratic countries, which are in turn scattered in separate clusters, including those around China and Russia. This arrangement aligns with the findings in Panel (a), indicating that countries tend to align with others that share

similar institutional characteristics in ideological conflicts.

4 Economic Costs of Media Bias

Media bias can yield significant economic consequences. Calomiris and Mamaysky (2019) show that the context and content of news articles, including topic-specific sentiment, predicts risk and return in stock markets in 51 developed and emerging economies. Gurun and Butler (2012) document the association between local media slant and firm equity values in the United States. Baloria and Heese (2018) demonstrate that media slant has a profound impact on firm behaviors such as information disclosure. However, those studies focus on the effect of media biases within the country border. The evidence on the economic costs of global media bias is rare. One exception is Kim (2018) who documents that Chinese newspapers are biased against foreign firms and promote protectionist measures through concealed trade barriers.

In this section, we assess the association between intensified media biases across countries and the economic costs using the quick responses from the financial markets. Specifically, we explore the market reactions of the equity market and the syndicated loan market as they demonstrate how investors and creditors price in the risks regarding media bias. Other observed outcomes, such as international trade and foreign investments, would take time to adjust and are subject to other factors. By contrast, detailed firm- and deal-level data from financial markets allow us to precisely gauge their exposures to global media bias and assess the effect in a timely fashion.

4.1 Equity Market Reactions

The efficient market hypothesis suggests that the equity market would quickly incorporate any relevant information into prices (Fama, 1970). Therefore, we first use the stock market as a laboratory assess the economic cost of global media biases. Specifically, we investigate how US listed firms respond to media bias arising from a foreign country against the US. Using information from corporate disclosure, we construct firm-level media exposure based on the revenue share from a given foreign country. We only focus on the reactions of US firms as the data on foreign sales are sparse for firms in other countries.

Following the standard practices in the asset pricing literature, we first construct a monthly panel of individual stock returns using data from the Center for Research in Security Prices (CRSP). We restricted the sample firms to US-headquartered firms using information

from Compustat. We construct

$$\text{Tone Exposure}_{i,m} = \sum_{c=1}^{C} Tone_{c,m} \times Rev_{i,c,t} \tag{19}$$

where $Tone_{c,m}$ is the average tone of media outlets from a given country c towards the US in month m. Following previous studies (e.g., Huang et al. (2023)), we source information from the Factset Revere database to capture a firm's revenue exposure to a country. $Rev_{i,c,t}$ is a firm's revenue share from a given country based on information from the Factset Revere database. A decrease in *Tone Exposure* indicates an intensified media bias toward the firm.

Merging this media exposure with the return panel, the resultant sample is at the firm-month level and consists of 2,590 distinct firms in the period between 2015 and 2022. Observations with missing $Tone\ Exposure_{i,m}$ are due to zero sales from a given country and are automatically excluded. Therefore, we compare firms with sales from countries with relatively positive sentiment towards the US with ones with sales from countries with relatively negative sentiment.[8] We estimate the following ordinary least squares (OLS) panel regression model:

$$\text{Returns}_{i,m} = \beta\, \text{Tone Exposure}_{i,m} + \delta_i + \theta_m + \epsilon_{i,m} \tag{20}$$

where $Tone\ Exposure_{i,m}$ is the exposure defined above for firm i in month m. δ_i denotes firm fixed effects; θ_m denotes year-month fixed effects; $\epsilon_{i,m}$ is an idiosyncratic error term. The standard errors are clustered at the firm level.

As shown in Table 10, we present the findings for the monthly raw returns (*Monthly Returns*) and standard asset pricing models (Fama and French, 1992, 1993) including market model adjusted returns (*Abnormal Monthly Returns (CAPM)*) and abnormal returns adjusted by the Fama-French three factor model (*Abnormal Monthly Returns (FF3)*). We consider firm fixed effect and year-month fixed effects with standard errors clustered at the firm level. In this sample, *Tone Exposure* is on average negative with a standard deviation of 0.406. As shown in column (1) of Table 10, one standard deviation decrease in *Tone Exposure* leads to 0.329% drop in monthly returns, which translates to 3.95% drop in annualized returns. The results are robust to alternative asset pricing models. The sizable impact on stock returns suggests stock market participants anticipate that exposed firms would suffer from decreased sales to countries with negative sentiment towards the US.

[8] It is insensible to consider the observations with the missing $Tone\ Exposure_{i,m}$, as firms with zero sales to a country cannot serve as proper counterfactuals.

4.2 Syndicated Loan Market Reactions

Next, we investigate how creditors respond to the intensified media bias across country borders. In the last subsection, we analyzed how US firms with sales to a country respond in stock returns to biases from a given country. In the following discussion, we will explore how banks choose their locations of borrowers to originate loans and make pricing decisions in response to media bias from foreign countries. We focus on syndicated loan market as it is a major financing source for corporate policies. For example, as documented in Sufi (2007), most of US listed companies have obtained syndicated loans.

Information on syndicated loans is sourced from the Dealscan database. The initial sample comprises syndicated loan deals involving borrowing firms from 169 countries and lending banks from 142 countries.

We measure inter-country media bias through the average tone of news articles at the country-pair and year level. To capture the banks' responses to media bias from potential borrowers' countries, we construct a lender-target country-year level sample. This refined sample includes 9,860,999 observations with 8,772 banks spanning from 2015 to 2022. Panel A presents the effects of media bias originating from one country on the quantity and size of loans issued to borrowers from another country. *Deal Number* refers to the count of syndicated loans extended by banks from a specific country to borrowers in different countries. *Deal Value* represents the aggregate value of these loans. The analyses in Panels A rely on a Poisson model, as the outcome variable is sparse and contains many zero entries. In Panel B, we report deal-level results. This subset contains 158,682 loan facilities with essential information on deal and media variables. Here, the dependent variable is the spread of each syndicated loan, which reflects the cost of borrowing. *Spread* is defined as the log value of the all-in drawn spread as provided in the Dealscan database. We consider country pair, lender, lender by target country, and year fixed effects. Standard errors are clustered at the lender level and reported in brackets.

The initial sample of syndicated loan deals consists of borrowing firms from 169 countries and lending banks from 142 countries. To capture the banks' responses to media bias from potential borrowers' countries, we construct a sample at the lender (the bank), country of borrower (the firm), and year level. Specifically, we create a sample that consists of the full combinations along three dimensions, including the lender, the country of the borrower and the year. This sample includes 9,860,999 observations with 8,772 banks spanning from 2015 to 2022. $Deal\ Number_{i,c,t}$ is defined as the count of syndicated loans extended by US lender i to borrowers in country c in year t. $Deal\ Value_{i,c,t}$ represents the aggregate value of these loans. Records in this sample are filled with zero if there is no loans for a lender-country pair in a year.

We estimate the following Poisson regression model:

$$\mathrm{Y}_{i,c,t} = \beta\, \mathrm{Tone}_{j,c,t} + \delta_{i,c} + \theta_t + \epsilon_{i,c,t} \tag{21}$$

where $Tone_{j,c,t}$ is the inter-country media bias measure from country j to country c in year t. $Y_{i,c,t}$ takes the value of either $Deal\ Number_{i,c,t}$ or $Deal\ Value_{i,c,t}$. $\delta_{i,c}$ denotes lender by target country fixed effects; θ_t denotes year fixed effects; $\epsilon_{i,c,t}$ is an idiosyncratic error term. The standard errors are clustered at the bank level. Following the development in the methodological literature (Cohn, Liu, and Wardlaw, 2022; Chen and Roth, 2023), we estimate a Poisson model, as the outcome variables are sparse and contain many zero entries.

Panel A of Table 11 presents a positive association between the average tone of media coverage in the loan issuer country with respect to the borrower country and the number of loan deals as well as the value of loans. As shown in columns (3) and (6) of Panel A, one standard deviation decrease in $Tone_{j,c,t}$ leads to a 4.94% (=0.029 $\times$ 1.702) drop in the deal number and a 8.34% (=0.049 $\times$ 1.702) drop in deal value. The results suggest the media bias from the source country deters lenders from the target country originate loans to borrowers from the source country.

We continue to investigate whether media bias from the source country heightens the cost of borrowing conditional on the loan origination. To this end, we construct a sample at the deal and lender level as a syndicated loan could involves multiple lenders in the deal. This sample contains 158,682 loan facilities with essential information on deal and media variables. In Panel B of Table 11, we report the results at the deal level. Here, the dependent variable is the logarithmic value of the spread of each syndicated loan, which reflects the cost of borrowing. The spread is defined as the all-in drawn spread as provided in the Dealscan database. Different from the estimation in Panel A, the dependent variable, $Spread_{i,c,t}$, is not count-like variable. We thus use ordinary least squares regression to estimate Equation (19) and replace $Y_{i,c,t}$ with $Spread_{i,c,t}$. The results in Panel B illustrate a negative correlation between the spread of loans and the average tone in the media coverage towards the borrower country. One standard deviation decrease in $Tone_{j,c,t}$ leads to a significant increase in the loan spread in the range between 2.19% and 2.65%.[9] This suggests that when the image of the borrower country is negative in the loan issuer country's media coverage, the borrowing costs for the borrower country tend to be higher.

[9]The standard deviation of independent variable, *Tone*, is 0.961 in this sample. As shown in column (1) of Panel B, one standard deviation of increase in *Tone*, leads to -2.65% ($= e^{-0.028\times0.961} - 1$) change in spread.

4.3 Public Opinion Reactions

We explore the impact of global media bias on public opinion towards foreign countries. Specially, we employ the Gallup World Poll Survey data to estimate the effect of the average media reporting tone of a source county i toward a target country j in year $t-1$ on the public opinion of country i toward country j in year t. Public opinion favorability toward a foreign country is measured using the approval rate of the target country's leadership, as reported in the Gallup data. Although this measure is imperfect, it serves as a useful proxy for the general sentiment of the population in the source country, given that leadership approval often reflects broader perceptions of the target country.

Table 12 provides evidence that the average media tone in a country, when reporting on another country, is positively correlated with the source country's public opinion of the target country. Our analysis reveals that this relationship is both statistically significant and substantially meaningful. In particular, we find that a one-standard-deviation increase in the average media tone toward a foreign country corresponds to a 7.8% rise in the source country's favorability rating for that country. This finding highlights the role of media in shaping perceptions of foreign countries.

5 Conclusion

In our paper, we have constructed a comprehensive dataset comprising 1.4 billion news with 55,240 distinct media sources in 176 countries and 177 reported countries between 2015 and 2022 and provided the first systematic evidence of global media bias. We have established that the institutional distance between the news source country and the target country has a significant negative impact on the sentiment of the news coverage.

The evidence indicates that this media bias is particularly pronounced when the target country is a liberal democracy; conversely, it is significantly mitigated when the source country is a liberal democracy. These findings underscore the interplay between political institutions and media bias, highlighting the importance of considering the institutional context in the study of media dynamics. In addition, we find that the information control exercised by a country — through mechanisms like media censorship and state media ownership — exacerbates media bias, highlighting the considerable impact of government interventions on global media narratives. Our work also uncovers evidence that a source country's economic conditions, particularly during downturns or periods of high inflation, can amplify media bias. Finally, we emphasize that the economic implications of media bias are nontrivial. We provide evidence from the equity market that U.S.-listed firms with substantial sales in

countries that broadcast negative media sentiment about the United States face immediate declines in their stock prices. We have also established that the tone of media coverage is positively correlated with the number and value of banking loans and negatively correlated with the cost of borrowing in the syndicated loan market.

In conclusion, our study enriches the existing literature by providing valuable insights into the driving forces behind global media bias. By examining the interplay between political systems, information control, democratic erosion, and economic performance, we deepen our understanding of the multifaceted nature of this phenomenon.

References

Abramenko, Serhii, Vasily Korovkin, and Alexey Makarin. 2024. "Social Media as an Identity Barometer: Evidence From the Russia-Ukraine War." *Available at SSRN* .

Acemoglu, Daron, Tarek A. Hassan, and Ahmed Tahoun. 2018. "The Power of the Street: Evidence from Egypt's Arab Spring." *The Review of Financial Studies* 31 (1):1–42.

Amarasinghe, Ashani. 2022. "Diverting Domestic Turmoil." *Journal of Public Economics* 208:104608.

———. 2023. "Public Sentiment in Times of Terror." *Journal of Development Economics* 162:103058.

Anderson, Simon P. and John McLaren. 2012. "Media Mergers and Media Bias with Rational Consumers." *Journal of the European Economic Association* 10 (4):831–859.

Bailey, Michael A., Anton Strezhnev, and Erik Voeten. 2017. "Estimating Dynamic State Preferences from United Nations Voting Data." *Journal of Conflict Resolution* 61 (2):430–456.

Baloria, Vishal P. and Jonas Heese. 2018. "The Effects of Media Slant on Firm Behavior." *Journal of Financial Economics* 129 (1):184–202.

Baron, David P. 2006. "Persistent Media Bias." *Journal of Public Economics* 90 (1-2):1–36.

Besley, Timothy and Andrea Prat. 2006. "Handcuffs for the Grabbing Hand? Media Capture and Government Accountability." *American Economic Review* 96 (3):720–736.

Blaydes, Lisa et al. 2021. "Authoritarian Media and Diversionary Threats: Lessons from 30 Years of Syrian State Discourse." *Political Science Research and Methods* 9 (4):693–708.

Caldara, Dario and Matteo Iacoviello. 2022. "Measuring Geopolitical Risk." *American Economic Review* 112 (4):1194–1225.

Calomiris, Charles W and Harry Mamaysky. 2019. "How News and its Context Drive Risk and Returns around the World." *Journal of Financial Economics* 133 (2):299–336.

Chen, Heng and Li Han. 2022. "Do the Media Bow to Foreign Economic Powers? Evidence from a News Website Crackdown." *Working Paper* .

Chen, Jiafeng and Jonathan Roth. 2023. "Logs with zeros? Some problems and solutions." *The Quarterly Journal of Economics* :qjad054.

Chen, Yuyu and David Y. Yang. 2019. "The Impact of Media Censorship: 1984 or Brave New World?" *American Economic Review* 109 (6):2294–2332.

Clayton, Christopher, Matteo Maggiori, and Jesse Schreger. 2023. "A framework for geoeconomics." Tech. rep., National Bureau of Economic Research.

Cohn, Jonathan B, Zack Liu, and Malcolm I Wardlaw. 2022. "Count (and count-like) data in finance." *Journal of Financial Economics* 146 (2):529–551.

Coppedge, Michael, John Gerring, Carl Henrik Knutsen, Staffan I. Lindberg, Jan Teorell, David Altman, Michael Bernhard, Agnes Cornell, M. Steven Fish, Lisa Gastaldi, Haakon Gjerløw, Adam Glynn, Sandra Grahn, Allen Hicken, Katrin Kinzelbach, Kyle L. Marquardt, Kelly McMann, Valeriya Mechkova, Anja Neundorf, Pamela Paxton, Daniel Pemstein, Oskar Rydén, Johannes von Römer, Brigitte Seim, Rachel Sigman, Svend-Erik Skaaning, Jeffrey Staton, Aksel Sundström, Eitan Tzelgov, Luca Uberti, Yi-ting Wang, Tore Wig, and Daniel Ziblatt. 2023. "V-Dem Dataset V13." *Varieties of Democracy (V-Dem) Project* .

Djankov, Simeon, Caralee McLiesh, Tatiana Nenova, and Andrei Shleifer. 2003. "Who Owns the Media?" *The Journal of Law and Economics* 46 (2):341–382.

Dow, Douglas and Amal Karunaratna. 2006. "Developing a Multidimensional Instrument to Measure Psychic Distance Stimuli." *Journal of International Business Studies* 37:578–602.

Durante, Ruben and Brian Knight. 2012. "Partisan Control, Media Bias, and Viewer Responses: Evidence from Berlusconi's Italy." *Journal of the European Economic Association* 10 (3):451–481.

