Analyzing Media Coverage of U.S. Foreign Policy

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Abstract - *In today's highly polarized media landscape, understanding the potential biases and relationships between news publications has become increasingly important. This study aims to investigate the existence of media bias by examining the content of online news articles. We leverage a dataset containing over 200,000 articles from various media outlets, spanning diverse political orientations and subject matter. Using unsupervised machine learning techniques, we first employ clustering algorithms, such as k-means and hierarchical clustering, to group similar articles based on their content. This analysis enables us to identify patterns and common themes within the clusters, shedding light on the potential ideological leanings of the publications. Our DID analysis shows that, on average, there is a slight negative shift in sentiment scores before and after the 2016 US presidential election for articles published by liberal-leaning publications compared to those published by conservative-leaning publications. The regression analysis indicates that the ideological leaning of the publication was significantly associated with the overall sentiment score of articles, with liberal-leaning publications having higher sentiment scores on average compared to conservative-leaning publications.*

1. Introduction

The news media plays an important part in our lives.In recent years, as information and communication technology has developed by leaps and bounds, news media has become an even more pervasive source of influence in our lives.. Traditional media such as newspapers have adopted to the demands of its audience and have become more easy to consume to mobile devices. The news also has a political aspect to it whereby it can influence public opinion, and policy-making.

A large body of research investigates how the news media reports on foreign affairs. Some research emphasizes the “gatekeeping” role that news media plays in not just selecting and reporting news but also interpreting it for its audience (Entman 1993; Gitlin 1980; Tuchman 1978). For example, Lippmann (1922) argued in his book “Public Opinion” that all news stories, with the exception of scores in athletic events, undergo some form of selection and exclusion, meaning that news media are inherently biased because they reflect their ideology or values in the news they cover, either through the reduction or partial attention to facts, or the complete distortion or outright ignoring of facts (de Vreese 2003).

The arbitrary selection or omission of relevant information about a particular issue and the differential credibility given to different sources of information, result in completely different reports of the same event. The use of information from only one side of an issue is defined as media bias and leads to selective exposure (Stroud 2007) and polarization (Iyengar et al. 2019) among the public. The political significance of media bias is that the information and messages that the public receives from the news media can cause them to change or reinforce their minds about a candidate or political party.

Research also shows that the media does not report on issues in an unbiased way. Some of the factors affecting media coverage that have been noted in research are:

- Dominant media are themselves corporate elite establishment
- Economic incentives of media companies
- Structural aspects of media, i.e. who owns the media companies
- Ideological bend of news organizations

This paper looks to compare media outlets’ coverage and reporting of foreign policy issues in the United States. **Our hypothesis is that media companies shift their coverage of foreign policy issues depending on which political party is in power.**

The news media often regards itself as the fourth branch of government. Some have referred to it as a watchdog that checks government access and holds elected officials accountable. However, research shows that media is influenced by a number of factors. Particularly, when reporting on foreign affairs the media is susceptible to “contesting government propaganda campaigns where the government can employ ideological weapons like anti-communism, a demonized enemy or alleged national security threats” (Herman, 1993).In particular, the public's selective exposure to partisan news media has a variety of effects and can have a significant impact on shaping public opinion on foreign affairs. Partisan media tends to support the policies of a particular political faction, which entails distortion and discrimination of objective facts. How does media coverage of U.S. foreign policy change in relation to which political party is in power in the U.S.? In particular, how has the media's stance on foreign affairs changed since the 2016 election?

Given the far-reaching impact of news media in our lives and the difficulty of obtaining clean estimates of media bias using conventional approaches, this paper makes use of unsupervised machine learning techniques to conduct a sentiment analysis of 27 news media outlets in the United States over a 5-year period. The paper is structured as follows: the next session considers existing scholarship and techniques used to analyze media bias and highlights issues of polarization in news media. The following section explains the data and methodology used for this analysis in more detail. The final section presents our main findings and discusses some of its implications.

