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CABLE NEWS CHANNELS' PARTISAN IDEOLOGY AND MARKET SHARE GROWTH AS PREDICTORS OF SOCIAL DISTANCING SENTIMENT DURING THE COVID-19 PANDEMIC

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The return of media partisanship

In times of heightened polarization, it is not surprising that the US public's adoption of methods to mitigate the spread of the COVID-19 virus, such as social distancing and related measures, became politicized. Liberals became more likely to practice mitigation, while conservatives less so (Rothberger et al., 2020; Hart et al., 2020; Christensen et al., 2020). This pattern was also observed in other countries, such as New Zealand (Becher, et al., 2020), Brazil (Ramos et al., 2020), and the UK (Harper & Rhodes, 2020).

Because the commercial media strive to increase audience share to raise advertising fees, they tend to produce news content to attract partisan audiences. In 2020, observers viewed the media as rising in partisanship in the climate of heightened polarization (Jurkowitz et al., 2020). Yet before considering the contemporary media partisanship climate, its historical trajectory merits a brief treatment.

The term "partisan press" refers to journalism that is systematically influenced and sometimes affiliated with the government and its parties. The frequency of the bigram "partisan press" is portrayed in Figure 4.1 using Google Books[1] of American English published since the 1800s. It indicates that this concept has gained a renewed interest in the 21st century. The period of highest turbulence, from 1820 to 1890, declined with the Progressive Era of the 1890s–1920s, further declined during World War II and the post-war period, and then increased in the 1980s to its highest levels since the turn of the previous century.

Data source: Google Books Ngram Viewer (https://books.google.com/ngrams)

As the 1800s unfolded in the post-Revolutionary War period, political parties funded newspapers, as hundreds grew to a thousand and more by the 1830s (Formisano, 2008). However, while press partisanship increased, most readers were unaware of this undercurrent shaping the stories on the surface (Baughman,

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FIGURE 4.1 "Partisan Press" mentions in Google books since the 1800s.

2011). The abolitionist movement further fueled partisanship, leading up to the Civil War. The Progressive Era's investigative journalism of the 1890s–1920s saw a critical, independent press emerge alongside the Democratic- and Republican-funded newspapers. When muckraking investigative journalism emerged, so did the reporting on corporate, union, and governmental corruption, and the resulting social injustices. The attention to these areas appears to have dampened the salience of press partisanship in that period.

Nevertheless, by the 1940s, issues emerged about some radio stations' biased coverage of local politics. A Federal Communications Commission policy formed that radio stations served the public interest and therefore could not take editorial positions on issues, a policy further articulated in the Fairness Doctrine in 1949 (Simmons, 1978) that required broadcasters to cover controversial issues and present opposing viewpoints, a sort of common carrier opinion model. At the same time, the US Marshall Plan for European recovery (Hogan & Hogan, 1987) reflected this policy but with a different implementation. To reduce the likelihood that a one-sided press with no opposition would re-emerge, the program funded diverse political parties to establish viable media outlets, resulting in a more balanced overall media domain.

Domestically, the Fairness Doctrine guided media coverage during the 1950s and early 1960s. The social movements of the 1960s–1970s appeared to increase media partisanship, perhaps because counterculture supporters' liberal orientations fit with journalistic norms. This may have contributed to the erosion of the Fairness Doctrine, as it ceased to be enforced and officially abandoned in 1987.

Another factor increasing media partisanship was the emergence and growth of cable news outlets, with CNN launched in 1980. It featured a popular primetime show, Crossfire, which pitted a conservative against a liberal commentator, an extension of the two-sided approach to media coverage fostered by the soon-to-be-defunct Fairness Doctrine. Then as Fox News and MSNBC emerged 16 years later, they tended toward a more partisan treatment, favoring one side over the other. CNN was ideologically positioned between them but closer to the liberal partisan perspective. In

2020, quantification of partisanship in the Gallup/Knight study, American Views 2020: Trust, Media, and Democracy, scaled MSNBC as left with a score of 1, CNN as left-center at 1.25, and Fox News as conservative at 4.75 on a five-point scale.