Egorov, Georgy, Sergei Guriev, and Konstantin Sonin. 2009. "Why Resource-Poor Dictators Allow Freer Media: A Theory and Evidence from Panel Data." *American Political Science Review* 103 (4):645–668.

Enikolopov, Ruben, Alexey Makarin, and Maria Petrova. 2020. "Social Media and Protest Participation: Evidence from Russia." *Econometrica* 88 (4):1479–1514.

Enikolopov, Ruben, Maria Petrova, and Ekaterina Zhuravskaya. 2011. "Media and Political Persuasion: Evidence from Russia." *American Economic Review* 101 (7):3253–3285.

Fama, Eugene F. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *The Journal of Finance* 25 (2):383–417.

Fama, Eugene F. and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47 (2):427–465.

———. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1):3–56.

Fu, King-Wa. 2023. "Propagandization of Relative Gratification: How Chinese State Media Portray the International Pandemic." *Political Communication* :1–22.

Gehlbach, Scott and Konstantin Sonin. 2014. "Government Control of the Media." *Journal of Public Economics* 118:163–171.

Gentzkow, Matthew and Jesse M. Shapiro. 2010. "What Drives Media Slant? Evidence from US Daily Newspapers." *Econometrica* 78 (1):35–71.

Goldstein, Joshua S. 1992. "A Conflict-Cooperation Scale for WEIS Events Data." *Journal of Conflict Resolution* 36 (2):369–385.

Groseclose, Tim and Jeffrey Milyo. 2005. "A Measure of Media Bias." *The Quarterly Journal of Economics* 120 (4):1191–1237.

Guriev, Sergei, Nikita Melnikov, and Ekaterina Zhuravskaya. 2021. "3G Internet and Confidence in Government." *The Quarterly Journal of Economics* 136 (4):2533–2613.

Guriev, Sergei and Daniel Treisman. 2019. "Informational Autocrats." *Journal of Economic Perspectives* 33 (4):100–127.

———. 2020. "A Theory of Informational Autocracy." *Journal of Public Economics* 186:104158.

Gurun, Umit G. and Alexander W. Butler. 2012. "Don't Believe the Hype: Local Media Slant, Local Advertising, and Firm Value." *The Journal of Finance* 67 (2):561–598.

Henderson, J. Vernon, Adam Storeygard, and David N. Weil. 2012. "Measuring Economic Growth from Outer Space." *American Economic Review* 102 (2):994–1028.

Herre, Bastian. 2023. "Identifying Ideologues: A Global Dataset on Political Leaders, 1945–2020." *British Journal of Political Science* 53 (2):740–748.

Hu, Minqing and Bing Liu. 2004. "Mining and summarizing customer reviews." In *Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining*. 168–177.

Huang, Haifeng. 2015. "International Knowledge and Domestic Evaluations in a Changing Society: The Case of China." *American Political Science Review* 109 (3):613–634.

Huang, Yi, Chen Lin, Sibo Liu, and Heiwai Tang. 2023. "Trade Networks and Firm value: Evidence from the U.S.-China Trade War." *Journal of International Economics* 145:103811.

Kim, Sung Eun. 2018. "Media Bias Against Foreign Firms as a Veiled Trade Barrier: Evidence from Chinese Newspapers." *American Political Science Review* 112 (4):954–970.

King, Gary, Jennifer Pan, and Margaret E. Roberts. 2013. "How Censorship in China Allows Government Criticism but Silences Collective Expression." *American Political Science Review* 107 (2):326–343.

———. 2017. "How the Chinese Government Fabricates Social Media Posts for Strategic Distraction, Not Engaged Argument." *American Political Science Review* 111 (3):484–501.

Korovkin, Vasily and Alexey Makarin. 2023. "Conflict and intergroup trade: Evidence from the 2014 Russia-Ukraine crisis." *American Economic Review* 113 (1):34–70.

Korovkin, Vasily, Alexey Makarin, and Yuhei Miyauchi. 2024. "Supply Chain Disruption and Reorganization: Theory and Evidence from Ukraine's War." *Available at SSRN 4825542* .

Larcinese, Valentino, Riccardo Puglisi, and James M. Snyder. 2011. "Partisan Bias in Economic News: Evidence on the Agenda-Setting Behavior of US Newspapers." *Journal of Public Economics* 95 (9-10):1178–1189.

Leetaru, Kalev and Philip Schrodt. 2013. "Gdelt: Global Data on Events, Location, and Tone, 1979–2012." In *ISA Annual Convention*, vol. 2. Citeseer, 1–49.

Liu, Ernest and David Yang. 2024. "International Power." *CESifo Working Paper Series* .

Loughran, Tim and Bill McDonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *The Journal of Finance* 66 (1):35–65.

Maerz, Seraphine F., Amanda B. Edgell, Matthew C. Wilson, Sebastian Hellmeier, and Staffan I. Lindberg. 2023. "Episodes of Regime Transformation." *Journal of Peace Research* (Online).

Marshall, Monty G., Ted Robert Gurr, and Keith Jaggers. 2019. "Polity IV Project: political Regime Characteristics and Transitions, 1800–2018." *Center for Systemic Peace* 17.

Martin, Gregory J. and Ali Yurukoglu. 2017. "Bias in Cable news: Persuasion and Polarization." *American Economic Review* 107 (9):2565–2599.

Martinez, Luis R. 2022. "How Much Should We Trust the Dictator's GDP Growth Estimates?" *Journal of Political Economy* 130 (10):2731–2769.

McMillan, John and Pablo Zoido. 2002. "How to Subvert Democracy: Montesinos in Peru." *Journal of Economic Perspectives* 18 (4):69–92.

Melitz, Jacques and Farid Toubal. 2014. "Native Language, Spoken Language, Translation and Trade." *Journal of International Economics* 93 (2):351–363.

Mohr, Cathrin and Christoph Trebesch. 2024. "Geoeconomics." *CESifo Working Paper Series* .

Nielsen, Finn Årup. 2011. "A new ANEW: Evaluation of a word list for sentiment analysis in microblogs." *arXiv preprint arXiv:1103.2903* .

Pemstein, Daniel, Kyle L. Marquardt, Eitan Tzelgov, Yi-ting Wang, Juraj Medzihorsky, Joshua Krusell, Farhad Miri, and Johannes von Römer. 2022. "The V-Dem Measurement Model: Latent Variable Analysis for Cross-National and Cross-Temporal Expert-Coded Data." *The Varieties of Democracy Institute* Working Paper.

Petersen, Mitchell A. 2008. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *The Review of Financial Studies* 22 (1):435–480.

Puglisi, Riccardo and James Snyder. 2015. "Empirical Studies of Media Bias." In *Handbook of Media Economics*, vol. 1, edited by Simon P. Anderson, Joel Waldfogel, and David Strömberg. Elsevier, 647–667.

Qian, Nancy and David Yanagizawa-Drott. 2017. "Government Distortion in Independently

Owned Media: Evidence from US News Coverage of Human Rights." *Journal of the European Economic Association* 15 (2):463–499.

Qin, Bei, David Strömberg, and Yanhui Wu. 2018. "Media Bias in China." *American Economic Review* 108 (9):2442–2476.

Reuter, Jonathan and Eric Zitzewitz. 2006. "Do Ads Influence Editors? Advertising and Bias in the Financial Media." *The Quarterly Journal of Economics* 121 (1):197–227.

Roberts, Margaret. 2018. *Censored: Distraction and Diversion Inside China's Great Firewall*. Princeton: Princeton University Press.

Rozenas, Arturas and Denis Stukal. 2019. "How Autocrats Manipulate Economic News: Evidence from Russia's State-Controlled Television." *The Journal of Politics* 81 (3):982–996.

Simonov, Andrey and Justin Rao. 2022. "Demand for Online News under Government Control: Evidence from Russia." *Journal of Political Economy* 130 (2):259–309.

Spolaore, Enrico and Romain Wacziarg. 2009. "The Diffusion of Development." *The Quarterly Journal of Economics* 124 (2):469–529.

Strapparava, Carlo and Alessandro Valitutti. 2004. "Word Net-affect: An affective extension of WordNet." *Proceedings of the 4th International Conference on Language Resources and Evaluation* .

Strömberg, David. 2015. "Media and Politics." *Annual Review of Economics* 7 (1):173–205.

Sufi, Amir. 2007. "Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans." *The Journal of Finance* 62 (2):629–668.

Sun, Liyang and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of econometrics* 225 (2):175–199.

Tella, Rafael Di and Ignacio Franceschelli. 2011. "Government Advertising and Media Coverage of Corruption Scandals." *American Economic Journal: Applied Economics* 3 (4):119–151.

Voeten, Erik. 2000. "Clashes in the Assembly." *International Organization* 54 (2):185–215.

———. 2013. "Data and Analyses of Voting in the United Nations General Assembly." In *Routledge Handbook of International Organization*, edited by Bob Reinalda. New York: Routledge, 54–66.

Voeten, Erik, Anton Strezhnev, and Michael Bailey. 2023. "United Nations General Assembly Voting Data." Harvard Dataverse. URL https://doi.org/10.7910/DVN/LEJUQZ. Accessed: 2023-12-20.

Weiss, Jessica Chen. 2014. *Powerful Patriots: Nationalist Protest in China's Foreign Relations*. Oxford: Oxford University Press.

Xia, Shouzhi, Huang Huang, and Dong Zhang. 2022. "Framing as an Information Control Strategy in Times of Crisis." *Journal of East Asian Studies* 22 (2):255–279.

You, Jiaxing, Bohui Zhang, and Le Zhang. 2018. "Who Captures the Power of the Pen?" *The Review of Financial Studies* 31 (1):43–96.

Zhuravskaya, Ekaterina, Maria Petrova, and Ruben Enikolopov. 2020. "Political Effects of the Internet and Social Media." *Annual Review of Economics* 12:415–438.

Tables

Table 1: Summary Statistics

Panel A: Variables at Domain - Target - Theme - Month Level (Baseline Sample)

	N	Mean	Median	Std	P25	P75
Monthly Average Tone	81,288,434	-1.929	-1.677	3.747	-4.228	.581
Monthly Average Positive Tone	81,288,434	2.722	2.466	1.663	1.589	3.548
Monthly Average Negative Tone	81,288,434	4.650	4.274	2.889	2.483	6.343

Panel B: Variables at the Country Pair - Year Level

	N	Mean	Median	Std	P25	P75
Institutional Distance	97,340	.313	.276	.223	.119	.482
Institutional Distance (Electoral Democracy)	97,340	.303	.267	.214	.119	.463
Institutional Distance (PolityV)	56,733	6.577	5.000	5.685	2.000	11.000
UN Voting Distance	91,227	.993	.844	.787	.298	1.561
Common Language	89,426	.140	.000	.347	.000	.000
Religious Distance	75,857	5.085	4.252	2.971	2.500	8.247
Geographic Distance	89,426	7181.598	6604.113	4323.596	3758.281	10007.979
Genetic Distance	82,821	.033	.036	.017	.016	.046

Panel C: Variables at Country-Year / Month Level

	N	Mean	Median	Std	P25	P75
Source Country						
Liberal Democracy Index	1,385	.411	.384	.264	.162	.640
Liberal Democracy Indicator (Yes=1)	1,385	.222	.000	.416	.000	.000
Growth of Average Night Light	11,230	.007	.002	.380	-.118	.122
Inflation Rate	1,343	6.210	2.792	24.546	1.120	6.051
Freedom of Traditional Media	1,385	.613	.796	1.537	-.427	1.723
Freedom of the Internet	1,385	.542	.941	1.377	-.453	1.733
Media Repression (Yes = 1)	1,385	.206	.000	.404	.000	.000
State-owned Print Media Percentage	1,220	-.806	-.836	1.236	-1.718	.028
State-owned Broadcast Media Percentage	1,220	-.624	-.858	.987	-1.247	-.120
Domestic Turmoil Proportion	15,963	.100	.100	.050	.070	.130
Target Country						
Liberal Democracy Index	1,416	.406	.380	.264	.155	.637
Liberal Democracy Indicator (Yes=1)	1,416	.217	.000	.412	.000	.000

Notes: This table presents summary statistics of the baseline sample. Main dependent variables at the media outlet, target country, theme, and month level are reported in Panel A. Independent variables at the country-pair level are presented in Panel B. We consider a series of country-year level variables as reported in Panel C. The sample is constructed in Online Appendix B. Variables are defined in Online Appendix E.

Table 2: Baseline Results

Panel A. Institutional Distance

	Dependent Variable: Monthly Average Tone		
	(1)	(2)	(3)
Institutional Distance	-0.280***	-0.263***	-0.260***
	(0.046)	(0.045)	(0.043)
Observations	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.263	0.278	0.291
Number of Country Pairs	14,379	14,379	14,379

Panel B. UN Vote Distance

	Dependent Variable: Monthly Average Tone		
	(1)	(2)	(3)
UN Vote Distance	-0.059***	-0.054***	-0.054***
	(0.012)	(0.012)	(0.011)
Observations	78,781,874	78,781,645	78,774,714
Adjusted R-squared	0.264	0.279	0.292
Number of Country Pairs	13,501	13,501	13,501

Panel C. Including Other Distance Measures

	Dependent Variable: Monthly Average Tone		
	(1)	(2)	(3)
Institutional Distance	-0.232***	-0.229***	-0.221***
	(0.058)	(0.057)	(0.055)
UN Vote Distance	0.015	0.019	0.016
	(0.015)	(0.016)	(0.014)
Common Language	0.229***	0.227***	0.219***
	(0.029)	(0.028)	(0.027)
Religious Distance	-0.001	-0.001	-0.002
	(0.006)	(0.006)	(0.006)
Geographic Distance	-0.020	-0.019	-0.016
	(0.014)	(0.013)	(0.013)
Genetic Distance	-0.568	-0.557	-0.420
	(1.474)	(1.426)	(1.357)
Observations	69,187,422	69,185,980	69,133,736
Adjusted R-squared	0.265	0.280	0.293
Number of Country Pairs	8,944	8,944	8,944
Std of Monthly Average Tone	3.747	3.747	3.747
Std of Institutional Distance	.223	.223	.223
Std of UN Vote Distance	.787	.787	.787
Target Country × Theme × Year FEs	Yes	Yes	Yes
Outlet FEs	Yes	No	No
Outlet × Year FEs	No	Yes	No
Outlet × Theme × Year FEs	No	No	Yes

Notes: This table presents the baseline estimation of the impact of institutional distance on global media bias. The dependent variable, *Tone*, measures cross-country media bias and is calculated as the monthly average tone using the data from GDELT GKG 2.0 database. The sample is at the media outlet, target country, theme, and month level. Standard errors in parentheses are clustered at the country pair level. Panel A presents the results using *Institutional Distance* as independent variable. Panel B shows the results for *UN Vote Distance*. Results considering all distance measures are presented in Panel C. Variables are defined in Online Appendix E. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Dynamic Effects

	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance	-0.193***	-0.191***		
	(0.045)	(0.043)		
Linear Time Trend × Institutional Distance	-0.024***	-0.023***		
	(0.008)	(0.008)		
D_{2015} × Institutional Distance			-0.208***	-0.205***
			(0.048)	(0.047)
D_{2016} × Institutional Distance			-0.217***	-0.217***
			(0.047)	(0.046)
D_{2017} × Institutional Distance			-0.221***	-0.224***
			(0.046)	(0.045)
D_{2018} × Institutional Distance			-0.265***	-0.261***
			(0.051)	(0.050)
D_{2019} × Institutional Distance			-0.292***	-0.280***
			(0.058)	(0.056)
D_{2020} × Institutional Distance			-0.294***	-0.282***
			(0.055)	(0.053)
D_{2021} × Institutional Distance			-0.375***	-0.375***
			(0.062)	(0.060)
D_{2022} × Institutional Distance			-0.352***	-0.350***
			(0.068)	(0.067)
Observations	81,288,433	81,288,434	81,288,432	81,288,434
Adjusted R-squared	0.278	0.291	0.278	0.291
Number of Country Pairs	14,379	14,379	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Notes: This table presents the dynamic effects of institutional distance on media bias. D_t is an indicator set for one for the year t. Other model specifications follow the convention in Table 2.

