

Bias or Diversity? Unraveling Fine-Grained Thematic Discrepancy in U.S. News Headlines

Jinsheng Pan*, Weihong Qi*, Zichen Wang, Hanjia Lyu, Jiebo Luo

University of Rochester

{jpan24,wqi3,zwang189,hlyu5}@ur.rochester.edu, jluo@cs.rochester.edu

* these authors contributed equally

Abstract

There is a broad consensus that news media outlets incorporate ideological biases in their news articles. However, prior studies on measuring the discrepancies among media outlets and further dissecting the origins of thematic differences suffer from small sample sizes and limited scope and granularity. In this study, we use a large dataset of 1.8 million news headlines from major U.S. media outlets spanning from 2014 to 2022 to thoroughly track and dissect the fine-grained thematic discrepancy in U.S. news media. We employ multiple correspondence analysis (MCA) to quantify the fine-grained thematic discrepancy related to four prominent topics - domestic politics, economic issues, social issues, and foreign affairs in order to derive a more holistic analysis. Additionally, we compare the most frequent n -grams in media headlines to provide further qualitative insights into our analysis. Our findings indicate that on domestic politics and social issues, the discrepancy can be attributed to a certain degree of media bias. Meanwhile, the discrepancy in reporting foreign affairs is largely attributed to the diversity in individual journalistic styles. Finally, U.S. media outlets show consistency and high similarity in their coverage of economic issues.

Introduction

News media plays a vital role in influencing public perceptions of domestic politics, economic policies, social issues, and foreign affairs (Soroka 2003; Linos and Twist 2016; Hitt and Searles 2018; Lyu et al. 2023). While diverse individual perspectives in news articles promote informed discussions and critical thinking, systematic bias can result in misinformation and heightened polarization of views (Entman 2007; Prior 2013; Mourão and Robertson 2019; Lyu and Luo 2022). Understanding the dynamics of fine-grained thematic variations and identifying the underlying causes of such discrepancies provide valuable insights into the media landscape, which is essential for the function of democracy. Fine-grained thematic discrepancy in news media refers to differences in the specific topics selected for the content of news coverage. For instance, when reporting on news related to abortion, a focus on abortion rights and a focus on abortion laws represent two distinct subtopics, even though they are both related to the general theme of abortion. Although existing literature has extensively studied various types of media bias (D’Alessio and Allen 2000), media use selectivity (Iyengar and Hahn 2009; Knobloch-Westerwick,

Mothes, and Polavin 2020), and the consequences of media bias (Jamieson and Cappella 2008), comprehensive research on the landscape of news media topics and whether the thematic differences are attributable to **media bias or perspective diversity** remains scarce. In this study, we use 1.8 million news headlines from nine U.S. national news media outlets and perform multiple correspondence analysis (MCA) to compute thematic similarity, exploring the American media landscape. We subsequently examine the thematic variations over time and between media outlets to uncover the underlying factors contributing to these differences.

Does the thematic discrepancy stem from media bias or diversity in perspectives? Existing literature presents conflicting arguments and evidence. While a substantial body of research agrees on the existence of ideological biases among the U.S. news media (Sutter 2000; Groseclose and Milyo 2005a; Gentzkow and Shapiro 2010), Budak, Goel, and Rao (2016) discover considerable similarities among major outlets, except for political scandals. The conflicting evidence may be due to the different study samples they focus on. For example, the study samples of D’Alessio and Allen (2000) are news articles about presidential elections, while the study samples of Budak, Goel, and Rao (2016) are general political articles. Additionally, different methods, such as meta-analysis and machine learning models based on crowd-sourced labels, can yield different results. To provide a holistic understanding of such thematic discrepancy, we extend the scope to **four prominent topics across multiple national media organizations ranging from 2014 to 2022 at a larger scale**. Three of the topics are domestic politics, social issues, and foreign affairs. Lyu et al. (2023) highlight the importance of these topics in the assessment of hyperpartisanship across different media. We further include economic issues because this topic also involves different perceptions despite its objectivity (Ang et al. 2022). Instead of full news articles, we concentrate on analyzing the thematic discrepancies in **news headlines** because they are more accessible and they frequently encapsulate the key opinions or events of the content. In addition, the headlines achieve an optimal balance between contextual impact and cognitive effort, effectively guiding readers to construct a coherent interpretation of the information presented, as confirmed by Dor (2003).