2. Literature Review

2.1. Estimating the bias and ideological position of news media

In general, the media strives to present reality as it is and in an objective light, but it does not place equal value on all issues and assigns different values to different situations. The media's perception of an issue is influenced by a variety of factors, and journalists interpret and evaluate the same issue differently depending on their personal values and philosophies, the culture and practices of the media organization, external pressures such as political and economic power, and, at the macro level, their ideological values (Bennett 2007; Shoemaker and Reese 1996). In particular, the media's ideology can lead to biases in the way they present and interpret perspectives on political, economic, and social issues (Gentzkow and Shapiro 2013). In this context, ideology is essentially the perception (Shoemaker and Reese 1996) that the media consciously or unconsciously reflects in the process of producing news, such as conservative media reporting on a particular issue from a conservative perspective and liberal media reporting from a liberal perspective. Therefore, news reflects different beliefs, perceptions, and values depending on political, economic, and social factors, and this process inevitably involves modification and discrimination of objective facts. Additionally, the facts presented in the media are not the real world, but a world that is biased toward one side or created through certain ideological judgments, and the news created by the media itself already implies an ideological bias toward some object.

If we divide the existing research on the sources of media bias into two categories, supply-side and demand-side, we find that on the supply side, media bias can be attributed to internal factors such as the personality, background, experience, values, beliefs, roles, political attitudes, and ideology of the journalist writing the story (Baron 2006). Next, the type of media organization or the political orientation of the media (Anderson and McLaren 2010; Djankov, et al. 2003; Shoemaker and Reese 1996) also has an impact, especially Shoemaker and Reese (1996), point out the production practices of media organizations and the political, economic, and socio-cultural values of the news media are important factors that influence news. Finally, external factors that can affect news bias include competition among media organizations, advertiser influence, government regulation and interference, pressure from interest groups and elites, and socio-cultural norms and moral values. In particular, political pressures can affect selection and coverage of news, especially when covering government-related events or political issues, and the tone of the story can vary depending on how political pressures relate to the political stance of the news media (Besley and Prat 2006; Ellman and Germano 2008).

On the other hand, consumer-driven media bias research suggests that news consumers who hold biased beliefs about certain facts want to read stories that are consistent with their beliefs. The media tends to emphasize news that conforms to audiences' pre-existing beliefs, either to cater to those consumers' beliefs (Mullainathan and Shleifer 2005) or to signal the high quality of news provided by the media (Gentzkow and Shapiro 2006). Other researchers argue that even if the media know the actual truth, the technical constraints of their reporting methods lead to the predominance of crude information, resulting in media bias.

On the other hand, Mullainathan and Shleifer (2005) show that when media consumers have heterogeneous political preferences, media outlets are 1.5 times more extreme than the political preferences of media consumers because it is more economically profitable for media outlets to differentiate themselves from other outlets through biased reporting than to focus on expanding their market share. Gentzkow and Shapiro (2010) also emphasize the demand side of media bias, finding that the political orientation of consumers in newspaper sales areas is a major determinant of newspaper bias.

To support these theoretical studies of media bias, it is important to empirically estimate the political and ideological position of the media. Many studies have used different approaches to analyze media bias, the most common of which is content analysis, which looks at the number and type of articles on a particular political issue across media outlets. For example, by reading the headlines and body copy of all articles related to a particular issue, positive and negative terms are categorized and summed to draw conclusions about the dominant meaning, or newspaper editorials are analyzed for official endorsements of a particular candidate or party (Ansolabehere et al. 2006; Kahn and Kenney 2002; Puglisi and Snyder 2015). Researchers have also analyzed the news media's support or opposition to decisions of political institutions such as the Supreme Court or Congress by applying Item Response Theory (Ho and Quinn 2008), and calculate a media bias index by comparing the ideological orientation and frequency of sources or think tanks that are often quoted in the news media (Groseclose and Milyo 2005). Another popular method is to use surveys to locate the ideological position of the media.

However, the existing methods of studying media bias can produce relatively accurate results in dealing with subtle expressions because the researcher analyzes and judges the articles by himself, but it requires considerable time, effort, and cost to analyze a large amount of data, and it is difficult to exclude the researcher's subjective values and ideology in the content analysis. To overcome these shortcomings, recent studies have used statistical models that directly estimate the ideological position of media or political actors by utilizing text scaling techniques. Text scaling techniques rely on the core assumption that the relative frequency of words varies according to their ideological position, so they estimate the relative ideological position of the media based on the number of mentions of different words (Laver et al. 2003; Slapin and Proksch 2008; Lowe 2016). A distinctive feature of these text-scaling-based statistical models is that they treat text as "data" rather than as something to be understood or interpreted, i.e., they use the relative frequency with which words are mentioned to estimate the ideological position of a document without regard to the meaning conveyed by individual words. Therefore, it has the advantage of being able to estimate the ideology of the news media without the subjective judgment of the researcher because it uses only the relative frequency of words in the document as data.