Although media partisanship is widely considered as a common practice in the US of 2020s, coloring coverage, the motive to attract larger audiences may interact with the sentiment expressed in the news toward issues of the day. When sentiment increases, both positive and negative, it heightens audience engagement (Arapakis et al., 2014), which leads to increased viewership. Accordingly, the market motive may be a stronger factor than ideology in channeling sentiments. Perhaps the rising interest of scholars in media partisanship results from the convergence between ideology and market logic. With the growing media fragmentation, the sensational partisan press sells more.

Nevertheless, media partisanship growth raises questions about whether ideological perspectives have taken a deeper root in infusing news content production or is a more transitory market-based orientation, capitalizing on differences in audience member's political orientation. Has the media profit-seeking model, which symbiotically links their media content with audiences' political perspectives, been altered by a new threshold of ideological framing? Have the media become a more active agent of change than the common carrier of news before the Fairness Doctrine's dissolution? Has the revenue-driven media become more the cause of partisan polarization than a reflector of it? Has ideology today become yet another commercial brand? Critical media theory (Schiller, 1991, 2013; Fuchs, 2011) would agree with this view, stressing that capitalist ideology frames and shapes media content. These two perspectives, one that partisan ideology accounts for social distancing sentiment, and the other that market share growth is stronger, is the basis for the two hypotheses addressed in this chapter. One is that ideology is the primary determinant of media sentiment toward social distancing, and the other is that market motives offer a better explanation. Over time, partisan ideology may have lost some of its meaning as it dissolved into the market logic. This would explain why we have seen a sharp decline in partisan media during the 20th century and now again a rise in attention in the partisan press. It may be that partisan press and market forces today do not compete as they did in the 20th century but rather complete each other.

The rise of social distancing and its political context

Merriam-Webster states that social distancing is a medical term, first used in 2003. However, as early as 1972, the scholarly literature used the term to refer to a different sense, the physical and social distance between social units, in this case teachers and students (Schwebel & Cherlin, 1972). Yet the concept of social distancing has a much longer history. Removing sick individuals from social settings to prevent the spread of disease dates back at least to 538 BC, when the Bible's Book of Leviticus was first written, describing removing lepers from the camp. Issac Newton isolated himself from the disease, and lepers were exiled to colonies on Molokai to prevent the disease spread to other Hawaiians.

Imagine the leper's distress in being forcefully excluded from the social network with no hope of return, a separation more extreme than experienced during the recent governmental campaigns, premised on a much shorter time horizon until returning to normal. Nevertheless, the adverse effects attributed to social distancing during the pandemic are significant: increased mental health problems, substance abuse (Panchal et al., 2020), suicide (Thakur & Jain, 2020), and domestic violence (Campbell, 2020). Moreover, participation in violent protests during the pandemic may have increased due to social distancing. These negative effects linked to social distancing offer unique evidence of the social network's importance in maintaining normative behavior. When the network is suppressed, negative consequences soon arise.

The social network's central role makes it difficult to promote social distancing, even on a short-term basis, so information campaigns require highly persuasive messages with many repetitions. The initial warrants in the argument were that social distancing would protect vulnerable elderly, a more collective intergenerational appeal. Not until later in the campaign did the rationale shift toward more individualistic protection of the self, as masks were advocated for the general public in addition to the medical providers, not only as a means of protecting others. Once the arguments reached this level, perhaps the altruistic motive dissipated, as individuals weighed their risks against the somatic limitations of mask-wearing and loss of personal freedom and practiced social distancing less.

These social distancing information campaign messages are filtered through partisan media biases. When the coronavirus campaign launched, daily press briefings from the White House were covered by the three cable channels, but by April 1, 2020, CNN and MSNBC ceased broadcasting the briefings (Wemple, 2020), while Fox News continued coverage until the daily briefings ended on April 26. Moreover, as the media reported on compliance, this likely reinforced the respective attitudes and behaviors regarding social distancing.