To distinguish the media bias and the perspective diver-

sity, we follow existing literature in defining media bias as 1) selecting and framing particular issues with ideological leaning, 2) distortion of facts, or 3) only reporting negative news about certain parties or ideologies (D’Alessio and Allen 2000; Budak, Goel, and Rao 2016; Gentzkow and Shapiro 2010).

Related work

Despite their role in democratic supervision, news reports may not be free of bias. For instance, Bourgeois, Rappaz, and Aberer (2018) find selection biases in the context of news coverage. Although the definition of media bias varies, it is widely agreed that **selecting and framing particular issues with ideological leaning, distortion of facts, and only reporting negative news about certain parties or ideologies are typical types of media bias** (D’Alessio and Allen 2000; Budak, Goel, and Rao 2016; Gentzkow and Shapiro 2010). By this definition, political partisan bias, which strategically manipulates headlines, article sizes, and framings to make reports consistent with their ideology is widespread in news media (Groeling and Kernell 1998; Groseclose and Milyo 2005b; Groeling 2013; Shultziner 2020). However, the thematic discrepancy in news articles does **not** necessarily attribute to media bias. For example, the different interpretations of the same event, the unique narrative style of individual journalists, and the different individual experiences can all lead to thematic differences in news articles but are not necessarily systematic biases. The aspect of discrepancy is rarely visited by academic scholars. Our study contributes to unraveling the fine-grained thematic variations in U.S. news headlines.

Understanding the thematic discrepancies among media has attracted much attention from the research community. Traditional methods (Guess et al. 2021; Spinde et al. 2021) collect public opinions from different surveys and polls and quantify the media bias into a certain range of values. However, collecting surveys on a large scale is often time-consuming and expensive. Compared to traditional methods, model-based methods are more feasible. Many prior studies (Benamara et al. 2007; Bautin, Vijayarenu, and Skiena 2021) have been conducted on measuring media bias from the perspective of sentiment analysis on news headlines. More recent work exploits masked language models to measure semantic discrepancies. For example, Guo, Ma, and Vosoughi (2022) mask the adjacent words of specific bigrams in news article sentences and then use fine-tuned language models to predict the possible words that could fill in the blank. They compare the prediction results to measure the attitudinal difference between media. However, it is noteworthy that pre-trained language models may contain unknown bias from the training corpus (Schramowski et al. 2022). Our study aims to explore potential thematic discrepancies among media outlets by constructing thematic representations using n -grams that are free from pre-training bias.

Material and Method

In this section, we describe how we collect and preprocess news headlines. We then discuss how we identify the news

headlines of the four topics (*i.e.*, domestic politics, economic issues, social issues, and foreign affairs). In the end, we detail our approach to analyzing the thematic discrepancy.

Data Collection and Preprocessing

Our study uses the dataset collected by Lyu et al. (2023). For the sake of a self-contained paper, we provide a brief overview of the data collection and preprocessing process. To collect data from the news media, they employed two approaches: using the official web API provided by the news media and crawling the web archives and search pages of the news media. They retrieved 1.8 million news headlines from the websites of nine representative media outlets including The New York Times, Bloomberg, CNN, NBC, Wall Street Journal, Christian Science Monitor, The Federalist, Reason, and Washington Times. These media outlets were categorized into three groups: `Left`, `Central`, and `Right` with respect to the political leaning of each media outlet, which is assessed by `allsides.com` and `mediabiasfactcheck.com`. More specifically, the `Left` group includes The New York Times, Bloomberg, CNN, and NBC. The `Central` group consists of Wall Street Journal and Christian Science Monitor. The `Right` group contains The Federalist, Reason, and Washington Times. The collected data range from January 2014 to September 2022 covering various topics. They pre-processed the data by performing lemmatization, eliminating stop words, and converting all text to lowercase.