Table 4: Biased Theme Selection

	Dependent Variable: Monthly Average Tone				
	Share		Report (Binary)		Share (Violence)
	(1)	(2)	(3)	(4)	(5)
Institutional Distance	-0.832***	-0.392***	-0.119***	-0.122***	1.428***
	(0.048)	(0.032)	(0.007)	(0.007)	(0.159)
Institutional Distance × Tone (Theme)	-0.413***		-0.012***		
	(0.031)		(0.001)		
Tone (Target - Theme - Year)		-0.164***		-0.013***	
		(0.006)		(0.001)	
Institutional Distance × Tone (Target - Theme - Year)		-0.163***		-0.016***	
		(0.016)		(0.002)	
Std of Dependent Variables	7.019	7.019	0.482	0.482	13.758
Std of Institutional Distance	0.212	0.212	0.212	0.212	0.212
Std of Tone (Theme)	0.863	0.863	0.863	0.863	-
Std of Tone (Target - Theme - Year)	1.546	1.546	1.546	1.546	-
Observations	5,925,850	5,925,850	5,925,850	5,925,850	247,808
Adjusted R-squared	0.204	0.205	0.459	0.460	0.227
Target by Theme FEs	Yes	Yes	Yes	Yes	Yes
Source Country FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the media bias with the theme selection approach. Other model specifications follow the convention in Table 2.

Table 5: Bias News Coverage on National Leaders

	Dependent Variable: Tone		
	(1)	(2)	(3)
Institutional Distance	-0.969***	-0.916***	-0.859***
	(0.163)	(0.142)	(0.123)
Std of Tone	3.418	3.418	3.418
Std of Institutioanl Distance	0.227	0.227	0.227
Observations	426,658	424,558	408,696
Adjusted R-squared	0.145	0.193	0.279
Number of Politicians	339	339	339
Number of Country Pairs	3,262	3,218	3,005
Domain FEs	Yes	No	No
Politician FEs	Yes	No	No
Year FEs	Yes	No	No
Domain by Year FEs	No	Yes	No
Politician by Year FEs	No	Yes	No
Domain by Year-Month FEs	No	No	Yes
Politician by Year-Month FEs	No	No	Yes

Notes: This table presents the media bias in biased reports on national leaders. Other model specifications follow the convention in Table 2.

Table 6: Regime Types

	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance	-0.394***	-0.387***	-0.119*	-0.106*
	(0.064)	(0.062)	(0.064)	(0.062)
Institutional Distance × Liberal Democracy Indicator (Source_country)	0.251***	0.246***		
	(0.080)	(0.078)		
Institutional Distance × Liberal Democracy Indicator (Target_country)			-0.298***	-0.318***
			(0.115)	(0.111)
Observations	81,288,434	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.278	0.291	0.278	0.291
Number of Country Pairs	14,379	14,379	14,379	14,379
Target Country x Theme x Year FEs	Yes	Yes	Yes	Yes
Media Outlet FEs	No	No	No	No
Media Outlet x Year FEs	Yes	No	Yes	No
Media Outlet x Theme x Year FEs	No	Yes	No	Yes

Notes: This table presents the heterogeneous effect of institutional distance on media bias conditional on the regime type of the source country or target country. *Liberal Democracy Indicator* is set to one if the source country or target country is a liberal democratic country, and zero otherwise. Other model specifications follow the convention in Table 2.

Table 7: Information Control

Panel A: Media Freedom

	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance	-0.352***	-0.346***	-0.329***	-0.327***
	(0.060)	(0.058)	(0.057)	(0.055)
ID × Freedom of Traditional Media	0.097***	0.095***		
	(0.027)	(0.026)		
ID × Freedom of the Internet			0.117***	0.119***
			(0.040)	(0.039)
Observations	81,288,434	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.278	0.291	0.278	0.291
Number of Country Pairs	14,379	14,379	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Panel B: Media Ownership

	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance	-0.433***	-0.423***	-0.329***	-0.322***
	(0.084)	(0.081)	(0.058)	(0.057)
ID × State-owned Print Media %	-0.145***	-0.140***		
	(0.045)	(0.043)		
ID × State-owned Broadcast Media %			-0.076**	-0.072**
			(0.034)	(0.032)
Observations	79,889,616	79,889,616	79,855,427	79,855,427
Adjusted R-squared	0.279	0.292	0.279	0.292
Number of Country Pairs	13,838	13,838	13,839	13,839
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Notes: This table presents the heterogeneous effect of institutional distance on media bias by country's information control. Models in Panel A analyze if the effect of institutional distance is conditioned on the media freedom of the source country. Models in Panel B analyze if the effect of institutional distance is conditioned on the media ownership structure of the source country. The sample is at the media outlet, target country, theme, and month level. Other model specifications follow the convention in Table 2.

Table 8: Economic Distress

	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance	-0.248***	-0.244***	-0.236***	-0.233***
	(0.047)	(0.045)	(0.050)	(0.048)
Growth of Monthly Light	-0.006	-0.006		
	(0.010)	(0.010)		
ID × Growth of Monthly Light	0.095***	0.090**		
	(0.036)	(0.036)		
ID × High Inflation			-0.155*	-0.154*
			(0.086)	(0.083)
Observations	66,414,057	66,411,598	80,117,942	80,117,942
Adjusted R-squared	0.289	0.302	0.279	0.292
Number of Country Pairs	12,640	12,640	14,326	14,326
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Notes: This table presents the heterogeneous effect of institutional distance on media bias by economic conditions. In this table, we analyze if the effect of institutional distance is conditional on the economic conditions of the source country. The sample is at the media outlet, target country, theme, and month level. Other model specifications follow the convention in Table 2.

Table 9: Domestic Turmoil

	All Sample		Non-Liberal	Liberal Democracy
	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance	-0.260***	-0.237***	-0.243**	-0.346*
	(0.043)	(0.084)	(0.099)	(0.201)
Turmoil Ratio	-0.602***	-0.543**	-0.108	-0.661**
	(0.094)	(0.220)	(0.257)	(0.303)
Institutional Distance × Turmoil Ratio		-0.201	-1.722**	0.552
		(0.706)	(0.761)	(0.996)
Observations	81,288,434	81,288,434	32,836,225	48,451,923
Adjusted R-squared	0.291	0.291	0.239	0.333
Number of Country Pairs	14,379	14,379	13,521	6,217
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes	Yes	Yes

Notes: This table presents the heterogeneous effect of institutional distance on media bias by economic conditions. In this table, we analyze if the effect of institutional distance is conditional on the domestic turmoil of the source country. The sample is at the media outlet, target country, theme, and month level. Other model specifications follow the convention in Table 2.

Table 10: Equity Market Reactions

	Dependent Variable		
	Monthly Returns	Abnormal Monthly Returns (CAPM)	Abnormal Monthly Returns (FF3)
	(1)	(2)	(3)
Tone Exposure	0.0081***	0.0065***	0.0067***
	(0.002)	(0.002)	(0.002)
Observations	149,173	147,497	146,383
Adjusted R-squared	0.188	0.045	0.015
mean(Tone Exposure)	-0.492	-0.492	-0.492
std(Tone Exposure)	0.406	0.406	0.406
mean(Dependent Variable)	0.010	-0.005	-0.003
std(Dependent Variable)	0.132	0.120	0.121
Firm FEs	Yes	Yes	Yes
Year-Month FEs	Yes	Yes	Yes

Notes: This table presents evidence on responses of the equity market to the global media bias. We retrieve the information on monthly stock returns for a sample of US firms from the Center for Research in Security Prices (CRSP) merged with Compustat. We construct $Tone\ Exposure_{i,t} = \sum_{c=1}^{C} Tone_{c,t} \times Rev_{i,c,t}$, where $Rev_{i,c,t}$ is a firm's revenue share from a given country based on information from Factset Revere database. $Tone_{c,t}$ is the average tone from media outlet from a given country towards US. The resultant sample is at the firm-month level and consists of 2,590 distinct firms in the period between 2015 and 2022. Observations with missing $Tone\ Exposure_{i,t}$ are excluded. Monthly Returns is the monthly return for a given firm. Abnormal Monthly Returns (CAPM) is abnormal monthly return adjusted by the market model. Abnormal Monthly Returns (FF3) is abnormal monthly return adjusted by the Fama-French 3 factor model. We consider firm fixed effect and year-month fixed effects. Standard errors are clustered at the firm level and reported in parentheses.

Table 11: Syndicated Loan Market Reactions

Panel A. Loan Originations

	Deal Number			Deal Value		
	(1)	(2)	(3)	(4)	(5)	(6)
Tone	0.0285***	0.0286***	0.0286***	0.0485***	0.0485***	0.0485***
	(0.010)	(0.010)	(0.010)	(0.017)	(0.017)	(0.017)
Observations (Full Sample)	9,860,999	9,860,999	9,860,999	9,860,999	9,860,999	9,860,999
Observations (Drop Singletons/Seperations)	6,193,432	2,579,074	132,309	6,193,432	2,560,506	131,774
Pseudo R-squared	0.337	0.753	0.690	0.379	0.852	0.844
mean(Tone)	-1.848	-1.848	-1.848	-1.848	-1.848	-1.848
std(Tone)	1.702	1.702	1.702	1.702	1.702	1.702
Country Pair FEs	Yes	Yes	No	Yes	Yes	No
Lender FEs	No	Yes	No	No	Yes	No
Lender-Target Country FEs	No	No	Yes	No	No	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Cost of Borrowing

	Spread		
	(1)	(2)	(3)
Tone	-0.028***	-0.023***	-0.027***
	(0.007)	(0.006)	(0.007)
Observations	158682	158242	156391
Pseudo R-squared	0.195	0.289	0.325
mean(Tone)	-0.975	-0.975	-0.975
std(Tone)	0.961	0.961	0.961
Country Pair FEs	Yes	Yes	No
Lender FEs	No	Yes	No
Lender-Target Country FEs	No	No	Yes
Year FEs	Yes	Yes	Yes

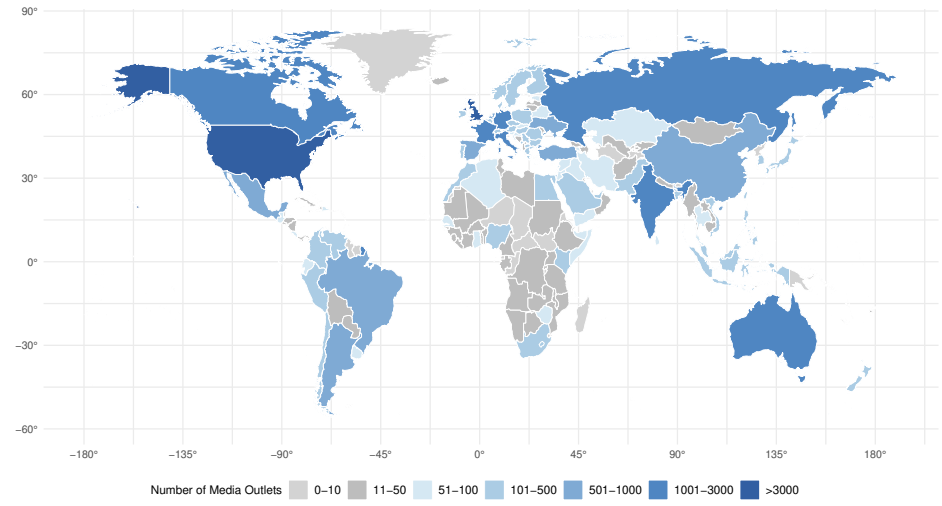
Notes: This table presents evidence on responses of the syndicated loan market to the global media bias. The information on syndicated loans is sourced from the Dealscan database. The initial sample comprises syndicated loan deals involving borrowing firms from 169 countries and lending banks from 142 countries. We measure inter-country media bias through the average tone of news articles at the country-pair and year level. To capture the banks' responses to media bias from potential borrowers' countries, we construct a lender-target country-year level sample. This refined sample includes 9,860,999 observations with 8,772 banks spanning from 2015 to 2022. Panel A presents the effects of media bias originating from one country on the quantity and size of loans issued to borrowers from another country. *Deal Number* refers to the count of syndicated loans extended by banks from a specific country to borrowers in different countries. *Deal Value* represents the aggregate value of these loans. The analyses in Panels A rely on a Poisson model, as the outcome variable is sparse and contains many zero entries. In Panel B, we report deal-level results. This subset contains 158,682 loan facilities with essential information on deal and media variables. Here, the dependent variable is the spread of each syndicated loan, which reflects the cost of borrowing. *Spread* is defined as the log value of the all-in drawn spread as provided in the Dealscan database. We consider country pair, lender, lender by target country, and year fixed effects. Standard errors are clustered at the lender level and reported in brackets.

Table 12: Public Opinion Reactions

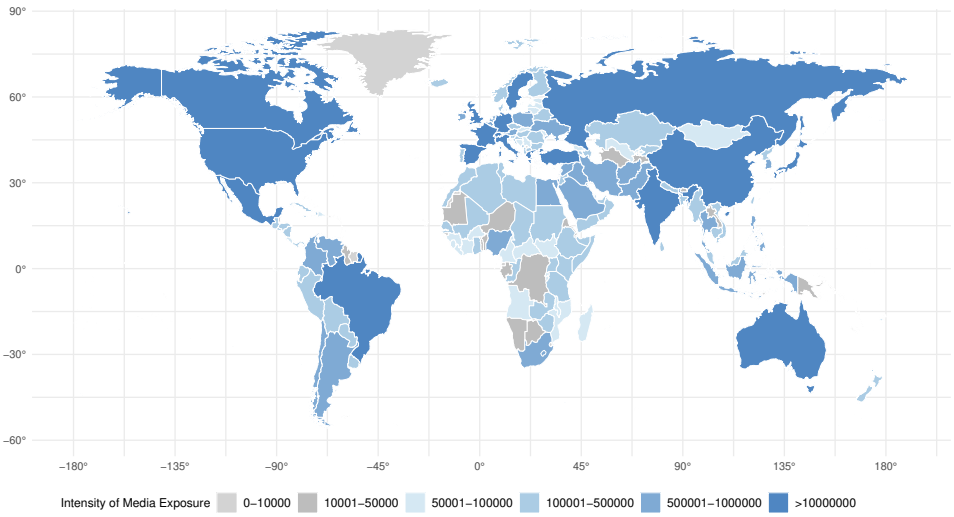
	Dependent Variable: Approval of Leadership	
	(1)	(2)
Average Tone	0.028***	0.027***
	(0.004)	(0.004)
Observations	2,658,239	2,614,458
Adjusted R-squared	0.036	0.043
Number of Country Pairs	745	744
Mean of Approval	0.537	0.537
SD of Approval	0.498	0.498
Mean of Tone	-1.878	-1.878
SD of Tone	1.385	1.385
Target Country FEs	Yes	Yes
Year FEs	Yes	Yes
Control Variables	No	Yes

Notes: This table presents evidence on responses of the public opinion to the global media bias.