The embracing of social distancing by the liberal press but not the conservative press may be due to the media channels attention to the base reaction of members of the public based on their partisan preferences, where conservatives more likely see social distancing as limiting personal freedom, while liberals would see more of the positive collective benefits of social distancing. A more contemporary current influencing media sentiment may be the fact that President Donald Trump was portrayed as somewhat negative toward social distancing as the COVID-19 campaign progressed and more concerned with the economic implications of the pandemic, while presidential candidate Joe Biden was more positive toward social distancing. In this immediate partisan election climate, the cable channels were aligned in apparent support of one candidate over the other. The fact that the same liberal/conservative stances toward social distancing were reported in other countries would reduce the likelihood that the social distancing sentiment was primarily based on election sentiment that media expressed during the period.

The partisan profile of cable news channels suggests the hypothesis that Fox News would be more negative toward social distancing, while MSNBC and CNN more positive. An alternative hypothesis is that market share growth predicts social distancing sentiment better than ideology, which suggests that CNN, with the largest increase in market share, should have the most sentiment expressed, followed by Fox News, and MSNBC.

Methods

Sentiment measurement model[2]

The dominant methods for sentiment analysis (Kharde & Sonawane, 2016) seek to classify messages as positive or negative for use in machine or deep learning using neural network models (Zhang et al., 2018). Less common are methods that measure the degree of positivity or negativity in texts. Classification of textual content into positive or negative categories (Liu & Zhang, 2012; Mäntylä et al., 2018) counts frequencies of sentiment words in a lexicon, a predefined list, or dictionary of positive and negative terms. Counting individual word frequencies is referred to as a "bag-of-words" model. The approach treats all of the words in textual units of observation disaggregated and jumbled together with no relations among them. The proximity of words in the text is ignored. The bag-of-words sentiment scores are typically based on counts of binary values for whether each word in the text appears in a document.

In communication science, rather than classification, content analysis of messages to measure the degree of positive and negative sentiment associated with a target is often the goal. This content analysis requires a different measurement model than bag-of-words, one based on a network approach. Although most social network analyses are of relationships among entities, such as individuals, groups, organizations, or nations (Rogers, 1987; Monge and Contractor 2003; Borgatti et al., 2009), a network model has also been useful in treating words in the text as nodes and their proximate co-occurrences as links, forming a semantic network (Danowski, 1982, 1993; Carley, 1993; Corman et al., 2002).

Some recent examples of semantic network analysis include work by Danowski and Park (2014), Jiang et al. (2016), and Danowski and Riopelle (2019). Semantic network analysis covers a wide range of meaning aspects (Osgood et al., 1957). An essential advantage of semantic network analysis is that it illustrates the relationships among words, thus generating insights about the entire text's structures and meanings. Here we are concerned not only with the sentiment, which is just one dimension among many that semantic network analysis can index in the study of texts. Nevertheless, we present a sentiment analysis approach building on word relationships and embeddedness in texts. This method can potentially be applied to other dimensions of texts, as long as researchers are interested in looking for the strength of relationships between a target word or phrase and a particular category of words.

Approaches to sentiment analysis

Lexicon-based measures

The most simple and common approach for sentiment analysis is using a predefined lexicon or dictionary containing sentiment words, affective orientations, and sometimes the strength of its orientation. Following the bag-of-words approach, lexicon-based approaches first break down a body of text into independent words. Then it counts the frequency of sentiment words (which are defined by the lexicon used) that appear in the text and computes a sentiment score of the text, usually in the form of a percentage based on the word count.

Commonly used sentiment lexicons include Linguistic Inquiry and Word Count (LIWC) (Tausczik & Pennebaker, 2010), SentiWordNet (Baccianella et al., 2010), and the Bing lexicon. Whereas some lexicons, such as Bing, contain words in binary categories, others, like SentiWordNet, provide a ratio indicating the words' orientation's strength. Lexicon-based sentiment analysis is an unsupervised method that is easy to apply and not domain-dependent. It can be highly accurate if used appropriately (Kundi et al., 2014; Asghar et al., 2014; Khoo & Johnkhan, 2018). However, a limitation of lexicon-based measures based on the bag-of-word approach is that it focuses only on the frequency of single, tokenized words. It omits the words' contexts based on their co-occurrences in the texts that are critical to sense-making. In other words, you get one score for an entire text regardless of the number of persons, organizations, or brands mentioned.