Relevant Title Identification

To identify the news headlines of the four topics, we first search for the most frequent n -grams. Following Guo, Ma, and Vosoughi (2022), we choose to find the most frequent bigrams. By examining each year’s data, we have isolated the bigrams that appeared no less than 100 times. In total, we have identified 797 bigrams meeting this criterion. Next, two annotators manually categorize these bigrams into the four relevant topics. Before the annotation, a pilot annotation session where the two annotators read a few sample titles together and discuss the labeling schema is performed. We find that it is easy to label because of the non-ambiguity of the bigrams. For example, (`‘ukrainian’, ‘refugee’`) falls under the category of foreign affairs, while (`‘health’, ‘law’`) pertains to social issues. Each annotator then labels half of the collected bigrams. Subsequently, we search for titles that contain at least one of these bigrams. Finally, we identify 295,311 news headlines from January 2014 to September 2022 that are related to the four topics. Table 1 summarizes the number of bigrams and corresponding titles.

Thematic Discrepancy Analysis

Although techniques such as text frequent pattern mining (Han et al. 2007) and term-based text clustering (Aggarwal and Zhai 2012) could be used for text analysis, we find multiple correspondence analysis (MCA) (Hirschfeld 1935) adequate for measuring thematic discrepancy, as demonstrated by Lakhanpal et al. (2022) who used MCA to investigate textual differences in online hate speech. MCA encodes

	# bigrams	# news headlines
Foreign affairs	94	38,137
Domestic politics	460	168,911
Economic issue	116	43,576
Social issue	127	44,687
Total	797	295,311

Table 1: Number of labeled bigrams and collected news headlines for each topic.

categorical data and represents them in low-dimensional Euclidean space (*i.e.*, 2-D in our study). The thematic discrepancy is calculated as the distance in the low-dimensional space. To perform MCA, we construct a contingency table in which each column represents one of nine media outlets and each row denotes the frequency of occurrence for each n -gram in the identified news headlines. To improve robustness, we select the n -grams that appear more than 50 times in the tiles of a single media outlet. Bigrams and trigrams are used to construct the contingency table. Unigrams are not included in this study because we observe that in news headlines, most subjects are bigrams or trigrams (*e.g.* names and events). For a more meaningful interpretation, we focus on bigrams and trigrams. Next, we perform singular value decomposition (SVD) to obtain the orthogonal vectors that represent the categorical data. Note that SVD is applied for dimensionality reduction for visualization purpose.

Results

To investigate the temporal patterns of fine-grained thematic discrepancies in news headlines of different media across various important topics, we employ MCA to analyze the titles of each topic for each year. We visualize the MCA results to reflect the media report discrepancies over time. Each point on the graphs represents a single media outlet, with markers indicating their respective ideological position. To further reveal the dynamics of media report discrepancies, for each topic, we present the top 10 most frequent n -grams in 2014, 2018, and 2022 from news headlines of all media outlets, representing the key subjects that these outlets highlight. The three years correspond to the shift in the presidency as well as the pre- and post-COVID eras. We then show the top 10 most frequent n -grams for representative outlets from the Left, Central, and Right categories, as well as within and diverging from the majority cluster, to explore the underlying factors contributing to the thematic variation.

Domestic politics

Figure 1 depicts the temporal characteristics of media discrepancies regarding *domestic politics*. Since 2017, we have observed an overall rising level of concentration among the analyzed media outlets. Specifically, these outlets were more sparsely distributed in 2014 but became notably concentrated by 2020, with CNN, Washington Times, and New York Times as outliers. Within the Left media, CNN has displayed an increasing discrepancy compared to other out-

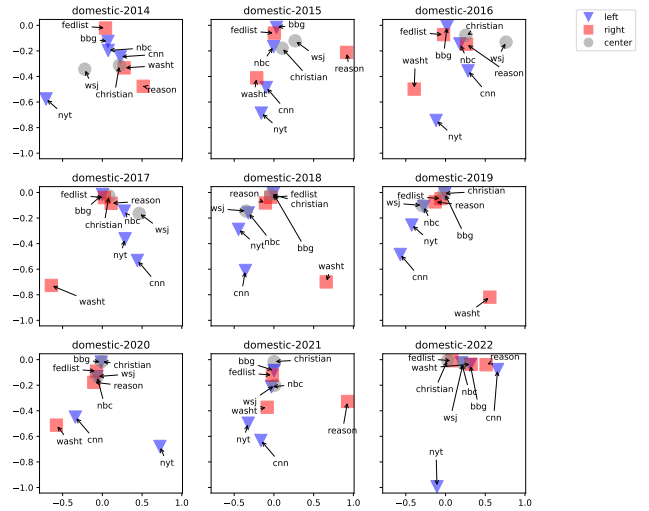


Figure 1: MCA results regarding the coverage of *domestic politics* by the media between 2014 and 2022 (Best viewed by zoom-in on screen).