These text scaling techniques have been used for media analysis in various countries. For example, Gentzkow and Shapiro (2010) measured the ideological position of newspapers by comparing the extent to which each newspaper used phrases similar to those used by Democrats or Republicans in the minutes of the 2005 U.S. Congress, and Yuan (2016) used hierarchical clustering of word frequencies in 21 newspapers' articles on the 18th National Congress to examine the media bias of Chinese newspapers. Most recently, Kaneko et al. (2021) used text scaling and topic modeling to measure the ideological ideal points of 10 Japanese newspapers on different issues. The reason why the text scaling method is used for comparative analysis of multiple newspapers or media is that there is little room for researcher arbitrariness compared to other analysis methods, and since the text is read directly into the software and the entire process is automated, the same results can always be obtained from the same data, and above all, it has the strength of being able to analyze quickly even when the amount of documents is large.

2.2. 'Selective Exposure' of the general public to partisan media

If the public's selective exposure to biased news media continues, negative political phenomena such as political polarization may increase. In general, selective exposure refers to the psychological tendency of individuals to select information or media that is consistent with their existing views or beliefs, while rejecting those that are not (Fischer et al. 2008; Klapper 1960). In a partisan media environment, the consequences of selective exposure are most notable for their impact on news recipients' political attitudes and beliefs. In fact, existing research on selective exposure and polarized attitudes shows inconsistent results (Knobloch-Westerwick 2012). While some scholars argue that selective exposure to partisan media leads to more polarized attitudes in the general public (Bennett and Iyengar 2008; Stroud 2008; Sunstein 2009), others argue that selective exposure to partisan media has nothing to do with polarization and merely reflects the reality that people with strong partisan leanings tend to consume media with similar leanings (Mills 1965; Sears and Freedman 1967). A recent study by Stroud (2010) provides empirical support for the first argument, that selective use of media leads to political polarization.

On the other hand, it has been argued that the increase in the number of media outlets has increased the likelihood that people will be exposed to like-minded media due to the rise of partisan news, and that this exposure to partisan media reinforces pre-existing attitudes, resulting in political polarization (Garrett et al. 2014; Stroud 2008; 2010). For example, listeners to the radio talk show of Rush Limbaugh, a leading conservative political commentator in the United States, held more conservative attitudes on a range of issues that conservatives generally consider important, including those that were frequently mentioned on Limbaugh's radio show, reflecting the fact that listening to the radio talk show influenced listeners' conservative attitudes (Barker and Knight 2000).

Recently, a number of scholars have demonstrated through empirical research that selective exposure to partisan media affects political polarization (Arceneaux and Johnson 2013; Leeper 2014; Levendusky 2013; Feldman et al. 2014; Stroud 2011). For example, a study by Feldman et al. (2014), which analyzed the relationship between partisan media use and global warming-related attitudes, found a statistically significant causal relationship between the public's selective exposure to partisan media and their liberal or conservative beliefs. These studies suggest that consistent exposure to certain media leads to a shift in political beliefs, which in turn promotes similar media choices and reinforces existing beliefs.

Given the far-reaching impact of news media in our lives and the difficulty of obtaining clean estimates of media bias using conventional approaches, this paper makes use of unsupervised machine learning techniques to conduct a sentiment analysis of 27 news media outlets in the United States over a 5-year period. The paper is structured as follows: the next session considers existing scholarship and techniques used to analyze media bias and highlights issues of polarization in news media. The following section explains the data and methodology used for this analysis in more detail. The final section presents our main findings and discusses some of its implications.

3. Data and Methods

We conduct a sentiment and network analysis of a large dataset composed of publication and text data from 27 news outlets in the United States. The source for this data is the All the News 2.0 dataset compiled by Andrew Thompson. This dataset contains 2,688,878 news articles and essays, spanning January 1, 2016 to April 2, 2020. It is an expanded edition of the original All the News dataset on Kaggle, which was compiled in early 2017. While the original dataset contains more than 100,000 articles, the new dataset's greater size and breadth makes it more broadly applicable for both training language models and studying a wider selection of media (Thompson, 2020). Table 1 below lists the publications in this data as well as the number of articles from each publication.