Machine learning classification

The machine learning approach utilizes supervised learning, which starts by extracting features from texts (Liu, 2012). Machine learning algorithms applying the bag-of-words approach treat single words as semantic features. The features and outcomes (e.g., annotated sentiment of texts) it learns from the training text data classifies texts into different sentiment categories, such as positive, negative, and neutral. The key to the performance of machine learning lies in the effectiveness of the features it extracts. The machine learning approach has the edge over the lexicon-based measures as it acquires information directly from the text body rather than a standard lexicon (D'Andrea et al., 2019. Therefore, it is better customized to the text data.

Several software vendors, including IBM (Watson), Google (Cloud Natural Language), Amazon (Comprehend), and Microsoft (Azure), have developed their own proprietary machine learning algorithms for sentiment analysis. These algorithms are relatively easy to use but are not transparent (since they are proprietary) and can be expensive for researchers. This is because a machine learning-based sentiment analysis can be costly to develop. It requires a considerable amount of text data to train an accurate classification algorithm and may need human coders to annotate the training texts. It may also work better for long documents than short reviews or tweets so that there are more words to serve as textual features for classification (Khoo & Johnkhan, 2018). Machine learning classification using a bag-of-words approach also shares the same limitation with the lexicon-based approach. It only uses independent words and ignores the contexts in which the words are embedded.

Word embeddings for sentiment analysis

A relatively recent development in natural language processing is word embeddings (Mikolov et al., 2013). Word embeddings are techniques that map words in a text into numeric vectors in a vector space. Instead of assuming words as independent, as the bag-of-words approach does, word embeddings often operate based on a sliding window and extract features from a sequence of words cooccurring in a body of text. This approach aligns with the semantic network perspective and takes into consideration word contexts. Based on how words appear with one another, word embedding algorithms represent the words in the vector space, in which words used in similar ways are closer to one another.

Word embeddings may be applied in two ways in sentiment analysis. The first is by extracting words and their relations in the texts as features for sentiment classification (Kumar & Zymbler, 2019). Researchers have also applied pre-trained word embedding corpora to classify texts. So, when target texts contain words that did not appear in the training dataset, the algorithm can judge text sentiment based on how close the new words are to the words that appear before in the relational corpora (Rudkowsky et al., 2018). Just like other machine learning models, training with word embeddings requires the dataset to be large to produce an accurate mapping of words in a text. If pre-trained word embedding corpora are used, then the algorithm does not directly learn from the body of text being analyzed and may not precisely capture the texts' local context under scrutiny.

Aspect-based sentiment analysis

Based on the unit of analysis, sentiment analysis can also be classified as either subjectivity/objectivity identification or feature/aspect based. Subjectivity/objective identification, as used by studies cited above (e.g., Kumar & Zymbler, 2019; Rudkowsky et al., 2018), classifies the sentiment of an entire text. By contrast, aspect-based sentiment analysis takes a more fine-grained approach, aiming to determine sentiment in parts of texts (e.g., opinions regarding different attributes of a product or service) (Pontiki et al., 2016; Thet et al., 2010; Wang & Liu, 2015). For example, when analyzing an online review of a hotel, the subject/objective identification estimates the review's general sentiment. In contrast, the aspect-based sentiment analysis may examine how positive the review is toward the hotel's location, service, room, and food. Therefore, the first step of aspect-based sentiment analysis involves parsing texts into different linguistic components through automated algorithms such as topic modeling (Thet et al., 2010). After the texts are broken down, researchers can then choose to apply the sentiment analysis discussed above to measure the aspect-specific sentiments. Aspect-based sentiment analysis thus provides more detailed and accurate information regarding the sentiment in texts, which can be particularly useful when one needs to understand opinions about specific features.