lets since 2015 (Figure 2). Among the Right media, Reason exhibits a marked discrepancy during Democratic presidencies, while the discrepancy decreases during the Republican administration. In contrast, The Washington Times displays a contrasting trend, exhibiting greater thematic discrepancies during the Republican presidency and reduced discrepancies during the Democratic administrations. The growing divergence between CNN and other media outlets could be attributed to the 2016 Presidential Election. Previous studies have highlighted the polarizing nature of this election and the controversies surrounding Donald Trump, which have led to subsequent changes in reporting styles across media outlets (Benkler, Faris, and Roberts 2018).

As shown by Table 2, political figures (highlighted in green) consistently attract considerable media attention, occupying two to six positions within the top 10 n -grams. In 2018, the n -grams representing Trump and his administration were more frequently used. Over time, judicial institutions (highlighted in orange) have continually garnered significant public attention, with the Supreme Court, Attorney General, and Justice Department consistently ranking among the top 10 headline topics. However, civil rights issues can be overshadowed by political upheavals. While free speech and civil rights received substantial attention in 2014, they were later supplanted by politically charged events such as the Capitol Riot and the January 6th Committee.

Table 3 shows the 10 most frequent n -grams in news headlines of the Christian Science Monitor, New York Times, and Reason in 2022, representing the Central, Left, and Right media, respectively. Despite their ideological differences, the Christian Science Monitor and Reason cover similar topics, with the New York Times being an outlier in Figure 1. The New York Times devotes more atten-

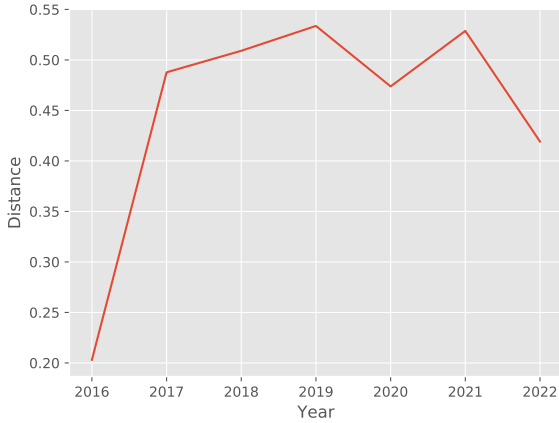


Figure 2: Distance between CNN and the centroid of the major cluster from the MCA results.

2014	2018	2022
white house	donald trump	supreme court
supreme court	white house	primary election result
bill de Blasio	supreme court	congressional district
hillary clinton	trump administration	biden administration
rand paul	2016 election	january committee
president obama	president trump	joe biden
attorney general	midterm election	attorney general
free speech	attorney general	justice department
civil right	melania trump	capitol riot
justice department	hillary clinton	senate race

Table 2: Top 10 most frequent n -grams in 2014, 2018, 2022 regarding *domestic politics*.

tion to elections and legislatures (highlighted in orange), but less to political figures (highlighted in green) compared to the other two outlets, resulting in a greater thematic distance between them. The results suggest that the discrepancy in domestic politics coverage is partly attributable to the choice of varying topics by different media outlets.

Economic Issues

Figure 3 shows the trend of media discrepancies regarding *economic issues* where topic selections within the economic domain exhibits similarities. From 2014 to 2022, the majority of media outlets are situated in the upper left corner of the plot. However, starting in 2019, Bloomberg and CNN have gradually become more distant from the upper left cluster.

We have noted minimal changes in the top 10 most frequent n -grams in news headlines relating to *economic issues*.¹ We compare the Reason, Wall Street Journal, and CNN, which represent the Right, Central and Left media, respectively. The three outlets exhibit a strong

¹Details regarding the temporal variation in the most frequent n -grams of the economic issues can be found in the Appendix.