TABLE 1: Representation of publications in the data

	Publication	Count		Publication	Count
1	Axios	47815	15	Refinery 29	111433
2	Business Insider	57953	16	Reuters	840094
3	Buzzfeed News	32819	17	TMZ	49595
4	CNBC	238096	18	TechCrunch	52095
5	CNN	127602	19	The Hill	208411
6	Economist	26227	20	The New York Times	252259
7	Fox News	20144	21	The Verge	52424
8	Gizmodo	27228	22	Vice	101137
9	Hyperallergic	13551	23	Vice News	15539
10	Mashable	94107	24	Vox	47272
11	New Republic	11809	25	Washington Post	40882
12	New Yorker	4701	26	Wired	20243
13	People	136488	27	Refinery 29	111433
14	Politico	46377			

The data processing started with first filtering out the articles from the dataset - focusing on strictly the foreign policy domain. To do this, we filter out using keywords - to be specific, the article should have more than 3 of the keywords to be counted as a foreign policy article. As foreign policy in itself is a very broad topic, we consider a number of different sub-domains such as foreign aid, international relations, conflict, etc. so that we do not miss out on any aspects of the topic. We use a number of methods from the Knowledge Mining domain, due to the expansive data available to us from the ATN 2.0 dataset. Since this is a large dataset, it requires a lot of computing power. To reduce the computing requirements to a more reasonable frame we use bootstrap sampling. Through bootstrap sampling, we also take advantage of parallel computing to further streamline the data filtering and analysis process. Sentiment Analysis on such a large scale requires these modifications due to the lack of better computing power available to us as students and researchers.

Our various hypotheses and research questions are regarding change in sentiment analysis for U.S. news publications through the Trump Presidency. One of the hypotheses we investigate is that news media shifts sentiments (either to more positive or negative) after Trump gets elected. This was a pivotal time in U.S. politics as derived from the literature review, and so it is important to understand if news media further played into the polarization. Figure 1 shows us the differences in the mean sentiment scores for publications before Trump was elected, which consisted of all articles in 2016 and the first month of 2017, and after Trump was elected - which is all the data after the first month of 2017. Through the plot, we see distinct differences in the mean sentiment scores between a range of the publications in our data. Washington Post, TMZ, New Yorker are the top 3 publications that shift to a more positive sentiment score after Trump gets elected. On the other side of the plot, we see that The Verge, Vice & Gizmodo shift to a negative sentiment score once Trump is in office. It is interesting to see that CNN is essentially neutral in our findings via this preliminary analysis, which goes against popular belief around that period of time which labeled CNN as a negative news outlet. This sentiment analysis is done through the 'AFINN' lexicon in the tidytext package in R. We conduct analysis through two such popular methods, the 'AFINN' and 'Syuzhet' lexicon. Due to the Syuzhet lexicon being more popular and more popular in the Natural Language Processing literature - we conduct deeper analysis through this method.

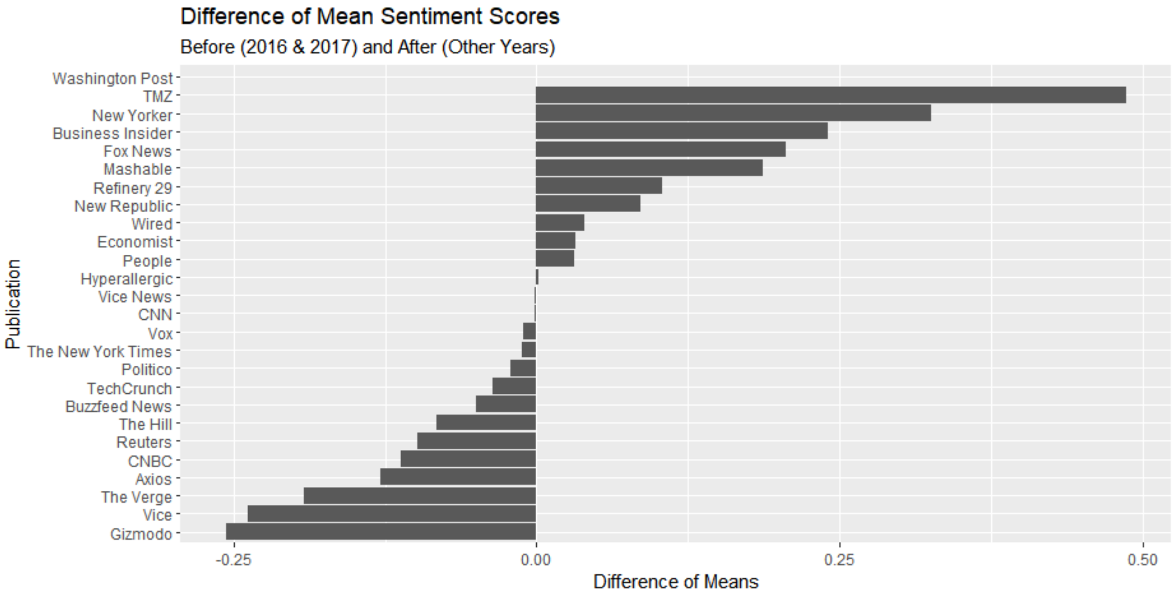

FIGURE 1 - Differences in Mean Sentiment Scores for Publications Before Trump was Elected