Figures



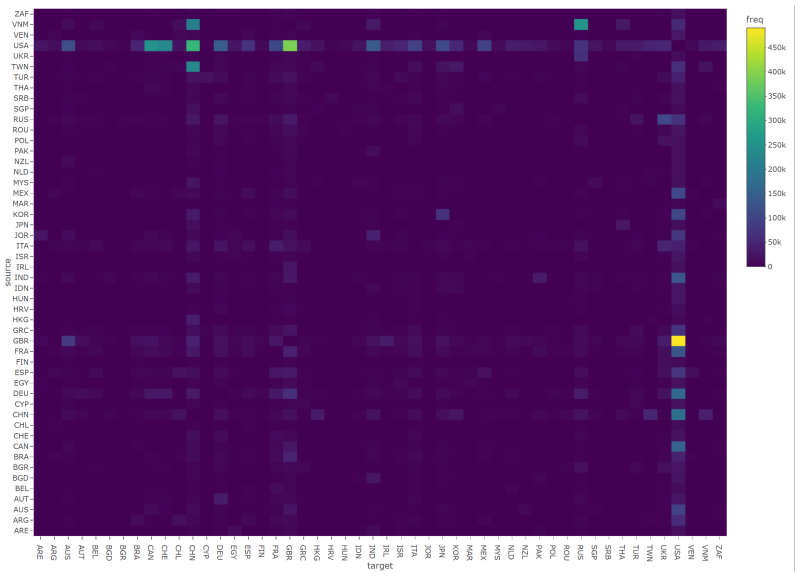
(a) Global Distribution of Media Outlets



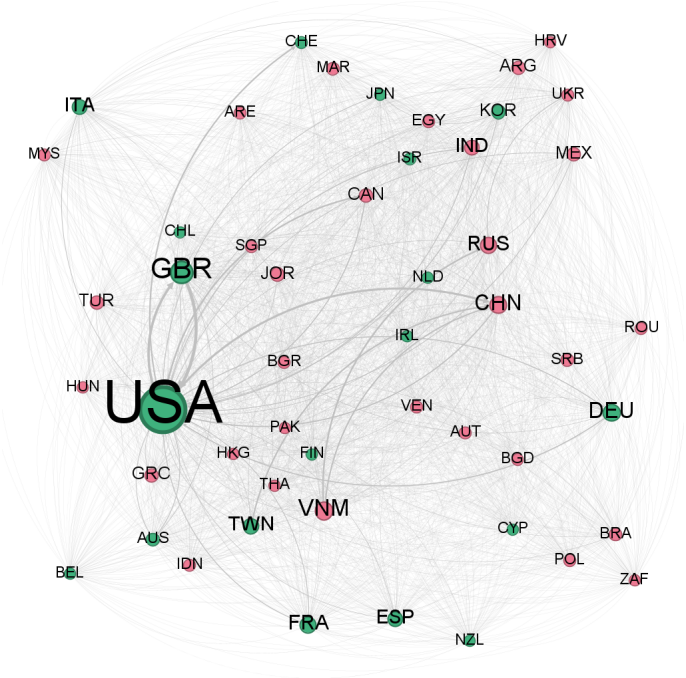
(b) Media Exposure

Figure 1: Media Landscape

Notes: This figure shows the geographical distribution of the media outlets and coverage. Panel (a) shows the number of media outlets in our sample. Panel (b) show the intensity of coverage across countries.



(a) Bilateral Frequency



(b) Reporting Network

Figure 2: Bilateral Reporting Relations

Notes: Panel (a) shows the heat map shows the intensity of news coverage from one country to another. For simplicity, we consider top 50 countries according to the total number of news articles issued by news outlets from these countries. Y-axis denotes the source country and X-axis denotes the target country. The color shows the number of news article from news outlets from source country covering issues from target country. Panel (b) shows the network figure where the size of the node indicates the total number of news articles issued. The thickness of the edges is based on the number of articles from one country to another. Blue nodes and red nodes indicate democratic countries and non-democratic countries, respectively.

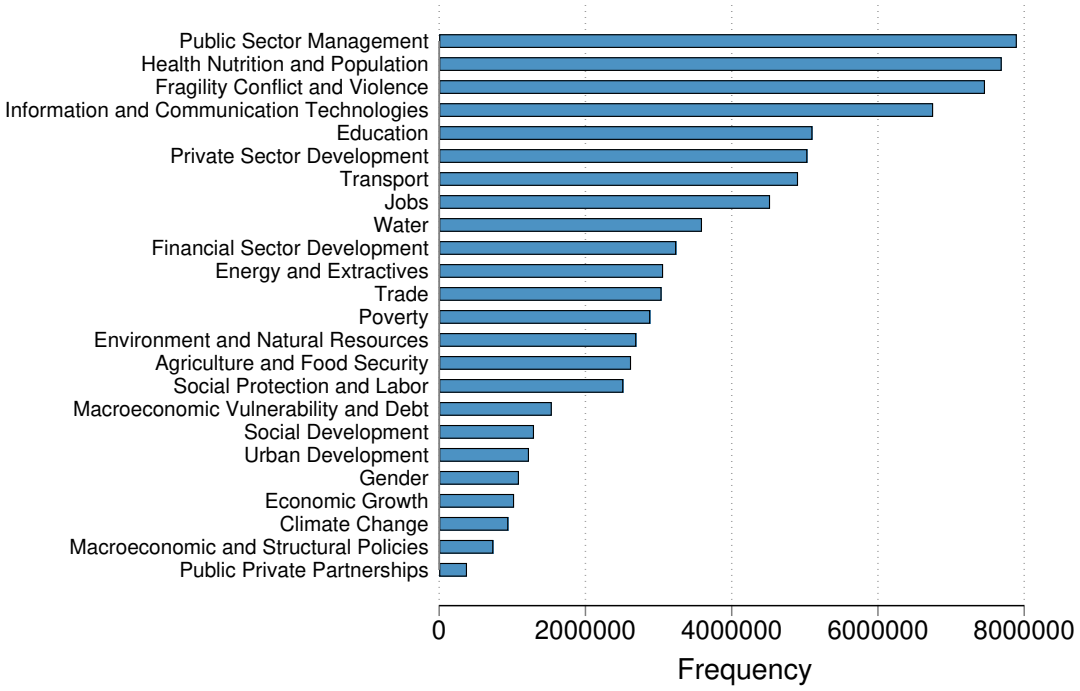
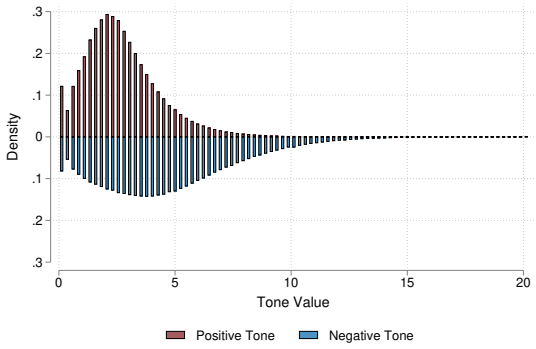
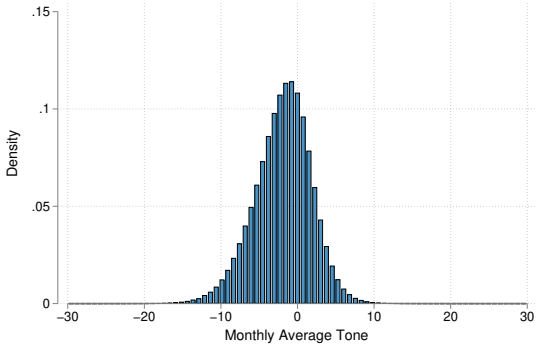


Figure 3: Themes Distribution

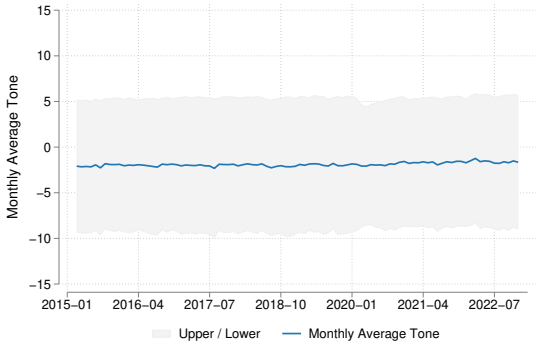
Notes: This figure shows frequency of the observations by media theme.



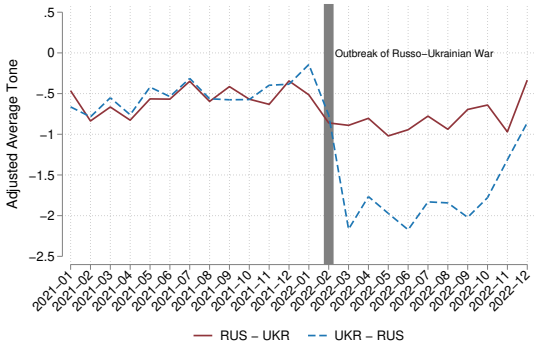
(a) Positive & Negative Tone Distribution



(b) Tone Distribution



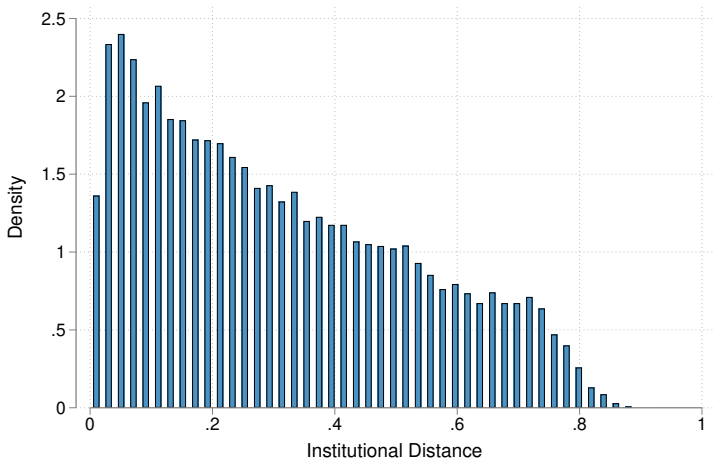
(c) Intertemporal Pattern of the Tone Measure



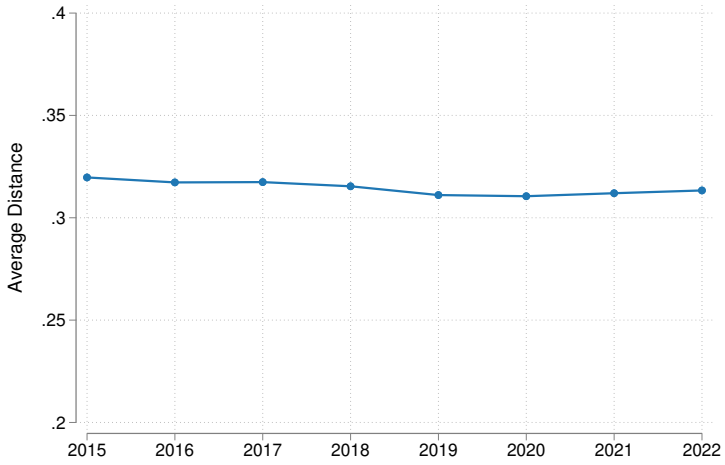
(d) Tone Changes in Russian and Ukrainian Media

Figure 4: Distribution of Tone Measures

Notes: Panel (a) shows the distribution of the dependent variable, the tone of the media. Panel (b) displays the distribution of positive and negative tones. Panel (c) shows the intertemporal pattern of the tone measure. Panel (d) shows the changes in adjusted tones of Russian and Ukrainian media when they reported each other. The tone in this graph is adjusted by removing the theme by year-month fixed effects.



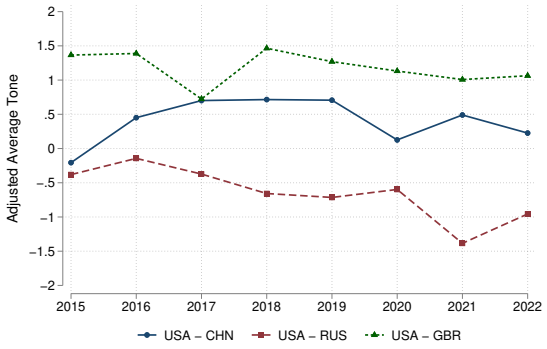
(a) Distribution of Institutional Distance



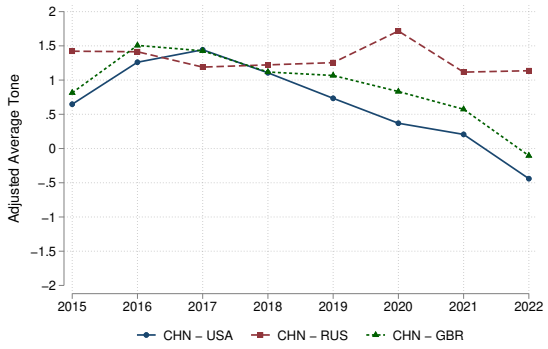
(b) Changes of Institutional Distance

Figure 5: Distribution of Institutional Distance

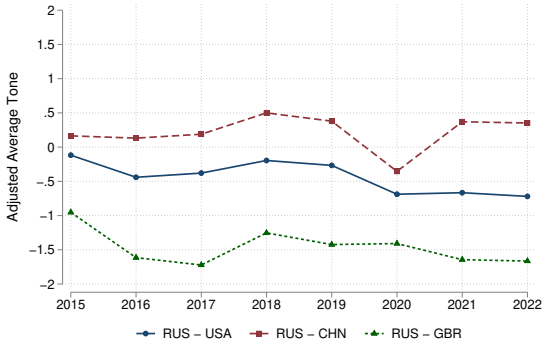
Notes: This figure shows the distribution of the main independent variable, the institutional distance.



(a) Source Country: USA



(b) Source Country: CHN



(c) Source Country: RUS

Figure 6: Tone Measures over Time by Country

Notes: Panel (a) shows the average tone of news articles issued by the United States covering issues in China, Russia, and United Kingdom. Panel (b) presents the average tone of news articles issued by the China covering issues in United States, Russia, and United Kingdom. Panel (c) shows the average tone of news articles issued by the Russia covering issues in United States, China, and United Kingdom. Tones in these panels are adjusted by removing the theme by year-month fixed effects.

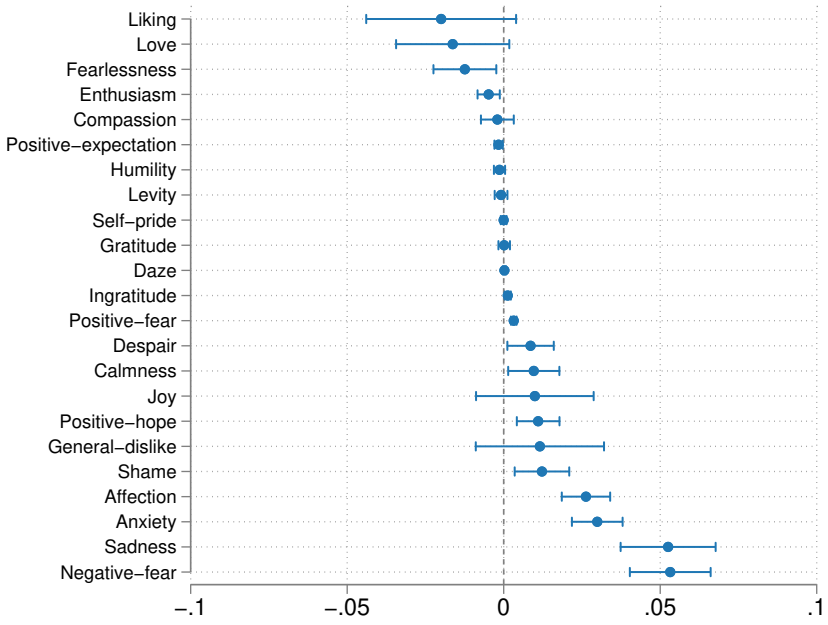


Figure 7: Effects on Sentiment Measures

Notes: This figure presents the estimated effects of institutional distance on a wide range of sentiment measures classified by the WordNet-Affect lexicon.