In summary, existing sentiment analysis methods commonly apply the bag-of-word approach, breaking texts down to independent words without considering word contexts. The more recently proposed word embeddings approach is gaining traction, but machine learning using the method requires a large amount of data. Using pre-trained word embeddings makes judgments based on previously collected data rather than the texts being analyzed. Therefore, it risks missing critical information in the local word context. The semantic network-based approach to sentiment analysis proposed in the current study complements the above methods. It overcomes the limitations of the bag-of-words model by gauging the contexts of words in texts based on word sequence and co-occurrence. It has an advantage over machine learning approaches as it does not need a large amount of data and measures sentiments based on the local information in a given text.

Moreover, the semantic network approach allows fine-grained sentiment analysis at the aspect or feature level like aspect-based sentiment analysis. Instead of relying on unsupervised learning algorithms such as topic modeling to identify features in a text, this approach enables researchers to name the target word or phrase of interest (person, organization, event, or brand, e.g., iPhone). It generates a score indicating sentiment toward this specific target. Thus, the sentiment network method can generate sentiment scores for multiple targets of interest in the same text, enabling a comparison of the results.

The sentiment network approach measures target-specific sentiment based on the shortest paths between the semantic network's target and sentiment words. The method has three significant advantages over bag-of-words classification approaches: 1) the network method measures sentiment concerning targets, which is possible because the basic unit of analysis is the word pair in a sentence, not a document; 2) the more micro-level word pairs are links in a chain, forming shortest paths that extend across text units, enabling tracing the closeness of sentiment words to a target word or phrase; and 3) the sentiment network approach can compare multiple targets in the same corpus, which expands the scope of testable hypotheses.

The software we used to measure sentiment in this fashion, SENET, is described in greater detail in Appendix B (see eResources), including the code in R. It covers greater detail on the computational aspects of the current study for those who may wish to explore the tools further: 1) data acquisition from GDELT, 2) semantic network analysis using WORDij, 3) group detection and graphing in NodeXL,[3] and 4) sentiment network analysis with SENET.

Data

Data for this study included 150-character snippets of news content containing the term social distancing from television transcripts from Fox News, MSNBC, and CNN from January through September 2020, produced by GDELT (https://gdeltproject.org). Here are examples of snippets:

> 8/20/2020 13:22 CNN … were on the strictest lockdown in the entire nation for
> approximately i believe 15 weeks. many people complied with wearing masks, practicing physical distancing. i know that we were social distancing, but we were practicing physical distancing and people took care of one …
> 8/20/2020 18:22 CNN … touches on their convention. thanks very much. appreciate it.
> los angeles shutting off power to a mansion that's been holding parties, despite social distancing rules, and they monitored to …
> 8/20/2020 5:14 CNN … he said i've been quarantining, self-isolating, social distancing
> for the past six months, but this election is important enough, i believe it's important enough for me, to go to the …

After pre-processing text to remove numbers, punctuation, and stop-words, we conducted semantic network analysis with WORDij software (http://WORDij.net). No stemming was performed to enable capturing sentiment nuances and a higher fidelity representation of meaning.

Media partisanship scores were obtained from a 2020 Gallup/Knight study on media trust and democracy.[4] Media partisanship was scaled based on the coding schemes of Media bias/Fact check[5] and Allsides.[6] MSNBC was rated as left at 1.0, CNN as left-center at 1.25, and Fox News as conservative at 4.75.

Market share growth refers to an increase in audience share during the pandemic in 2020. The data were reported (Schneider, 2020) in *Variety*.[7] Table 4.1 shows the market share growth of the three cable outlets. CNN has the largest growth, followed by Fox News and CNN. Market share is in millions of viewers as of January 1, 2020.