Another method that we use to further differentiate between the publications and get a better understanding of the data is cluster analysis. This is an example of unsupervised learning, which is an important aspect of Knowledge Mining.\The cluster package in R generated three clusters as seen in Figure 2 below. Cluster 1 is a combination of tech news sources and depicts positive sentiments across the time period that is analyzed in our analysis. This is quite an interesting observation as it gives us a preliminary look at the type of publications that have a positive sentiment score.

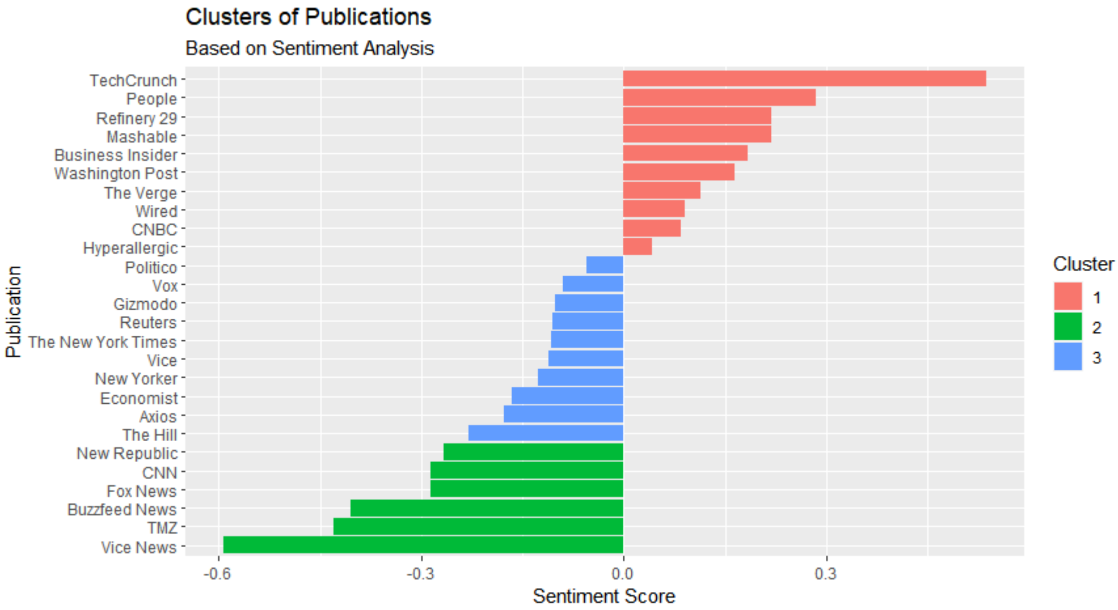

FIGURE 2 - Cluster Analysis Using Unsupervised Learning

The nexus between business, foreign policy and technology has grown closer and more important in the last decade or so with the advent of easily accessible consumer technology through manufacturing booms in countries such as China, India, Mexico, etc. Cluster 2 contains traditional news media outlets and publications such as Reuters, The New York Times, Economist, etc. and these publications are in line with what we conceptualize as the more neutral sources of news. Cluster 3 contains publications that are much more negative than the other clusters, and contain CNN, Fox News, New Republic, etc. This cluster is interesting as it follows the reporting cycle around the time period of our study regarding the sensationalization and polarization caused due to CNN and Fox News in particular. Our results that focus on Foreign Policy news further substantiates that hypothesis.