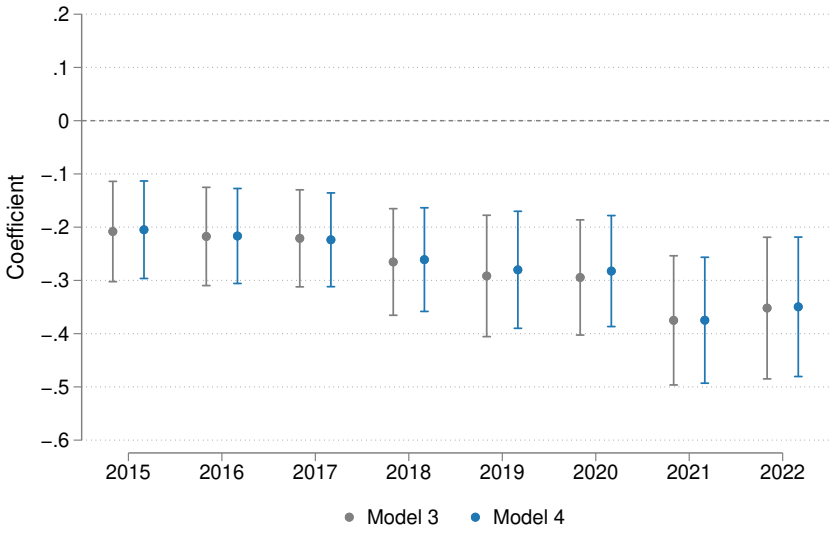


Figure 8: Dynamic Effects

Notes: This figure presents the dynamic effects of institutional distance on media bias. The plot is based on coefficients in models (3) and (4) of Table 3.

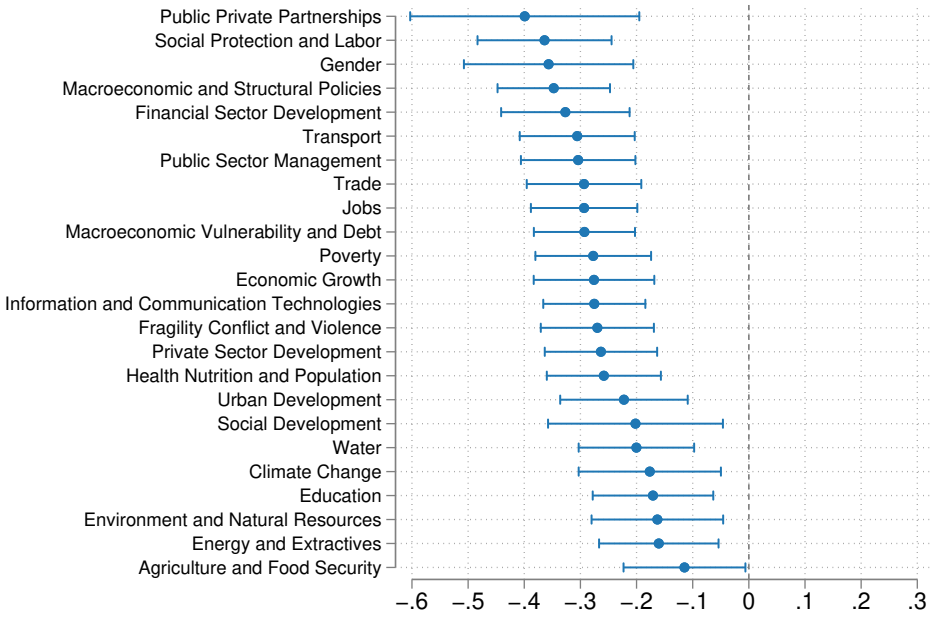
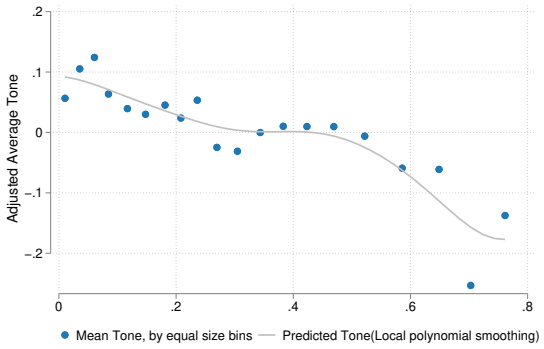
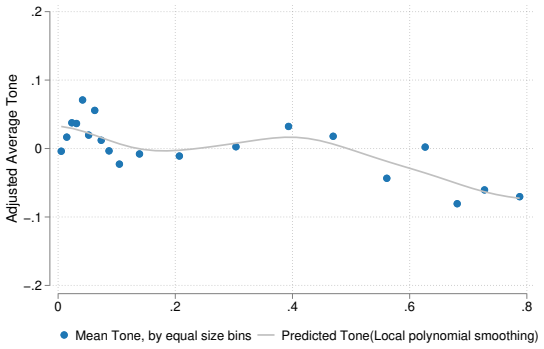


Figure 9: Heterogeneous Effect by Media Theme

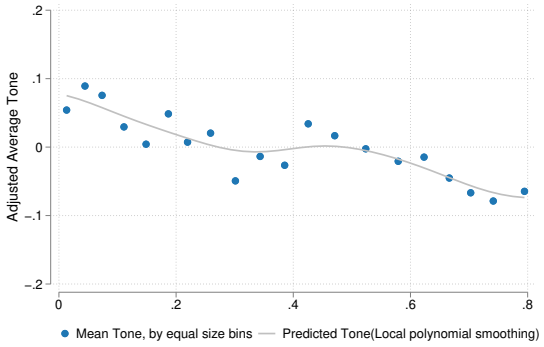
Notes: This figure shows the heterogeneous effect of Institutional Distance by media theme. We consider the level 1 of World Bank theme category.



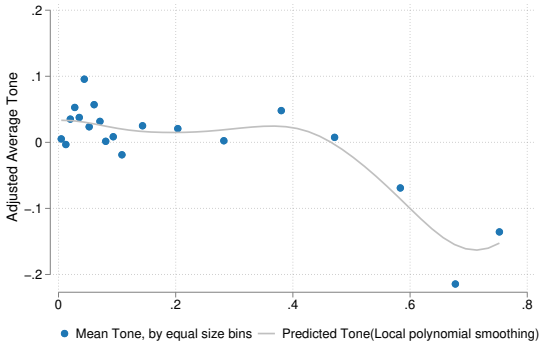
(a) Non-Democracies as Source Countries



(b) Liberal Democracies as Source Countries



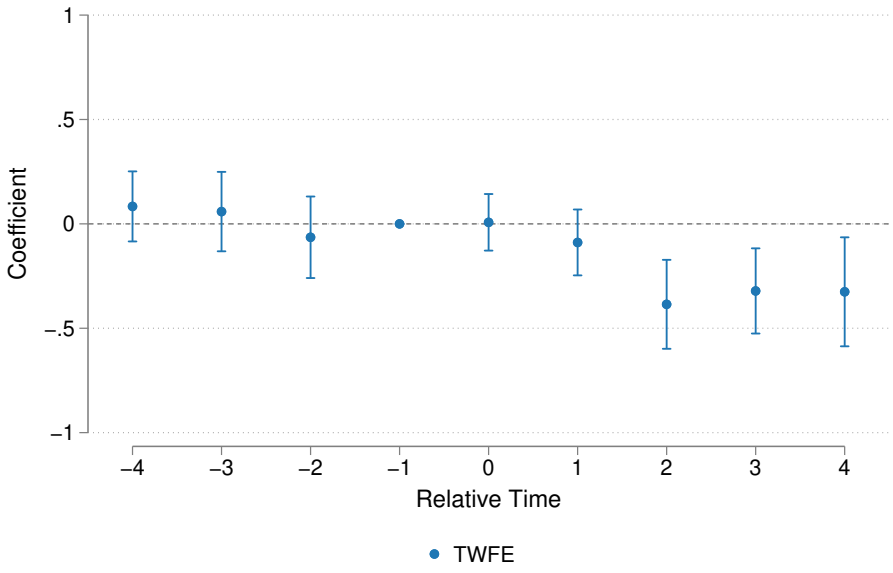
(c) Non-Democracies as Target Countries



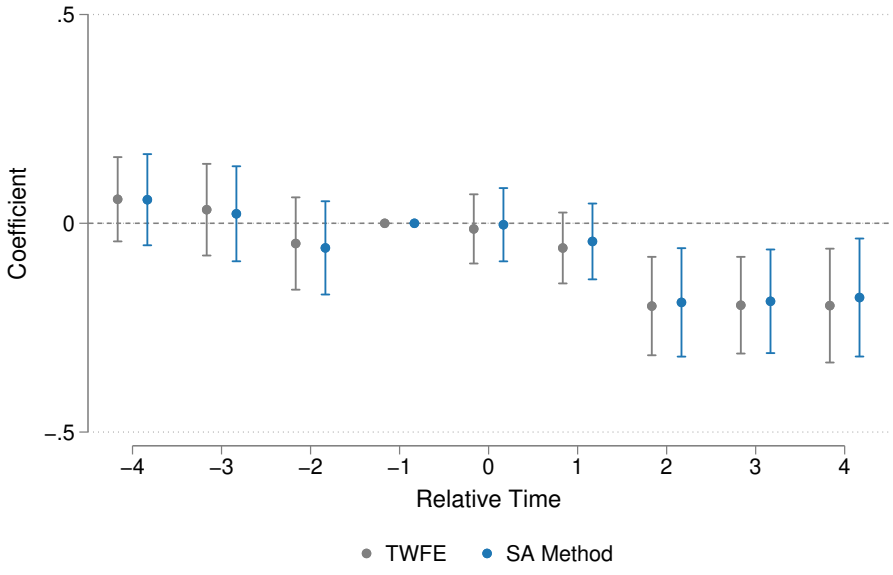
(d) Liberal Democracies as Target Countries

Figure 10: Democracy and Media Bias

Notes: This figure visualize the effect of institutional distance on media bias across different regime types. We adjust the tone measure by considering the two main sets of fixed effects considered in our baseline analysis (Outlet × Theme × Year, Target Country × Theme × Year) and retrieve the residual. The sample is split by Liberal Democracy Indicator$^{\text{Source Country}}_{c,t}$ and Liberal Democracy Indicator$^{\text{Target Country}}_{c,t}$. We group the observations into 20 bins and plot the mean of the adjusted tone against the institutional distance for four separate subsamples.



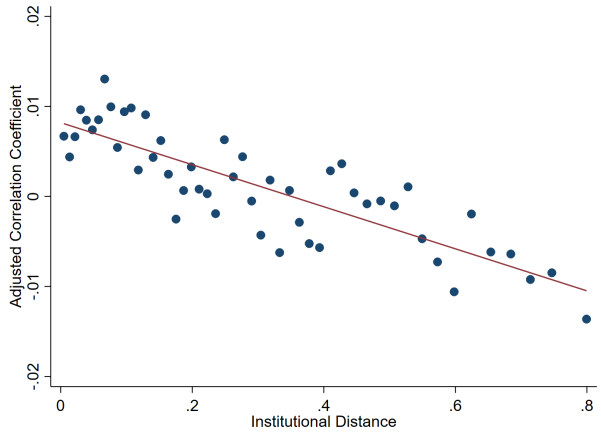
(a) Continuous DiD



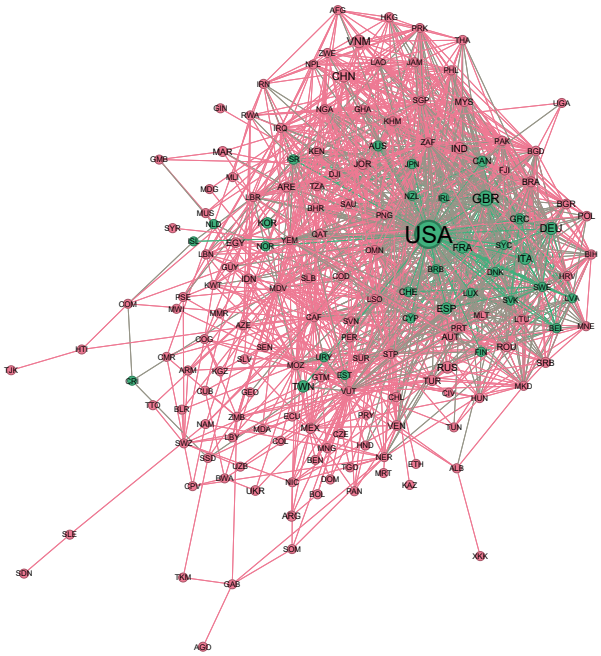
(b) Staggered DiD

Figure 11: DID Event Study

Notes: This figure presents the dynamic effects in the natural experiments based on regime shifts. The coefficients are based on models in Table A16.



(a) Institutional Distance and Alliances



(b) Alliance Networks

Figure 12: Institutional Distance and Alliance Networks

Notes: This figure shows the how institutional distance affect the alliances in media coverage between countries. Panel (a) shows the bin scatter plot of correlation coefficients (ρ) in media tone between two countries based on how they cover other countries against the institutional distance between the two. The correlation coefficients (ρ) is adjusted by removing the target country, source country and year fixed effects. Panel (b) show the network graph where nodes are countries. Two countries are linked if the correlation coefficient in 2022 is in the top 10% percentile. Blue nodes indicates democratic countries. Red nodes denotes non-democratic countries. The size of the nodes is based on the number of news articles reported by outlet from a given country.

Online Appendix

Table of Contents

A Additional Tables and Figures **58**

B Data Construction **72**

C Examples of New Articles from GDELT **76**

D Major News Producers by Country **78**

E Variable Definitions **79**

A Additional Tables and Figures

Table A1: Additional Summary Statistics

Panel A: Summary Statistics by Selective Country Pairs

	Tone				
Source Country - Target Country	Mean	Median	Std	P25	P75
USA - GBR	-.800	-.633	3.245	-2.710	1.297
GBR - USA	-.896	-.858	3.159	-3.107	1.331
USA - CHN	-1.551	-1.408	3.235	-3.548	.571
CHN - USA	-1.379	-1.237	3.019	-3.090	.398
USA - RUS	-2.546	-2.400	3.387	-4.706	-.284
RUS - USA	-1.912	-1.887	2.840	-3.571	-.183
CHN - RUS	-.424	-.263	3.564	-2.463	1.823
RUS - CHN	-1.467	-1.306	3.022	-3.246	.469
USA - IRN	-3.079	-2.825	3.660	-5.405	-.502
IRN - USA	-2.833	-2.859	3.019	-4.782	-.879

Panel B: Summary Statistics by Top 10 Themes

	Tone				
Theme	Mean	Median	Std	P25	P75
Public Sector Management	-2.579	-2.473	3.785	-4.952	.000
Health Nutrition and Population	-2.470	-2.290	3.785	-4.764	.000
Fragility Conflict and Violence	-3.795	-3.682	3.914	-6.291	-1.158
Information and Communication Technologies	-1.762	-1.508	3.751	-4.104	.771
Education	-1.405	-1.205	3.681	-3.596	.991
Private Sector Development	-1.624	-1.401	3.622	-3.791	.775
Transport	-2.037	-1.812	3.754	-4.444	.575
Jobs	-.740	-.563	3.377	-2.722	1.440
Water	-1.652	-1.393	3.600	-3.846	.720
Financial Sector Development	-1.633	-1.362	3.377	-3.554	.544

Table A2: Positive Tone VS. Negative Tone

	Dependent Variable			
	Postive Tone		Negative Tone	
	(1)	(2)	(3)	(4)
Institutional Distance	-0.050***	-0.049***	0.213***	0.211***
	(0.017)	(0.017)	(0.034)	(0.032)
Observations	81,288,434	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.181	0.194	0.293	0.306
Number of Country Pairs	14,379	14,379	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Notes: This table presents the baseline estimation of the impact of institutional distance on global media bias by positive and negative tones. Dependent variables, *Positive Tone* and *Negative Tone*, are the average percentage of positive words and negative words in the news articles, respectively. The sample is at the media outlet, target country, theme, and month level. Other model specifications follow the convention in Table 2.