We measured positive and negative sentiment toward "social distancing" with the SENET semantic network sentiment analysis package in R (Danowski et al., 2020). The procedure begins with the creation of the word co-occurrence network based on the sliding window that tracks the appearance of pairs of words in

TABLE 4.1 Market share and growth for Fox News, MSNBC, and CNN

Cable News Channel	*Share*	*Growth*
Fox News Channel	2.501	+43%
MSNBC	1.741	+23%
CNN	.965	+83%

it, cumulating the counts. With this network, we then use a lexicon of positive and negative words developed through the compilation of the lexicons of others and measure the distance to and from each sentiment word to the target word or phrase, in this case "social distancing", by tracing the shortest paths linking them. Then we inverted these values, squared them, and multiplied them by the co-occurrence frequencies along the path. Appendix B (see eResources) describes this in more detail, including the R code to compute the sentiment scores.

Results

Figure 4.2 shows the volume of coverage of social distancing. Data for January and February 2020 do not appear because there were fewer than five references. On March 16, the federal government introduced the first campaign, 15 Days to Slow the Spread. The mentions of social distancing increased to a peak in April 2020, followed by a decline toward June 2020. Figure 4.2 further shows that the same pattern occurs for negative and positive sentiment. CNN has the most negative and positive sentiment expressed. Comparing the curves for the frequency of coverage and sentiment suggests an association between the frequency of coverage and sentiment, which are consistent with findings of earlier research (Danowski & Riopelle, 2019) that sentiment produces an increase in the volume of coverage. As well, there appears to be a relationship between positive and negative sentiment. As one increases so does the other, although the differences between them over time show considerable variability in this association, particularly as seen for April and August. Although the coverage of Fox News, MSNBC, and CNN are parallel for

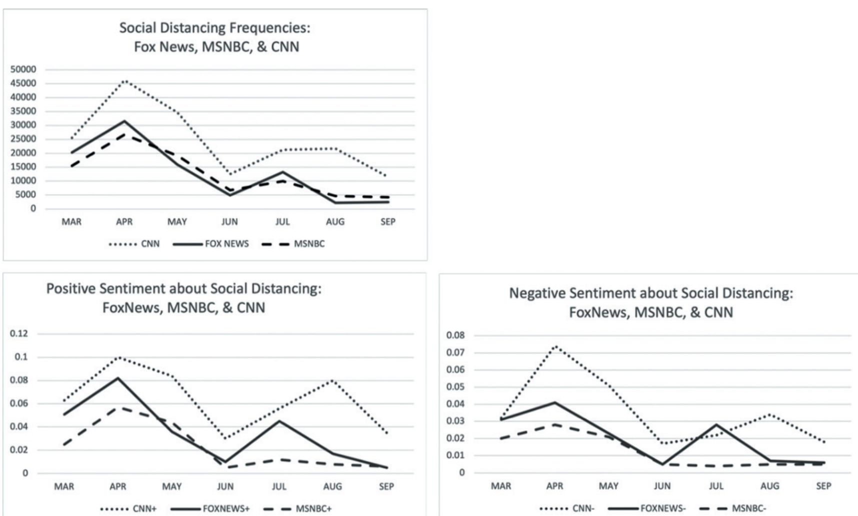

FIGURE 4.2 Social distancing frequencies and sentiment for Fox News, MSNBC, and CNN.

most of the duration. In August there is a deviation where CNN has higher sentiment than Fox News and MSNBC, both of which decline, while CNN increases its expression, particularly of positive sentiment.

The key analysis tests the ideology vs. the market share hypothesis for the overall expression of sentiment (both positive and negative). Figure 4.3 has the y-axis normalized for the two variables. It shows evidence for a linear relationship between market share growth and the amount of sentiment expressed (right), while for ideology and total market share (left), this is not the case. The lines cross. This supports the market share growth hypothesis over that of ideology.

The finding that August had the greatest deviation among the cable news channels motivated our analysis of the word co-occurrences for the outlets. Because MSNBC did not have coverage above the lower frequency threshold of three co-occurrences, its network is null, and the comparison is between CNN and Fox News. The bigram "social distancing" was converted to the unigram "socialdistancing" to create a semantic target to represent the concept; otherwise, targeting social or distancing would introduce much measurement error. We examined the data to see the differences in word pair co-occurrences, shown in Tables 4.2 and 4.3. The differences found motivated an analysis of the overall semantic networks for the two channels.