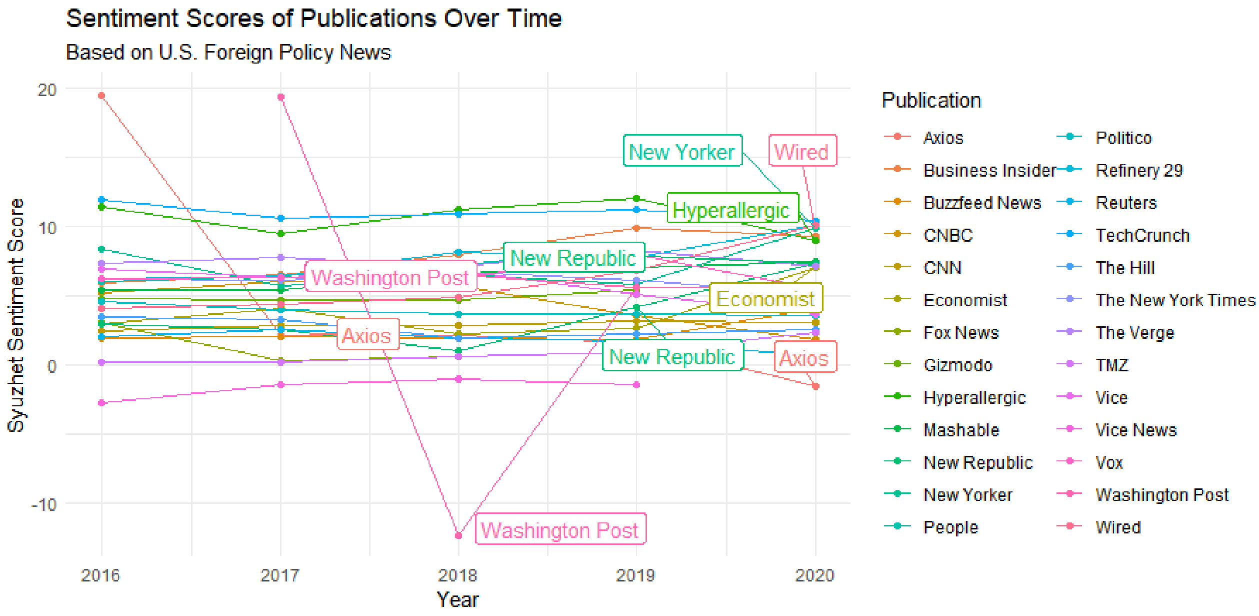

FIGURE 3 - Sentiment Score of Publications Over Time

To explore the sentiment across time periods using the Syuzhet lexicon, Figure 4 describes how publications shift in their sentiments. Washington Post is a distinct data point that we see has a drastic change in the sentiments - from a large negative value to a very positive value around the end of the data time period. To check if our results are robust, we further do a similar analysis using syuzhet, through the R package of the same name.