Table A3: Alternative Model Specifications

	Dependent Variable: Monthly Average Tone				
	(1)	(2)	(3)	(4)	(5)
Institutional Distance	-0.158**	-0.154**	-0.247***	-0.166***	-0.160***
	(0.063)	(0.062)	(0.043)	(0.058)	(0.058)
Observations	81,288,234	81,255,725	74,700,750	74,700,489	74,662,739
Adjusted R-squared	0.300	0.306	0.330	0.339	0.344
Number of Country Pairs	14,185	13,566	14,340	14,120	13,488
Target Country × Theme × Year FEs	Yes	Yes	No	No	No
Outlet × Theme × Year FEs	Yes	Yes	No	No	No
Target Country × Theme × Month FEs	No	No	Yes	Yes	Yes
Outlet × Theme × Month FEs	No	No	Yes	Yes	Yes
Country Pair FEs	Yes	No	No	Yes	No
Country Pair × Theme FEs	No	Yes	No	No	Yes

Notes: We consider alternative model specifications in addition to models in Table 2. Other variable construction and model specifications follow the convention in Table 2.

Table A4: Alternative SE Cluster Methods

	Dependent Variable: Monthly Average Tone				
	(1)	(2)	(3)	(4)	(5)
Institutional Distance	-0.260***	-0.260***	-0.260***	-0.260***	-0.260***
	(0.046)	(0.058)	(0.059)	(0.013)	(0.023)
SE Cluster Level	Country-pair × Year	Source country	Source country × Year	Outlet	Outlet × Year
Observations	81,288,434	81,288,434	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.291	0.291	0.291	0.291	0.291
Number of Cluster 1	14,379	176	176	55,240	55,240
Number of Cluster 2	8	0	8	0	8
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table presents robustness checks to the baseline estimation by using different clustered standard errors. Other variable construction and model specifications follow the convention in Table 2.

Table A5: Alternative Measures of Tone

	Dependent Variable			
	Tone (LSD)		Tone (SWN)	
	(1)	(2)	(3)	(4)
Institutional Distance	-0.176***	-0.175***	-0.001***	-0.002***
	(0.045)	(0.043)	(0.000)	(0.000)
Observations	81,288,434	81,288,434	81,288,433	81,288,433
Adjusted R-squared	0.289	0.301	0.150	0.158
Number of Country Pairs	14,379	14,379	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Notes: This table presents results based on alternative measures of sentiments. We consider two alternative measures with Lexicoder Sentiment Dictionary (LSD) and SentiWordNet 3.0 (SWN) provided in GDELT GKG 2.0 database. Tone (LSD) is measured with the difference between positive word frequency and negative word frequency used by media outlets. Tone(SWN) is measured with the difference between the positive values and negative values of news. Other variable construction and model specifications follow the convention in Table 2.

Table A6: Alternative Measures of Institutional Distance

	Dependent Variable: Monthly Average Tone			
	(1)	(2)	(3)	(4)
Institutional Distance (Electoral Democracy)	-0.304***	-0.300***		
	(0.051)	(0.049)		
Institutional Distance (PolityV Index)			-0.014***	-0.014***
			(0.003)	(0.003)
Observations	81,288,434	81,288,434	57,984,858	57,980,165
Adjusted R-squared	0.278	0.291	0.280	0.294
Number of Country Pairs	14,379	14,379	12,684	12,684
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes
Outlet × Year FEs	Yes	No	Yes	No
Outlet × Theme × Year FEs	No	Yes	No	Yes

Notes: This table presents robustness checks to the baseline estimation by using different measures of institutional distance. Other variable construction and model specifications follow the convention in Table 2.

Table A7: Effects on WNA Sentiments

	Dependent Variable				
	Joy	Love	Affection	Liking	Enthusiasm
Institutional Distance	0.010	-0.016*	0.026***	-0.020	-0.005***
	(0.010)	(0.009)	(0.004)	(0.012)	(0.002)
Observations	81,288,425	81,288,397	81,288,434	81,288,416	81,288,434
Adjusted R-squared	0.158	0.129	0.051	0.220	0.103
	Gratitude	Self-pride	Levity	Calmness	Fearlessness
Institutional Distance	0.000	-0.000	-0.001	0.010**	-0.012**
	(0.001)	(0.000)	(0.001)	(0.004)	(0.005)
Observations	81,288,434	81,288,434	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.089	0.046	0.117	0.108	0.102
	Positive-expectation	Positive-fear	Positive-hope	Negative-fear	Sadness
Institutional Distance	-0.002**	0.003***	0.011***	0.053***	0.053***
	(0.001)	(0.000)	(0.003)	(0.007)	(0.008)
Observations	81,288,434	81,288,434	81,288,434	81,288,427	81,288,426
Adjusted R-squared	0.065	0.026	0.090	0.045	0.089
	General-dislike	Ingratitude	Shame	Compassion	Humility
Institutional Distance	0.012	0.001***	0.012***	-0.002	-0.001
	(0.010)	(0.001)	(0.004)	(0.003)	(0.001)
Observations	81,288,424	81,288,434	81,288,434	81,288,434	81,288,434
Adjusted R-squared	0.119	0.082	0.080	0.106	0.119
	Despair	Anxiety	Daze		
Institutional Distance	0.009**	0.030***	0.000		
	(0.004)	(0.004)	(0.000)		
Observations	81,288,434	81,288,434	81,288,434		
Adjusted R-squared	0.074	0.062	0.138		
Target Country × Theme × Year FEs	Yes	Yes	Yes		
Outlet × Theme × Year FEs	Yes	Yes	Yes		

Notes: This figure presents the estimated effects of institutional distance on a wide range of sentiment measures classified by the WordNet-Affect lexicon.

Table A8: Winsorization

	Dependent Variable: Monthly Average Tone		
	Winsor 0.5%	Winsor 1%	Winsor 5%
	(1)	(2)	(3)
Institutional Distance	-0.264***	-0.266***	-0.264***
	(0.043)	(0.042)	(0.039)
Observations	81,288,433	81,288,433	81,288,432
Adjusted R-squared	0.295	0.297	0.303
Number of Country Pairs	14,379	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes	Yes

Notes: This table presents robustness checks to the baseline estimation by winsorizing the dependent variable, *Tone*. We winsorize the dependent variable at 0.5%, 1%, and 5%, respectively. Other variable construction and model specifications follow the convention in Table 2.

Table A9: Excluding Observations Related to the United States

	Dependent Variable: Monthly Average Tone		
	(1)	(2)	(3)
Institutional Distance	-0.296***	-0.276***	-0.303***
	(0.044)	(0.045)	(0.047)
Observations	63,127,811	76,624,788	56,279,085
Adjusted R-squared	0.260	0.289	0.259
Number of Country Pairs	14,265	14,265	14,089
Drop USA as Source Country	Yes	No	Yes
Drop USA as Target Country	No	Yes	Yes
Target Country × Theme × Month FEs	Yes	Yes	No
Outlet × Theme × Year FEs	Yes	Yes	Yes

Notes: This table presents robustness checks to the baseline estimation by removing observations related to the United States. Other variable construction and model specifications follow the convention in Table 2.

Table A10: Domain Source Identification Rules

	Dependent Variable: Monthly Average Tone				
	(1)	(2)	(3)	(4)	(5)
Institutional Distance	-0.263***	-0.240***	-0.262***	-0.575***	-0.313***
	(0.042)	(0.062)	(0.043)	(0.066)	(0.059)
Domain Source Rule	Most Frequency Rule	DNS	ChatGPT	Wiki	Top Level Domain
Observations	81,198,262	78,975,513	81,202,902	1,693,339	35,135,302
Adjusted R-squared	0.291	0.292	0.291	0.228	0.250
Target Country × Theme × Year FEs	Yes	Yes	Yes	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes	Yes	Yes	Yes

Notes: This table presents robustness checks to the baseline estimation by using different domain source identification strategies. Other variable construction and model specifications follow the convention in Table 2.

Table A11: Controlling for Economic Interdependence and Conflicts

	Dependent Variable: Monthly Average Tone		
	(1)	(2)	(3)
Institutional Distance	-0.253***	-0.255***	-0.250***
	(0.047)	(0.046)	(0.042)
Trade Dependence	0.137		
	(0.092)		
Trade Balance		-0.285	
		(0.277)	
Sanctioned			-0.042
			(0.045)
Observations	77,527,780	77,513,860	81,288,434
Adjusted R-squared	0.293	0.293	0.291
Target Country × Theme × Year FEs	Yes	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes	Yes

Notes: This table presents robustness checks to the baseline estimation by including control variables related to trade relations. Other variable construction and model specifications follow the convention in Table 2.

Table A12: Alternative Sample Construction

	Dependent Variable: Monthly Average Tone		
	(1)	(2)	(3)
Institutional Distance	-0.350***	-0.332***	-0.355***
	(0.035)	(0.034)	(0.032)
Std of Monthly Average Tone	3.988	3.988	3.988
Std of Institutional Distance	0.226	0.226	0.226
Observations	34,958,288	34,958,288	34,958,288
Adjusted R-squared	0.304	0.314	0.331
Number of Country Pairs	14,200	14,200	14,200
Target Country × Theme × Year FEs	Yes	Yes	Yes
Outlet Fes	Yes	No	No
Outlet × Year FEs	No	Yes	No
Outlet × Theme × Year FEs	No	No	Yes

Notes: We replicate the baseline results in Table 2 using data from the GDELT Event 2.0 Database

Table A13: Media Bias by Theme

	Dependent Variable: Monthly Average Tone	
	(1)	(2)
Institutional Distance × Information and Communication Technologies	-0.285***	-0.275***
	(0.0495)	(0.0464)
Institutional Distance × Social Development	-0.153*	-0.202**
	(0.0877)	(0.0794)
Institutional Distance × Transport	-0.310***	-0.306***
	(0.0516)	(0.0522)
Institutional Distance × Water	-0.232***	-0.200***
	(0.0543)	(0.0525)
Institutional Distance × Agriculture and Food Security	-0.157***	-0.115**
	(0.0592)	(0.0554)
Institutional Distance × Macroeconomic and Structural Policies	-0.246***	-0.347***
	(0.0668)	(0.0511)
Institutional Distance × Education	-0.152***	-0.171***
	(0.0541)	(0.0548)
Institutional Distance × Economic Growth	-0.160**	-0.276***
	(0.0779)	(0.0548)
Institutional Distance × Energy and Extractives	-0.0766	-0.160***
	(0.0823)	(0.0543)
Institutional Distance × Environment and Natural Resources	-0.261***	-0.163***
	(0.0608)	(0.0598)
Institutional Distance × Climate Change	-0.208***	-0.176***
	(0.0786)	(0.0646)
Institutional Distance × Gender	-0.168	-0.357***
	(0.109)	(0.0770)
Institutional Distance × Health Nutrition and Population	-0.338***	-0.258***
	(0.0576)	(0.0518)
Institutional Distance × Poverty	-0.237***	-0.277***
	(0.0627)	(0.0526)
Institutional Distance × Public Sector Management	-0.409***	-0.304***
	(0.0575)	(0.0520)
Institutional Distance × Social Protection and Labor	-0.358***	-0.364***
	(0.0672)	(0.0609)
Institutional Distance × Trade	-0.247***	-0.294***
	(0.0635)	(0.0520)
Institutional Distance × Urban Development	-0.355***	-0.222***
	(0.0993)	(0.0579)
Institutional Distance × Macroeconomic Vulnerability and Debt	-0.191***	-0.293***
	(0.0676)	(0.0459)
Institutional Distance × Financial Sector Development	-0.379***	-0.327***
	(0.0917)	(0.0584)
Institutional Distance × Private Sector Development	-0.205***	-0.263***
	(0.0558)	(0.0511)
Institutional Distance × Public Private Partnerships	-0.319***	-0.399***
	(0.119)	(0.104)
Institutional Distance × Fragility Conflict and Violence	-0.257***	-0.270***
	(0.0585)	(0.0514)
Institutional Distance × Jobs	-0.192***	-0.293***
	(0.0560)	(0.0483)
Observations	81288434	81288434
Adjusted R-squared	0.278	0.291
Number of Country Pairs	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes
Outlet × Year FEs	Yes	No
Outlet × Theme × Year FEs	No	Yes

Notes: This table presents the media bias by news article theme. We consider first level of World Bank Theme Category. Other variable construction and model specifications follow the convention in Table 2.

Table A14: Timing of the Democratic Erosion

Country	Treatment Year
Afghanistan	2016
Albania	2018
Austria	2021
El Salvador	2018
Guatemala	2018
Guinea	2019
Iran	2021
Lithuania	2016
Mali	2017
Myanmar (Burma)	2021
Nigeria	2021
Philippines	2016
Poland	2016
Portugal	2021
Sudan	2019
Togo	2016
Trinidad and Tobago	2021

Notes: This table presents timing of the democratic erosion in the natural experiments as shown in Table 8. We show the treatment countries in our sample period between 2015 and 2022.

Table A15: Autocratization and Media Bias

	Dependent Variable: Monthly Average Tone	
	(1)	(2)
Autocratization × Liberal Democracy Index (Target Country)	-0.127**	
	(0.060)	
Autocratization × Liberal Democracy Indicator (Target Country)		-0.089***
		(0.032)
Observations	60,330,253	60,330,253
Adjusted R-squared	0.372	0.372
Number of Country Pairs	11,040	11,040
Target Country × Theme × Year FEs	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes
Outlet × Target Country FEs	Yes	Yes

Notes: This table presents the result of democratic erosion. At this step, we drop the always-treated group and close autocracy countries that cannot experience democratic erosion.