CNN's co-occurrence frequencies were 5.9 times higher than Fox News's, which produced a difficult to comprehend hairball network graphic, so to sparsify

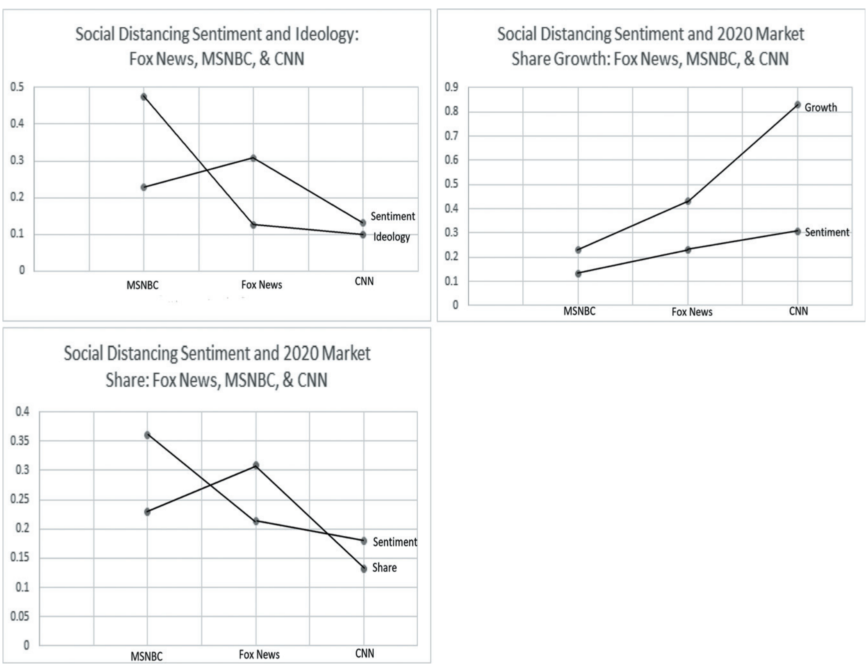

FIGURE 4.3 Ideology, market share, and market share growth vs. social distancing sentiment.

TABLE 4.2 Higher August word pair frequencies for CNN

WORD PAIR		*CNN FRQ*	*FOX FRQ*	*%*	*%*	*Z-SCORE*
masks	socialdistancing	312	0	0.0195	0.0000	6.92
no	socialdistancing	194	0	0.0121	0.0000	5.44
not	socialdistancing	180	0	0.0112	0.0000	5.24
socialdistancing	masks	156	0	0.0097	0.0000	4.88
wearing	socialdistancing	142	0	0.0089	0.0000	4.65
mask	socialdistancing	118	0	0.0074	0.0000	4.24
socialdistancing	wearing	113	0	0.0071	0.0000	4.14
no	masks	111	0	0.0069	0.0000	4.11
socialdistancing	not	106	0	0.0066	0.0000	4.01
people	socialdistancing	95	0	0.0059	0.0000	3.80
white	house	78	0	0.0049	0.0000	3.44
socialdistancing	mask	67	0	0.0042	0.0000	3.19
people	wearing	101	3	0.0063	0.0012	3.10
right	now	62	0	0.0039	0.0000	3.07
masks	social	55	0	0.0034	0.0000	2.89
wearing	masks	280	23	0.0175	0.0095	2.88
ensure	socialdistancing	54	0	0.0034	0.0000	2.86
masks	required	53	0	0.0033	0.0000	2.83
masks	distancing	52	0	0.0032	0.0000	2.81