Christian	NYT	Reason
supreme court	election result	supreme court
sandy hook	primary election	first amendment
biden sandy	congressional district primary	free speech
biden sign	supreme court	court decision
donald trump	white house	biden administration
jan panel	governor primary	kentajin brown jackson
far right	runoff election	joe biden
overtum roe	attorney general	court reject
alex jones	first congressional	capitol riot
right wings	second congressional	ron desantis

Table 3: Top 10 most frequent n -grams of the Christian Science Monitor, New York Times, and CNN in 2022 regarding *domestic politics*.

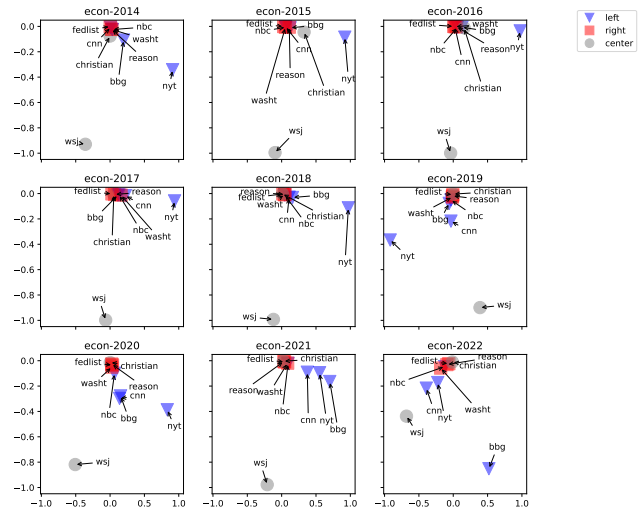


Figure 3: MCA results regarding the coverage of *economic issues* by the media between 2014 and 2022 (Best viewed by zoom-in on screen).

interest in topics including interest rates, the stock market, energy, electronic cars, and essential economic policies. Our findings indicate that the media outlets reveal limited variation in their coverage of economic issues, and are similar in both topics and perspectives.

Social Issues

Figure 4 shows the discrepancies among media outlets relating to *social issues*. A similar trend is observed in social issues as in domestic politics, with media outlets becoming more concentrated over time. Some left-wing media outlets, such as CNN, NBC, and Bloomberg, have diverged from the cluster since 2017. Meanwhile, centrist and right-wing media outlets, such as the Christian Science Monitor and Washington Times, have progressively moved closer to the majority.

The focus on social issues is likely influenced by ongoing social movements according to the results in Table 5. In 2014, due to the Medicaid expansion (Himmelstein

Reason	WSJ	CNN
student loan forgiveness	stock market	gas price
gas price	supply chain	rate hike
biden student debt	interest rate	mortgage rate
formula shortage	central bank	student loan
high gas	student loan	interest rate
baby formula shortage	gas price	oil price
gas tax	natural gas	stock market
interest rate	oil price	natural gas
electric vehicle	real estate	electric car
fossil fuel	electric vehicle	supply chain

Table 4: Top 10 most frequent n -grams of CNN, Wall Street Journal, and Reason in 2022 regarding *economic issues*.

2014	2018	2022
health care	health care	climate change
climate change	climate change	social medium
social medium	social medium	mass shooting
gay marriage	school shooting	abortion right
sexual assault	gun control	hate crime
health law	sexual assault	abortion ban
same sex marriage	sexual harassment	health care
global warming	sex abuse	fatally shoot
health insurance	sexual misconduct	school shooting
gun report	gun violence	human right

Table 5: Top 10 most frequent n -grams in 2014, 2018, 2022 regarding *social issue*.

2019) and the promotion of same-sex marriage (Liptak 2014), healthcare and gay marriage (both highlighted in blue) obtained significant attention. In 2018, the #MeToo movement sparked widespread debate and discussion about sexual harassment (highlighted in red) in the news media (Pomarico 2018). In addition, the overturn of *Roe v. Wade* in mid-2022 (Liptak 2022) drew considerable attention to abortion laws and rights (highlighted in green).