Table A16: Dynamic Effect of Democratic Erosion

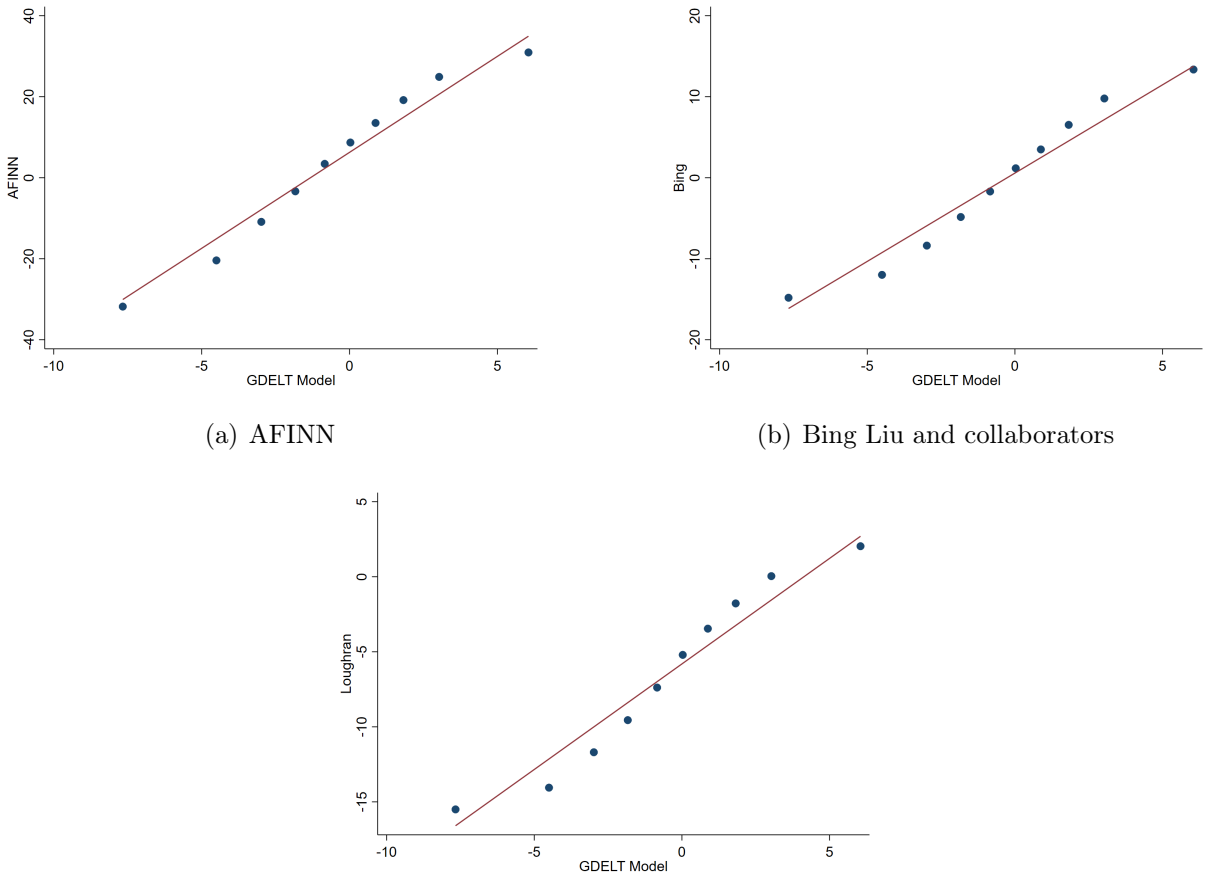
	Dependent Variable: Monthly Average Tone		
	TWFE	TWFE	SA Method
	(1)	(2)	(3)
t-4 × Liberal Democracy Index (Target Country)	0.084		
	(0.086)		
t-3 × Liberal Democracy Index (Target Country)	0.059		
	(0.097)		
t-2 × Liberal Democracy Index (Target Country)	-0.064		
	(0.100)		
t × Liberal Democracy Index (Target Country)	0.007		
	(0.069)		
t+1 × Liberal Democracy Index (Target Country)	-0.089		
	(0.080)		
t+2 × Liberal Democracy Index (Target Country)	-0.385***		
	(0.109)		
t+3 × Liberal Democracy Index (Target Country)	-0.321***		
	(0.104)		
t+4 × Liberal Democracy Index (Target Country)	-0.325**		
	(0.133)		
t-4 × Liberal Democracy Indicator (Target Country)		0.058	0.056
		(0.051)	(0.056)
t-3 × Liberal Democracy Indicator (Target Country)		0.033	0.023
		(0.056)	(0.058)
t-2 × Liberal Democracy Indicator (Target Country)		-0.048	-0.059
		(0.056)	(0.057)
t × Liberal Democracy Indicator (Target Country)		-0.013	-0.003
		(0.042)	(0.045)
t+1 × Liberal Democracy Indicator (Target Country)		-0.059	-0.043
		(0.043)	(0.046)
t+2 × Liberal Democracy Indicator (Target Country)		-0.198***	-0.189***
		(0.060)	(0.066)
t+3 × Liberal Democracy Indicator (Target Country)		-0.196***	-0.187***
		(0.059)	(0.063)
t+4 × Liberal Democracy Indicator (Target Country)		-0.197***	-0.178***
		(0.070)	(0.072)
Observations	60,330,253	60,330,253	60,330,253
Adjusted R-squared	0.372	0.372	0.372
Number of Country Pairs	11,040	11,040	11,040
Target Country × Theme × Year FEs	Yes	Yes	Yes
Outlet × Theme × Year FEs	Yes	Yes	Yes
Outlet × Target Country FEs	Yes	Yes	Yes

Notes: This table presents the dynamic result of democratic erosion. At this step, we drop the always-treated group and close autocracy countries that cannot experience democratic erosion.

Table A17: State Media and Media Bias

	Dependent Variable: Monthly Average Tone	
	(1)	(2)
Institutional Distance	-0.231***	-0.228***
	(0.043)	(0.041)
Institutional Distance × State Media Indicator	-0.295***	-0.293***
	(0.079)	(0.079)
Observations	81,288,434	81,288,434
Adjusted R-squared	0.278	0.291
Number of Country Pairs	14,379	14,379
Target Country × Theme × Year FEs	Yes	Yes
Outlet × Year FEs	Yes	No
Outlet × Theme × Year FEs	No	Yes

Notes: This table presents the heterogeneous effect of institutional distance on media bias conditional on the media ownership.



(a) AFINN

(b) Bing Liu and collaborators

(c) Loughran-McDonald

Figure A1: Validation of the Tone Measures

Notes: This figure shows the validation of GDELT sentiment variables. We extract a random sample of 100,000 news articles and download the raw text of each article. We construct three sentiment variables based on commonly used lexicon dictionaries and plot the correlation between each of those three variable against the GDELT sentiment variable. We show the scatter plot in ten bins. Panels (a), (b) and (c) show the sentiment variable based on AFINN lexicon, lexicon from Bing Liu and collaborators, and Loughran-McDonald lexicon, respectively. The Pearson correlation coefficients range between 0.52 and 0.60.

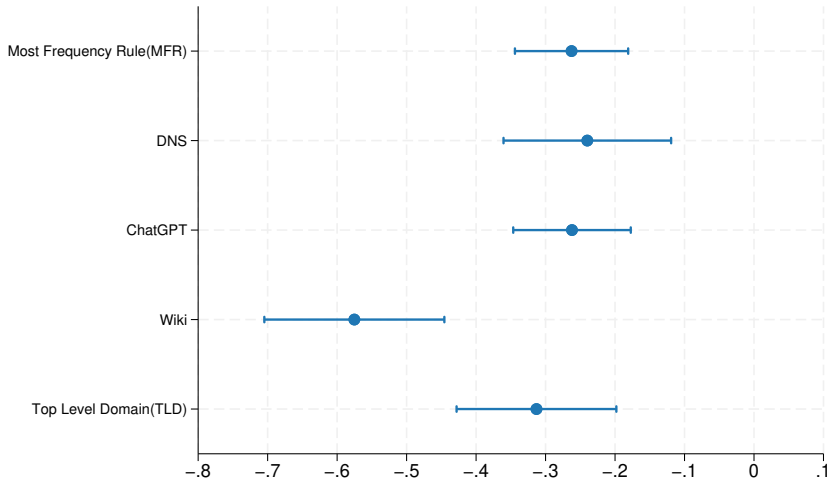
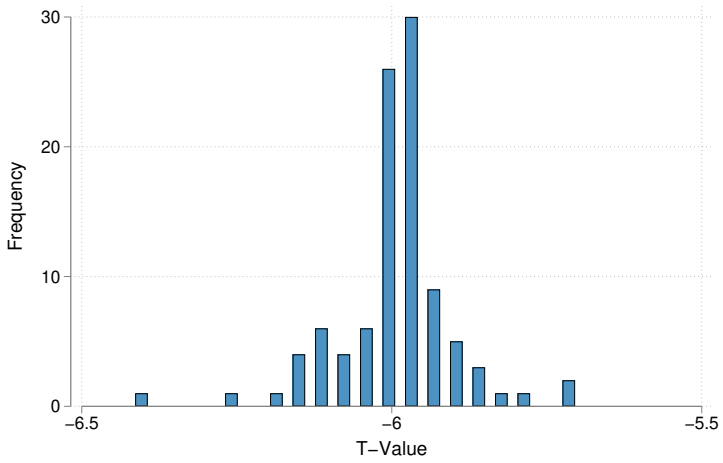
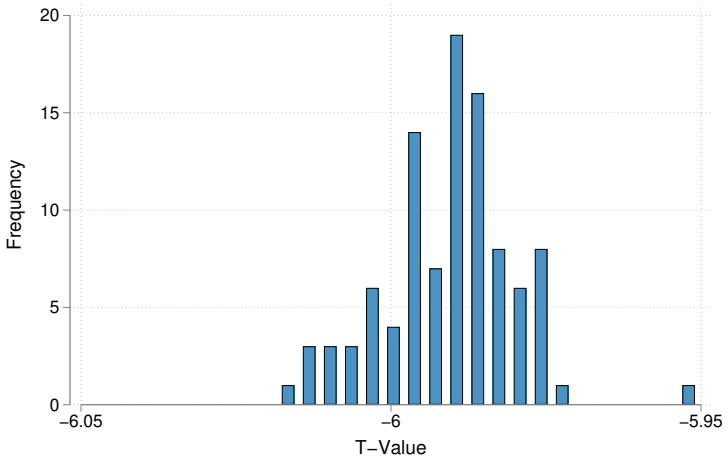


Figure A2: Results Using Difference Domain Source Identification Methods

Notes: This figure presents the baseline results using different media source country identification rules. More details of the estimation can be found in Online Appendix Table A10.



(a) Excluding a Top 100 Country Pair once a Time



(b) Randomly Excluding 5% Sample Once a Time

Figure A3: Robustness Checks Based on Alternative Samples

Notes: This figure shows the robustness checks based on alternative samples. Panel (a) shows the t-values for the coefficient of interest in the sample excluding one of top 100 country-pair in terms of observations. Panel (b) shows results based on sample randomly excluding 5% of the observations once a time. We repeat this practice 100 times and plot the t-values for the coefficient of interest in each sample.

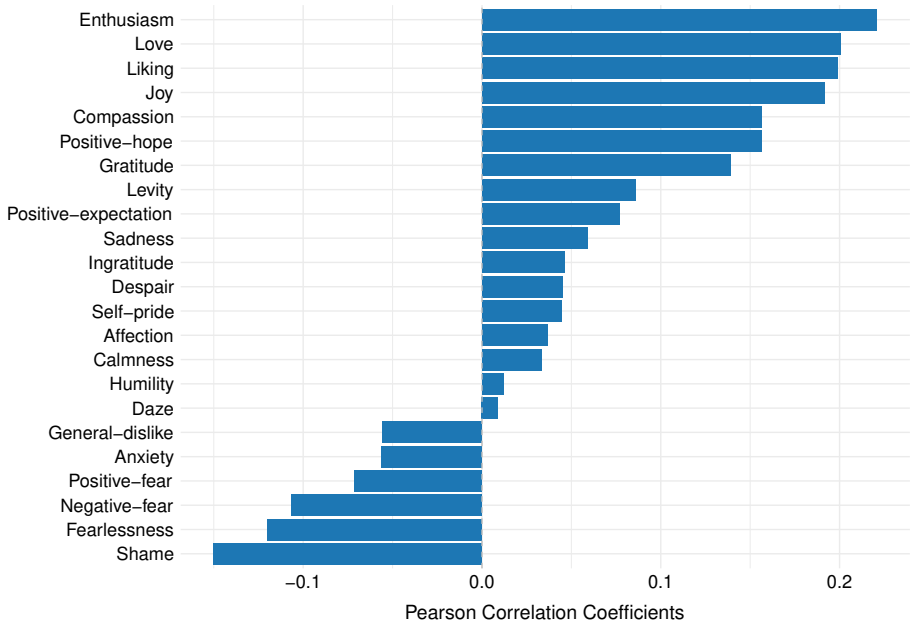


Figure A4: Correlations between Tone Measures and WNA Sentiment Measures

Notes: This figure presents Pearson correlations between our tone measures from the main analysis and WordNet-Affect (WNA) sentiment measures. Using a random sample of 100,000 news articles, we compute the proportion of words associated with each WNA sentiment per article and analyze their correlation with tone measures. The results reveal strong positive correlations between positive sentiments — such as "enthusiasm," "love," "liking," and "joy" — and tone measures, while demonstrating strong negative correlations with negative sentiments, including "shame," "fearlessness," "positive-fear," "negative fear," and "anxiety." These consistent patterns lend credibility to our use of WNA sentiment measures as nuanced indicators of sentiment in the news text.

B Data Construction

B.1 Construction of Baseline Sample

B.1.1 Introduction to GDELT GKG 2.0

In contrast to previous research that used data from the GDELT Event 2.0 dataset, we employ data from the GDELT Global Knowledge Graph (GKG) 2.0 for our study. Compared to the GDELT Event 2.0 Dataset, the GKG 2.0 offers several benefits which should be highlighted here. Firstly, the Event 2.0 dataset only includes news articles where actors and actions are clearly identified. As of 2022, the Mentions table in the GDELT Event 2.0 dataset contains around 667 million events extracted from 420 million news articles. In contrast, the GKG 2.0 collects more than 1.4 billion news articles from more than 15,000 media outlets, providing much more detailed information. Secondly, the GKG 2.0 identifies every country mentioned in a news article, enabling us to focus on news related to a unique target country. Lastly, as of 2022, the GKG 2.0 has identified over 60,000 themes in news articles using various classification taxonomies. This is more detailed than the relatively ambiguous event types provided by the CAMEO classification used in the GDELT 2.0 Event dataset.

We also replicate our baseline results using data constructed from the the GDELT Event 2.0 database. Results displayed in Table A12 show that our baseline results are robust when using a different sample and employing different theme classification methods based on the GDELT Event 2.0 database.

B.1.2 Data Collection and Cleaning

We obtained the raw data of GKG 2.0 from the official GDELT website. The final dataset comprises around 15.5 TB files and covers over 1.4 billion (1,432,371,248) global news articles. We validated and confirmed the data size by comparing it with the summarized result from the GDELT dataset stored in Google Big-Query.

We performed the following data-cleaning steps. Firstly, we restricted the news articles to online articles with distinct URLs to ensure comparability. We removed a small amount of data from broadcast and journals from our sample. Then, we removed news articles that mentioned more than one country with V2Locations in the GKG 2.0 dataset. We did not consider news articles with multiple target countries because the aggregated tone of a news article would be influenced by multiple targets simultaneously, making it difficult to identify the impact of institutional distance. With these two steps, we retained news articles that reported on a single country and had a unique URL. Around 40% of news articles were left for further analysis.

Next, we aggregated the sample to the media outlet by target country by theme by year-month level. We identified the themes covered in each news article using the World Bank Group Topical Taxonomy, which we will discuss in the next section. News articles without a theme coded by World Bank Group Topical Taxonomy were removed in the aggregation process. At the aggregated level, we calculated the monthly average sentiment of news articles from each media outlet that targeted a given country, using the V2Tone indicator provided by the GKG 2.0 dataset. This variable records the sentiment of every news article using a dictionary method and has been available since the beginning of the GKG 2.0 project. In contrast, other sentiment scores were included in the GKG 2.0 data in subsequent waves and are not provided for every news article. We validated the reliability of the V2Tone indicator using three widely used sentiment measures, as shown in Figure A1. We also provide consistent results using the other two sentiment measures provided by the GKG 2.0 dataset in Table A5.

The aggregated data includes around 100 million observations at the media outlet-target country-theme-month level. Each observation represents the sentiment from a media outlet to a target country on a given theme in a specific month. We confirmed the source country of every media outlet (see details in section B.1.4 below) and dropped media outlets without a clear source country. Then, we removed observations where the media outlet reported on domestic issues. This step reduced our sample to around 80 million observations. We then further restricted the baseline sample to 81,288,434 by removing countries without V-Dem data and dropping singletons.

The final baseline sample encompasses news articles from 55,240 media outlets across 176 source countries reporting on issues related to 177 target countries between 2015 and 2022. 14,379 country pairs are included. Figure 1 displays the global distribution of the source countries and target countries.

B.1.3 Themes Classification

We identified the themes covered in each news article using the World Bank Group Topical Taxonomy, which consists of around 2,000 entries in the version used by GDELT project. The GDELT project has incorporated the entire World Bank Group Topical Taxonomy into the GDELT GKG 2.0 dataset since March 2015, providing a comprehensive classification typology for news articles. Using this typology, we determined if any of the themes were mentioned in each news article. It's worth noting that a news article can cover multiple themes simultaneously.

The GDELT project has included and identified over 60,000 themes from different classification systems, such as the World Bank Group Topical Taxonomy, UN My World Survey

Topics, and CrisisLex Taxonomies, in the GKG 2.0 dataset. Among these, we found that the World Bank Group Topical Taxonomy was the most suitable for our research for two main reasons.