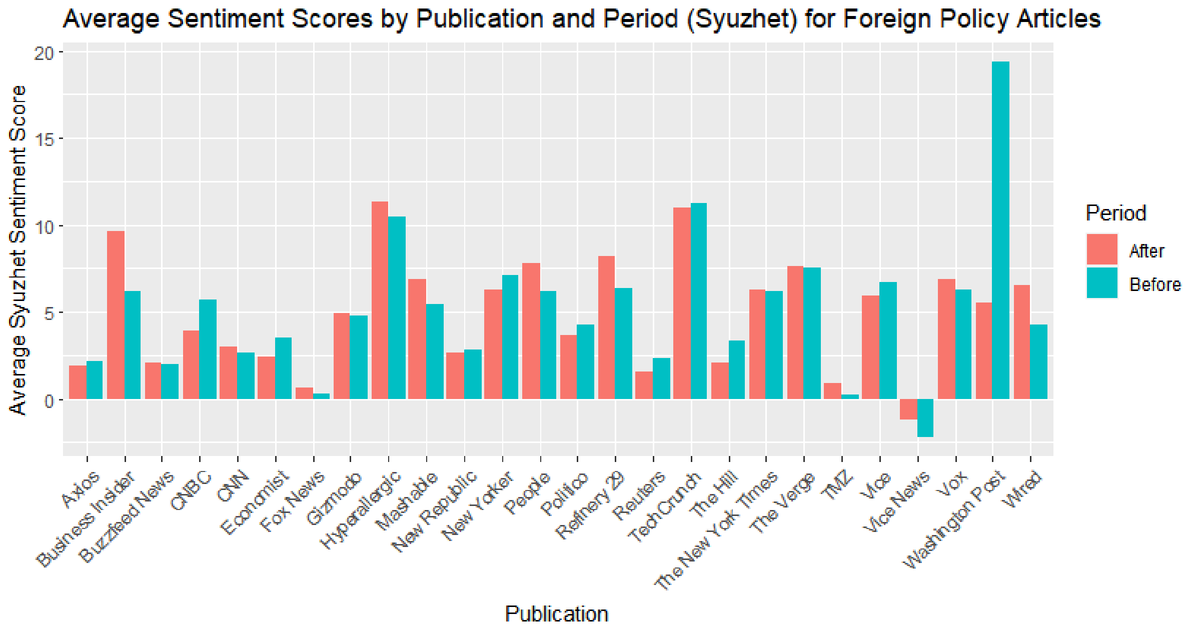

FIGURE 4 - Changes in Publication Sentiments before and after the 2016 election

We also conduct a per-publication based before and after analysis to see the true extent of the change of sentiments due to President Trump's election in 2016. To remain consistent, we do the same filtering based on Foreign Policy keywords to do this analysis, with Figure 4 showing the changes in sentiment for each publication in the ATN 2.0 database before and after Trump's election. The Washington Post is a publication that once more has the highest difference in sentiments between the two time periods that we look at here. We also plot the sentiment score distributions by publications to get a broad view of the data, as given in Figure 5. We see that the sentiments across publications are distributed in a bell shaped curve, or have a normal distribution with a slight right skew.

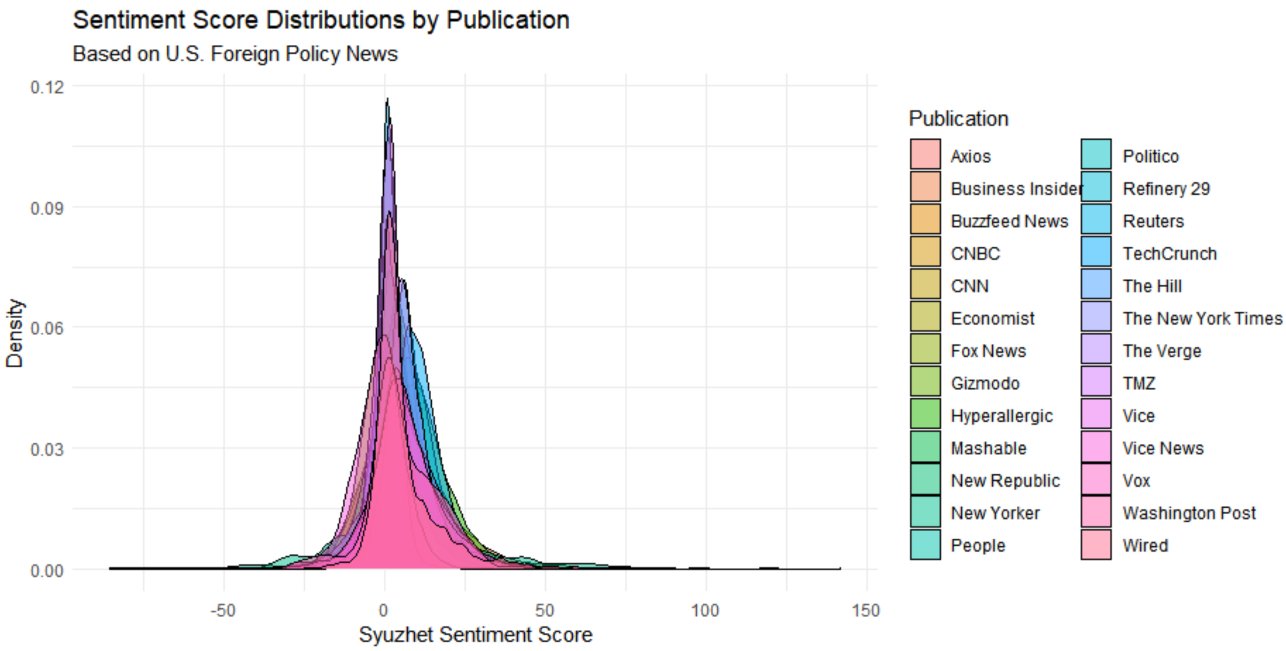

FIGURE 5 - Sentiment Score Distributions by Publications

These exploratory analyses give us a good idea of the trend of the data, but causal inference is difficult to establish with these methods. To understand the causal mechanism and posit a model to understand the effects of change in sentiments across both conservative and liberal groups of publications we use a differences-in-differences method as shown in Table 2.

The results of the difference-in-differences (DD) analysis show that being a liberal publication (i.e., being in the treatment group) had a positive effect on sentiment scores compared to being a conservative publication (i.e., being in the control group), after controlling for the effect of time. The intercept (0.14375) represents the average sentiment score for the control group (i.e., conservative publications) in the "Before" period. The coefficient for “periodbefore” (0.12725) suggests that, on average, sentiment scores were 0.12725 units higher in the "Before" period compared to the "After" period, after controlling for the effect of the treatment variable. The coefficient for is_treatment (0.08116) indicates that, on average, sentiment scores for liberal publications (i.e., the treatment group) were

0.08116 units higher than for conservative publications (i.e., the control group), after controlling for the effect of the period variable.