Table 6 presents the thematic discrepancies in social issues among the Christian Science Monitor, CNN, and Reason in 2022. We choose the three media outlets to represent the Central, Left, and Right media groups. Notably, the three media outlets cover similar topics including climate change, social media, abortion issues, hate crime, public health, and gun control, but show subtle differences in their approaches and perspectives. For example, while Reason emphasizes “abortion law”, CNN underscores its ideological position by using “abortion rights”. Meanwhile, the Christian Science Monitor focuses on “abortion law”, “abortion rights”, and “anti-abortion”. When addressing gun control issues, Reason employs terms like “mass shooting”, CNN emphasizes “fatally shoot”, and the Christian Science Monitor uses “gun violence”. These nuanced differences in the choice of terms reveal the media bias (D’Alessio and Allen 2000; Budak, Goel, and Rao 2016).

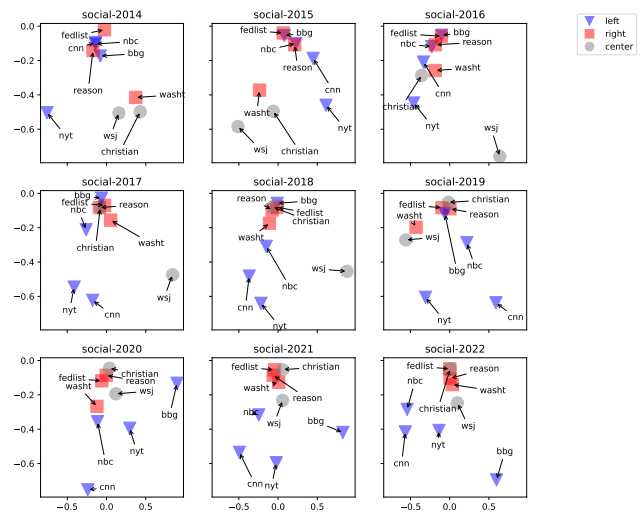


Figure 4: MCA results regarding the coverage of *social issues* by the media between 2014 and 2022 (Best viewed by zoom-in on screen).

Christian	Reason	CNN
climate change	social medium	mass shooting
mass shooting	gun control	social medium
social medium	abortion ban	hate crime
gun violence	public health	climate crisis
abortion law	climate change	fatally shoot
gun control	health care	school shooting
abortion right	mass shooting	gun violence
hate crime	green energy	uvalde school
green energy	abortion law	abortion right

Table 6: Top 10 most frequent n -grams of the Christian Science Monitor, Reason, and CNN in 2022 regarding *social issues*.

Foreign Affairs

Figure 5 shows that there has been no significant change in thematic discrepancy relating to *foreign affairs* from 2014 to 2022. The majority of media outlets are clustered in the upper-left corner of the graph, while the New York Times, Wall Street Journal, and CNN emerge as outliers. These three outlets have gradually formed a separate cluster. Additionally, Bloomberg has been distancing itself from the majority since 2020. The emerging outliers may be attributed to the distinct journalistic styles of media outlets. For example, the Wall Street Journal and Bloomberg primarily concentrate on the economic and financial implications of geopolitical tensions, resulting in differing perspectives compared to other media outlets.

The coverage of foreign affairs remains consistent over time, with the exception of war outbreaks.² Geopolitical

²Details regarding the temporal variation in the most frequent n -grams of the foreign affairs can be found in the Appendix.

veloped by these outlets help prevent gross misinformation and overt bias, which may result in minimal discrepancies in some issues. Future research could compare national and local media, offering a more comprehensive view of the American news landscape. Second, we only focus on four prominent topics featured in news headlines. To expand upon this, future work could conduct a more fine-grained investigation across a broader range of subjects.

Acknowledgments

This work was partially supported by the Goergen Institute for Data Science at the University of Rochester.