Firstly, this taxonomy was incorporated into the dataset within just one month after the beginning of GKG 2.0 project, whereas other classification schemes were included later. For example, the UN My World Survey Topics were updated in January 2016. Secondly, the World Bank Group Topical Taxonomy is organized by World Bank teams to record their comprehensive and even any trivial work on a global scale. Therefore, it covers a wide range of subjects, from socioeconomic problems to natural issues. In contrast, other classification schemes used by the GKG 2.0 dataset were less systematic or just focused on specific media outlets. For instance, the CrisisLex Taxonomies primarily measure emergent issues.

The World Bank Group Topical Taxonomy comprises 10 hierarchical levels, with 24 Level 1 themes). We obtained the topical structure from the World Bank's official website and assigned each theme identified by GKG 2.0 to one or more Level 1 themes. Approximately 66% of news articles from GKG 2.0 dataset contained at least one theme from the World Bank Group Topical Taxonomy.

B.1.4 Identifying the Country of Origin of Media Outlets

A critical empirical challenge in this study was the identification of source countries for tens of thousands of news outlets. This task was complicated by the difficulty of accessing consistent and reliable location data, as well as registration records for media outlets. Even for well-known news outlets, pinpointing their actual location was still challenging, as many outlets operate abroad to circumvent censorship or for other strategic reasons in today's interconnected media landscape. Additionally, conventional methods such as IP geolocation through Domain Name System (DNS) records proved inadequate, since many outlets outsource server operations to third-party hosting companies or rely on cloud-based hosting services.

To overcome these challenges, we adopted a multi-step approach to identify media outlets' source countries. First, we obtained a comprehensive list of news agencies by country from Wikipedia (`https://en.wikipedia.org/wiki/List_of_news_agencies`). This step ensured that all major media outlets were accurately classified by their country of origin. The list included 187 outlets with corresponding websites, organized by country. Second, we used domain suffix analysis (top-level domains, TLDs) to determine the source country. However, it is acknowledged that many media outlets frequently opt for generic suffixes (.com, .net, .org) rather than country-specific domains. Therefore, this method alone was insufficient for identifying source countries in today's digital media landscape.

For outlets not identified through the Wikipedia list or TLD analysis, we turned to ChatGPT-4o for country-of-origin identification. It is worth mentioning that the GDELT Project team recommends the "Most Frequency Rule" (MFR) for similar cases (https://blog.gdeltproject.org/mapping-the-media-a-geographic-lookup-of-gdelts-sources/). This approach infers the source location based on the country with the highest frequency of coverage, under the assumption that news outlets primarily focus on domestic issues. While useful, this method has its limitations. For instance, according to GKG 2.0 data, the British newspaper *Daily Mail* (www.dailymail.co.uk) frequently covers the United States over domestic UK issues.

To ensure greater accuracy, we relied on the ChatGPT-4o API as our primary method for identifying media outlets' source countries. To validate its performance, we randomly selected 1,000 news outlets from our dataset, manually coded their country of origin, and compared the results with ChatGPT's classifications. The ChatGPT-4o model achieved an impressive 94% accuracy rate in this validation exercise. Additionally, as a robustness check, we used the most frequently reported country for each outlet as an alternative source identification measure.

In Figure A2 and Table A10, we show the baseline results using different source country identification methods. The estimated effects are comparable across different methods.

B.2 Construction of National Leader News Sample

B.2.1 List of National Leaders

We constructed a comprehensive dataset of de facto supreme leaders across all sovereign states and autonomous regions spanning 2015–2022. The initial data collection utilized the Herre Database on Political Leaders as our primary source (Herre, 2023), supplemented by the Wikipedia list of heads of state and government (https://en.wikipedia.org/wiki/List_of_current_heads_of_state_and_government). To ensure accuracy, we specifically identified leaders who wielded actual executive authority rather than ceremonial roles, taking into account various political systems including presidential, parliamentary, and one-party states. For instance, in parliamentary monarchies like the United Kingdom, we listed the Prime Minister rather than the monarch, while in one-party states like China, we included the General Secretary of the ruling party.

B.2.2 Identifying Popular Names of National Leaders

We manually coded the various forms of names used by news media outlets to report on national leaders in our dataset. We conducted comprehensive searches for articles featuring each leader on Google News and compiled the names (and nicknames) most frequently used by news media. Our focus was on documenting both standardized naming conventions and region-specific variations in leader identification, including formal titles, common abbreviations, and culturally specific designations.

Using this comprehensive name reference dictionary, we then identified relevant media coverage in the GDELT dataset through a two-step verification process. Articles were considered relevant to a leader if: (1) the article headline must contain at least one documented name reference and (2) the target country of the news article, as identified by GDELT, was the same as the country where the leader holds power. This approach ensured accurate identification of relevant news coverage.

Finally, we aggregate the data at the outlet-leader-month level for our analysis.

Top National Leaders by Reporting Frequency

Rank	National Leaders	Country
1	Donald Trump	United States of America
2	Joe Biden	United States of America
3	Boris Johnson	United Kingdom
4	Benjamin Netanyahu	State of Israel
5	Vladimir Putin	Russian Federation
6	Imran Khan	Islamic Republic of Pakistan
7	Narendra Modi	Republic of India
8	Emmanuel Macron	French Republic
9	Angela Merkel	Federal Republic of Germany
10	Jinping Xi	People's Republic of China

Notes: This table presents the top 10 most frequently reported national leaders in our sample.

B.3 Construction of Event Sample

As a parallel project of the GDELT, GDELT Event 2.0 extracts events from global news happening in different societies. Like GKG 2.0, Event 2.0 collects information from news articles with diverse languages using machine learning algorithms on a 15-minute basis. Accordingly, it provides variables for each event, including but not limited to actors, event types, event locations, and news sentiment. Detailed information on Event 2.0 data is available in the codebook provided by the GDELT official (https://blog.gdeltproject.org/gdelt-2-0-our-global-world-in-realtime/).

While the event data has limitations in theme classification and restricted data size, it remains valuable for robustness checks. Following the data cleaning strategies applied to the GKG 2.0 Dataset used in the main results, we generate country-pair reporting data from the Event 2.0 dataset through the following steps.

Firstly, we identify the target country of each event using location variables. The Event 2.0 dataset provides location information for both actors involved in each event. We extract the unique address values from these location attributes to designate the target country. Consequently, events with multiple locations are excluded from the final analysis. Additionally, we remove news articles that mention multiple target countries.

Next, we map the source country for each media outlet using the same method employed in our main results. Finally, we aggregate the data at the Media Outlet $\times$ Target Country $\times$ Event Type $\times$ Year-Month level and calculate the average tone of the news articles. It is important to note that Event 2.0 classifies news themes using a variable called event type, based on the coding scheme from the Conflict and Mediation Event Observations (CAMEO) framework. We apply the top level of this classification scheme, which includes 20 event types, to our data analysis. This aggregated data is utilized for the robustness check, with results presented in Table A12.

C Examples of New Articles from GDELT

Example 1

Below is a news article collected by the GDELT project from CNN with a focus on Russian politics. The tone of this news article is -3.88.



Vladimir Putin is not invincible

Analysis by Nathan Hodge, CNN

3 minute read · Updated 5:53 AM EDT, Thu September 27, 2018

Example 2

Below is a news article collected by the GDELT project from China.org.cn, which highlighted the problem of gun violence in the USA. The tone is - 7.78.

Research on gun violence thwarted in U.S.: report

Xinhua, June 25, 2022 0 Comment(s) Print E-mail

Adjust font size:

NEW YORK, June 24 (Xinhua) -- For more than 20 years, the U.S. federal government failed to properly support research into gun violence, reported Scientific American on Thursday.

"We spent about 63 U.S. dollars in research dollars per life lost to gun violence, compared to roughly 1,000 dollars per life lost to car crashes and nearly 7,000 dollars per life researching sepsis, a life-threatening response to infection," said the report.

"Two decades without these critical investments has left us myriad open questions about the effects of gun policies," it noted.

More than 45,000 people died from firearm injuries in 2020. Firearms have also become the leading cause of death for children, according to the report.

"These deaths come amid a surge in the domestic sale of firearms. The most recent Small Arms Survey estimates there are nearly 400 million guns in the United States," it added. Enditem

*Follow China.org.cn on **Twitter** and **Facebook** to join the conversation.*
ChinaNews App Download

D Major News Producers by Country

	United State	United Kingdom	China	Russia
1	yahoo.com	reuters.com	xinhuanet.com	sputniknews.com
2	msn.com	dailymail.co.uk	china.org.cn	regnum.ru
3	reliefweb.int	bbc.com	sina.com.cn	rt.com
4	humanitariannews.org	theguardian.com	eastmoney.com	rg.ru
5	prnewswire.com	lexology.com	cnfol.com	ria.ru
6	sfgate.com	bbc.co.uk	people.com.cn	tass.ru
7	marketwatch.com	trust.org	peopledaily.com.cn	lenta.ru
8	chron.com	mondaq.com	sina.com	runews24.ru
9	businessinsider.com	mirror.co.uk	china.com	riafan.ru
10	washingtonpost.com	aawsat.com	cfi.net.cn	life.ru

Notes: This table presents the top 10 most frequent news sources from four major countries. The ranking is based on the total number of observations in our baseline sample.

E Variable Definitions

Panel A: Variables at Domain - Target - Theme - Month Level (Baseline Sample)

	Definition	Source
Tone	Monthly average tone of news article. Tone of each news article is calculated with the difference between positive tone and negative tone.	GDELT GKG 2.0
Positive Tone	Monthly average positive tone of news articles. Positive tone of each news article is measured with the percentage of all positive words used in the article.	GDELT GKG 2.0
Negative Tone	Monthly average negative tone of news articles. Negative tone of each news article is measured with the percentage of all negative words used in the article.	GDELT GKG 2.0
Tone (LSD)	Monthly average tone of news article measured with the Lexicoder Sentiment Dictionary (LSD). Tone (LSD) of each news article is calculated with the difference between positive tone (LSD) and negative tone (LSD). Positive / Negative tone (LSD) is measured with the percentage of positive/negative words used in a article.	GDELT GKG 2.0
Tone (SWN)	Monthly average tone of news article measured with the SentiWordNet 3.0 (SWN) scores. Tone (SWN) of each news article is calculated with the difference between positive tone (SWN) and negative tone (SWN) .	GDELT GKG 2.0

Panel B: Variables at the Country Pair - Year Level

	Definition	Source
Institutional Distance	Dissimilarity of political institutions between two countries in the past year, measured by the difference between their scores in the liberal democracy index (v2x_libdem) provided by the V-Dem project. This index assesses to what extent the ideal of liberal democracy is achieved in a country.	V-Dem Project
Institutional Distance (Electoral Democracy)	Dissimilarity of political institutions between two countries in the past year, measured by the difference between their scores in the electoral democracy index (v2x polyarchy) provied by the V-Dem project. This index assesses to what extent is the ideal of electoral democracy in its fullest sense achieved in a country.	V-Dem Project
Institutional Distance (PolityV Index)	Dissimilarity of political institutions between two countries in the past year, measured by the difference between their scores in the Polity 2 index. This index assesses the general democratic level in a country.	Polity V
UN Voting Distance	Dissimilarity of voting preference between two countries in the past year, measured by the difference between their ideal point estimates derived from the United Nations General Assembly (UNGA) Voting Data.	Voeten, Strezhnev, and Bailey (2023)
Common Language	A dummy variable indicating if two countries share the same official language.	CEPII
Geographic Distance	Geographic distance between capitals of two countries.	CEPII
Religious Distance	Religious dissimilarity between two countries generated from a principal component analysis using three indicators.	Dow and Karunaratna (2006)
Genetic Distance	Genetic dissimilarity between two countries, measured by the distance to the most recent common ancestors of two populations, or equivalently, the length of time since two populations split apart	Spolaore and Wacziarg (2009)
Trade Dependence	Trade dependence of country i on country j in the past year, with data from the UN Comtrade. It is determined by summing the exports from country i to country j and the imports from country j to country i, and then dividing this sum by the total exports and total imports of country i.	UN Comtrade
Trade Balance	The balance of trade for country i with respect to country j in the past year, with data from the UN Comtrade. It is determined by subtracting the imports from country j to country i from the exports from country i to country j, and then dividing this difference by the GDP of country i.	UN Comtrade
Trade Sanction	A dummy variable indicating if country i was sanctioned by country j in the past year, with data from the Global Sanctions Data Base (GSDB).	GSDB

Panel C: Variables at Country-Year / Year-Month Level

	Definition	Source
Liberal Democracy Index	An index (v2x_libdem) assessing to what extent is the ideal of liberal democracy achieved in a country in the past year.	V-Dem Project
Liberal Democracy Indicator (Yes=1)	A dummy variable indicating if a country has been a liberal democracy or not in the past year, re-coded from the regime of the world (Row) measures provided by the V-Dem project.	V-Dem Project
Democratic Erosion	A dummy variable indicating if a country experiencing democratic backlash in or before the current year.	V-Dem Project
GDP Growth Rate	Growth of night light rate in the past month.	VIIRS-DNB
Inflation Rate	Inflation (annual %) rate in the past year, measured by the "NY.GDP.DEFL.KD.ZG" indicator from the World Bank database.	World Bank
Freedom of Traditional Media	An index (v2mecenefm) from the V-Dem project assessing does the government directly or indirectly attempted to censor the print or broadcast media in the past year? A higher value means a higher freedom of traditional media.	V-Dem Project
Freedom of the Internet	An index (v2mecenefi) from the V-Dem project assessing to what extent the government attempted to censor information (text, audio, or visuals) on the Internet in the past year. A higher value means a higher freedom of the Internet.	V-Dem Project
State-owned Print Media Percentage	An index (v2medstateprint) from the V-Dem project assessing out of the top four national print media with the highest readership in th past year, how many are state-owned.	V-Dem Project
State-owned Broadcast Media Percentage	An index (v2medstatebroad) from the V-Dem project assessing out of the top four national broadcast media with the largest audience in th past year, how many are state-owned.	V-Dem Project
Domestic Turmoil	Share of domestic turmoil events in the past month, generated by approaches from Amarasinghe (2022) with data from GDELT Event 2.0.	GDELT Event 2.0

Panel D: Variables at the Media Outlet Level

State Media	A dummy variable indicating the ownership status of the media outlet, whether state-owned or not, labeled by ChatGPT 4.0 API.	ChatGPT 4.0

Panel E: Variables in Equity Market Analysis

	Definition	Source
Tone Exposure	The firm-month level measure. $Tone\ Exposure_{i,m} = \sum_{c=1}^{C} Tone_{c,m} \times Rev_{i,c,t}$. $Rev_{i,c,t}$ is a firm's revenue share from a given country c in year t. $Tone_{c,m}$ is the average tone of the media from country c towards United States in month m.	GDELT GKG 2.0, Factset Revere
Monthly Returns	The monthly stock returns for US listed firms.	CRSP
Abnormal Monthly Returns (CAPM)	The monthly abnormal stock returns for US listed firms adjusted by the market model.	CRSP, Kenneth R. French website
Abnormal Monthly Returns (FF3)	The monthly abnormal stock returns for US listed firms adjusted by the Fama-French 3 factor model.	CRSP, Kenneth R. French website

Panel F: Variables in Syndicated Loan Market Analysis

Tone	The country-pair yearly measure defined as the average tone of the media from a country towards another country in a year.	GDELT GKG 2.0
Deal Number	The number of syndicated loans extended by a bank from a specific country to borrowers in another country in a given year.	Dealscan
Deal Value	The total value of syndicated loans extended by a bank from a specific country to borrowers in another country in a given year.	Dealscan
Spread	The log value of the all-in drawn spread for a syndicated loan.	Dealscan