This finding suggests that being a liberal publication had a positive effect on sentiment scores. The coefficient for the interaction term periodbefore:is_treatment (-0.07989) suggests that the effect of the treatment on sentiment scores changed over time. Specifically, the negative coefficient indicates that the difference in sentiment scores between liberal and conservative publications was smaller in the "Before" period compared to the "After" period. This finding suggests that the effect of being a liberal publication on sentiment scores may have increased over time. Taken together, these results suggest that being a liberal publication had a positive effect on sentiment scores compared to being a conservative publication, and this effect was relatively stable over time. However, the difference in sentiment scores between liberal and conservative publications appears to have increased over time, with a larger difference observed in the "After" period compared to the "Before" period.

TABLE 2 - Differences in Differences Results

Diff-in-Diff	Estimate	Std. Error
(Intercept)	0.14375	0.09643
periodbefore	0.12725	0.14010
is_treatment	0.08116	0.12292
periodbefore:is_treatment	-0.07989	0.17787

We also run a panel regression model with fixed effects to understand the temporal changes in our data and sentiment scores. The output in Table 3 shows the results of a one-way (individual) effect within model, which is used to estimate the average effect of time (represented by the year variable) on sentiment scores, while controlling for any individual-specific effects that are constant over time. The coefficients for 2017, 2018, and 2019 represent the change in sentiment score relative to the base year, in each respective year.

The coefficient for 2020 represents the change in sentiment score relative to the base year, in the final year of the study.

The estimates suggest that sentiment scores decreased over time, with all yearly coefficients being negative. Specifically, the coefficients for 2017, 2018, 2019, and 2020 were -0.145047, -0.198490, -0.139595, and -0.154673, respectively. These findings suggest that, on average, sentiment scores decreased by approximately 0.14 to 0.20 units per year, depending on the specific year. However, it is important to note that the statistical significance of these coefficients is somewhat mixed, with only the coefficients for 2018 and 2020 being statistically significant at the 0.01 and 0.05 level, respectively. The coefficients for year2017 and year2019 are only marginally significant at the 0.1 level.

TABLE 3 - Fixed Effects Regression Model Results

	Estimate	Std. Error	tvalue	pvalue
2017	-0.145	0.0736	-1.97	0.0517
2018	-0.198	0.0736	-2.697	0.0083
2019	-0.14	0.0746	-1.872	0.0643
2020	-0.155	0.0777	-1.99	0.0495

4. Conclusion and Limitations

Our analysis shows that media bias in reporting of foreign policy issues does change around the 2016 Presidential election. We find distinct differences in the mean sentiment scores between a range of the publications in our data. Washington Post, TMZ, New Yorker are the top 3 publications that shift to a more positive sentiment score after Trump gets elected. In our cluster analysis we can see that the third cluster contains publications that are much more negative than the other clusters, and contain CNN, Fox News, New Republic. This might be driven by the fact that news media organizations try to differentiate themselves from others by taking more extreme positions on news. This needs to be broken down further by using heard analysis to see which news organizations are leading this shift and if others are following.

The preliminary causal analysis shows that being a liberal publication has a positive effect on sentiment scores compared to being a conservative publication. When we control for temporal changes using a fixed effects model we find that coefficients for 2017, 2018, 2019, and 2020, compared to the base year of 2016, were all negative. We find that on average sentiment scores decreased by approximately 0.14 to 0.20 units per year. This is interesting because it substantiates other research that shows the increase in negative reporting in news media over time.

There were a number of limitations that became apparent through the data analysis phase of this project. In our proposal, we looked to extend the ATN 2.0 dataset with our own sources that were based in countries other than the United States. That however would require even more computing power and time to conduct, and would be the next steps in a future research project that follows this one. Another limitation faced has been referenced several times in this paper, and that is the amount of computing power that is required to conduct sentiment analysis on such a large dataset - thus the bootstrap sampling method used in the final data analysis. Future research would consolidate a larger number of sentiment analysis lexicons along with the full population data (all the articles instead of a sample as we do here) to get more accuracy with the results. Another limitation was with R not having as many machine learning packages as Python, which is the software that will be used in the case of any future studies regarding this topic.

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