References

- Aggarwal, C. C.; and Zhai, C. 2012. A Survey of Text Clustering Algorithms. In *Mining Text Data*.
- Ang, Z.; Reeves, A.; Rogowski, J. C.; and Vishwanath, A. 2022. Partisanship, Economic Assessments, and Presidential Accountability. *American journal of political science* 66(2): 468–484. ISSN 0092-5853.
- Bautin, M.; Vijayarenu, L.; and Skiena, S. 2021. International Sentiment Analysis for News and Blogs. *Proceedings of the International AAAI Conference on Web and Social Media* 2(1): 19–26. doi:10.1609/icwsm.v2i1.18606. URL <https://ojs.aaai.org/index.php/ICWSM/article/view/18606>.
- Benamara, F.; Cesarano, C.; Picariello, A.; Recupero, D. R.; and Subrahmanian, V. S. 2007. Sentiment analysis: Adjectives and adverbs are better than adjectives alone. *ICWSM* 7: 203–206.
- Benkler, Y.; Faris, R.; and Roberts, H. 2018. *Network propaganda: Manipulation, disinformation, and radicalization in American politics*. Oxford University Press.
- Bourgeois, D.; Rappaz, J.; and Aberer, K. 2018. Selection bias in news coverage: learning it, fighting it. In *Companion Proceedings of the The Web Conference 2018*, 535–543.
- Brookes, R.; Lewis, J.; and Wahl-Jorgensen, K. 2004. The media representation of public opinion: British television news coverage of the 2001 general election. *Media, Culture & Society* 26(1): 63–80.
- Budak, C.; Goel, S.; and Rao, J. M. 2016. Fair and balanced? Quantifying media bias through crowdsourced content analysis. *Public Opinion Quarterly* 80(S1): 250–271.
- D’Alessio, D.; and Allen, M. 2000. Media bias in presidential elections: A meta-analysis. *Journal of communication* 50(4): 133–156.
- Dor, D. 2003. On newspaper headlines as relevance optimizers. *Journal of pragmatics* 35(5): 695–721.
- Entman, R. M. 2007. Framing bias: Media in the distribution of power. *Journal of communication* 57(1): 163–173.
- Gentzkow, M.; and Shapiro, J. M. 2010. What drives media slant? Evidence from US daily newspapers. *Econometrica* 78(1): 35–71.
- Groeling, T. 2013. Media Bias by the Numbers: Challenges and Opportunities in the Empirical Study of Partisan News. *Annual Review of Political Science* 16(1): 129–151. ISSN 1094-2939.
- Groeling, T.; and Kernell, S. 1998. Is network news coverage of the president biased? *The Journal of Politics* 60(4): 1063–1087.
- Groseclose, T.; and Milyo, J. 2005a. A measure of media bias. *The quarterly journal of economics* 120(4): 1191–1237.
- Groseclose, T.; and Milyo, J. 2005b. A Social-science Perspective on Media Bias. *Critical review (New York, N.Y.)* 17(3-4): 305–314. ISSN 0891-3811.
- Guess, A.; Barberá, P.; Munzert, S.; and Yang, J. 2021. The consequences of online partisan media. *Proceedings of the National Academy of Sciences* 118: e2013464118. doi:10.1073/pnas.2013464118.
- Guo, X.; Ma, W.; and Vosoughi, S. 2022. Measuring Media Bias via Masked Language Modeling. *Proceedings of the International AAAI Conference on Web and Social Media* 16(1): 1404–1408. doi:10.1609/icwsm.v16i1.19396. URL <https://ojs.aaai.org/index.php/ICWSM/article/view/19396>.
- Han, J.; Cheng, H.; Xin, D.; and Yan, X. 2007. Frequent pattern mining: current status and future directions. *Data Mining and Knowledge Discovery* 15: 55–86.
- Himmelstein, G. 2019. Effect of the Affordable Care Act’s Medicaid Expansions on Food Security, 2010–2016. *American journal of public health (1971)* 109(9): 1243–1248. ISSN 0090-0036.
- Hirschfeld, H. O. 1935. A Connection between Correlation and Contingency. *Mathematical Proceedings of the Cambridge Philosophical Society* 31(4): 520–524. doi:10.1017/S0305004100013517.
- Hitt, M. P.; and Searles, K. 2018. Media coverage and public approval of the US Supreme Court. *Political Communication* 35(4): 566–586.
- Iyengar, S.; and Hahn, K. S. 2009. Red media, blue media: Evidence of ideological selectivity in media use. *Journal of communication* 59(1): 19–39.
- Jamieson, K. H.; and Cappella, J. N. 2008. *Echo chamber: Rush Limbaugh and the conservative media establishment*. Oxford University Press.
- Knobloch-Westerwick, S.; Mothes, C.; and Polavin, N. 2020. Confirmation bias, ingroup bias, and negativity bias in selective exposure to political information. *Communication Research* 47(1): 104–124.
- Lakhanpal, S.; Zhang, Z.; Li, Q.; Lee, K.; Kim, D.; Chae, H.; and Kwon, H. K. 2022. Sinophobia, misogyny, facism, and many more: A multi-ethnic approach to identifying anti-Asian racism in social media. *arXiv preprint arXiv:2210.11640*.
- Linos, K.; and Twist, K. 2016. The Supreme Court, the Media, and Public Opinion: Comparing Experimental and Observational Methods. *The Journal of legal studies* 45(2): 223–254. ISSN 0047-2530.

Liptak, A. 2014. Justices Reject Call to Halt Gay Marriages in Oregon. URL <https://www.nytimes.com/2014/06/05/us/politics/supreme-court-rebuffs-call-to-end-same-sex-marriages-in-oregon.html>.

Liptak, A. 2022. In 6-to-3 Ruling, Supreme Court Ends Nearly 50 Years of Abortion Rights. URL <https://www.nytimes.com/2022/06/24/us/roe-wade-overturned-supreme-court.html>.

Lyu, H.; and Luo, J. 2022. Understanding Political Polarization via Jointly Modeling Users, Connections and Multimodal Contents on Heterogeneous Graphs. In *Proceedings of the 30th ACM International Conference on Multimedia*, 4072–4082.

Lyu, H.; Pan, J.; Wang, Z.; and Luo, J. 2023. Computational Assessment of Hyperpartisanship in News Titles. *arXiv preprint arXiv:2301.06270*.

Mourão, R. R.; and Robertson, C. T. 2019. Fake news as discursive integration: An analysis of sites that publish false, misleading, hyperpartisan and sensational information. *Journalism studies* 20(14): 2077–2095.

Pomarico, N. 2018. 11 of the biggest moments of the #MeToo movement in 2018. URL <https://www.insider.com/me-too-movement-moments-2018-12>.

Prior, M. 2013. Media and political polarization. *Annual Review of Political Science* 16: 101–127.

Schramowski, P.; Turan, C.; Andersen, N.; Rothkopf, C. A.; and Kersting, K. 2022. Large pre-trained language models contain human-like biases of what is right and wrong to do. *Nature Machine Intelligence* 4(3): 258–268.

Shultziner, Doron; Stukalin, Y. 2020. Politicizing What’s News: How Partisan Media Bias Occurs in News Production. *Mass Communication and Society* 24(3): 372–393. ISSN 1520-5436. doi:10.1080/15205436.2020.1812083. URL <https://browzine.com/articles/406719000>.

Soroka, S. N. 2003. Media, public opinion, and foreign policy. *Harvard International Journal of Press/Politics* 8(1): 27–48.

Spinde, T.; Kreuter, C.; Gaissmaier, W.; Hamborg, F.; Gipp, B.; and Giese, H. 2021. Do You Think It’s Biased? How To Ask For The Perception Of Media Bias .

Sutter, D. 2000. Can the media be so liberal-the economics of media bias. *Cato J.* 20: 431.

Appendix

Tables 8 and 9 show the 10 most frequent n -grams in 2014, 2018, and 2022 regarding *economic issues* and *foreign affairs*.

2014	2018	2022
small business	central bank	gas price
profit rise	real estate	supply chain
minimum wage	silicon valley	student loan
oil price	stock market	central bank
central bank	oil price	stock market
real estate	government bond	interest rate
natural gas	interest rate	electric car
silicon valley	u.s government bond	real estate
interest rate	tax cut	russian gas
government bond	supply chain	electric vehicle

Table 8: Top 10 most frequent n -grams in 2014, 2018, and 2022 regarding *economic issues*.

2014	2018	2022
hong kong	north korea	hong kong
north korea	trade war	ukraine war
south korea	saudi arabia	north korea
cease fire	south korea	south africa
foreign policy	kim jong un	boris johnson
prime minister	hong kong	prime minister
ukraine	north korean	south korea
south africa	prime minister	saudi arabia
south sudan	trump trade	russian oil
middle east	nuclear deal	ukraine invasion

Table 9: Top 10 most frequent n -grams in 2014, 2018, and 2022 regarding *foreign affairs*.