TABLE 4.3 Higher August word pair frequencies for Fox News

WORD PAIR		*CNN FRQ*	*FOX FRQ*	*%*	*%*	*Z-SCORE*
health	people	11	6	0.0000	0.0281	–21.26
should	masks	11	6	0.0000	0.0277	–21.10
people	together	14	7	0.0000	0.0273	–20.94
lot	people	38	14	0.0000	0.0273	–20.94
think	people	13	9	0.0000	0.0273	–20.94
students	socialdistancing	0	10	0.0000	0.0215	–18.58
without	socialdistancing	0	10	0.0000	0.0211	–18.40
wear	socialdistancing	0	11	0.0000	0.0202	–18.03
no	socialdistancing	0	12	0.0000	0.0202	–18.03
socialdistancing	guidelines	0	12	0.0000	0.0202	–18.03
socialdistancing	mask	0	13	0.0000	0.0153	–15.67
socialdistancing	wearing	0	14	0.0000	0.0136	–14.79
practicing	socialdistancing	0	15	0.0032	0.0289	–14.62
socialdistancing	people	0	15	0.0000	0.0124	–14.10

(*Continued*)

TABLE 4.3 Cont.

WORD PAIR		*CNN FRQ*	*FOX FRQ*	*%*	*%*	*Z-SCORE*
mask	socialdistancing	0	18	0.0000	0.0124	–14.10
not	without	0	18	0.0000	0.0112	–13.38
wearing	socialdistancing	0	27	0.0000	0.0074	–10.92
socialdistancing	masks	0	30	0.0000	0.0074	–10.92
socialdistancing	not	0	30	0.0000	0.0062	–9.97
face	coverings	51	70	0.0000	0.0062	–9.97

Note. The headings in this table are as follows: FRQ is the word co-occurrence frequency, % is the proportion based on the total number of words for CNN and Fox News, respectively. Only values of p < .001 are displayed.

the network we set the lower frequency threshold at 10. The size of nodes in the graphs is based on betweenness centrality (Brandes, 2001). Figure 4.4 shows the networks of CNN and Fox News. The main substance of the two is seen in Tables 4.4 and 4.5, which show the top ten words in the top seven groups in each. Word groups were identified using the Clauset-Newman-Moore community detection

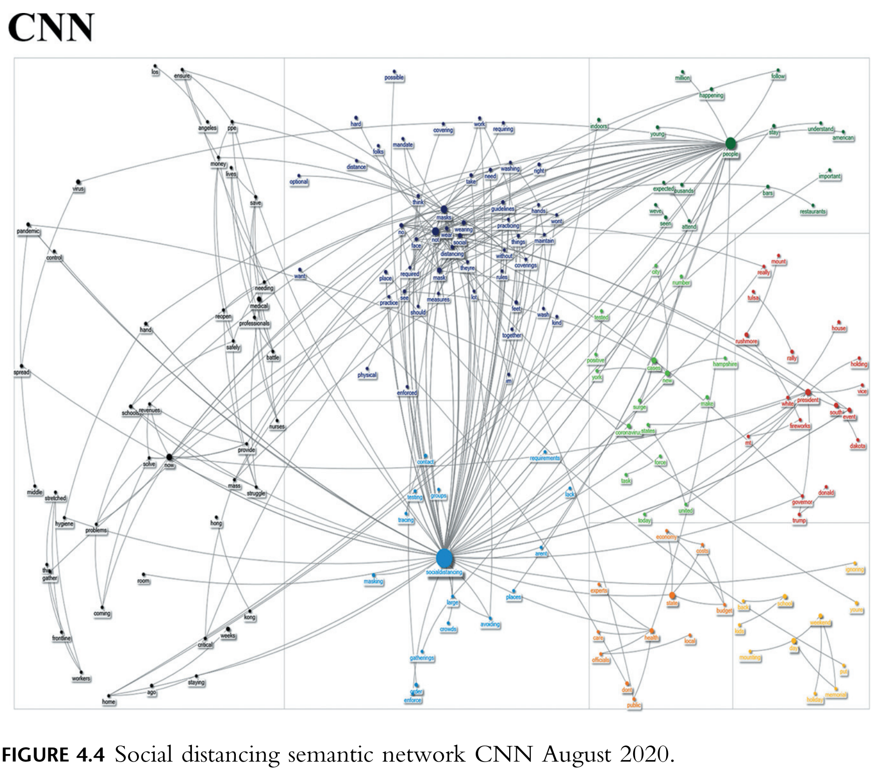

FIGURE 4.4 Social distancing semantic network CNN August 2020.

Fox News

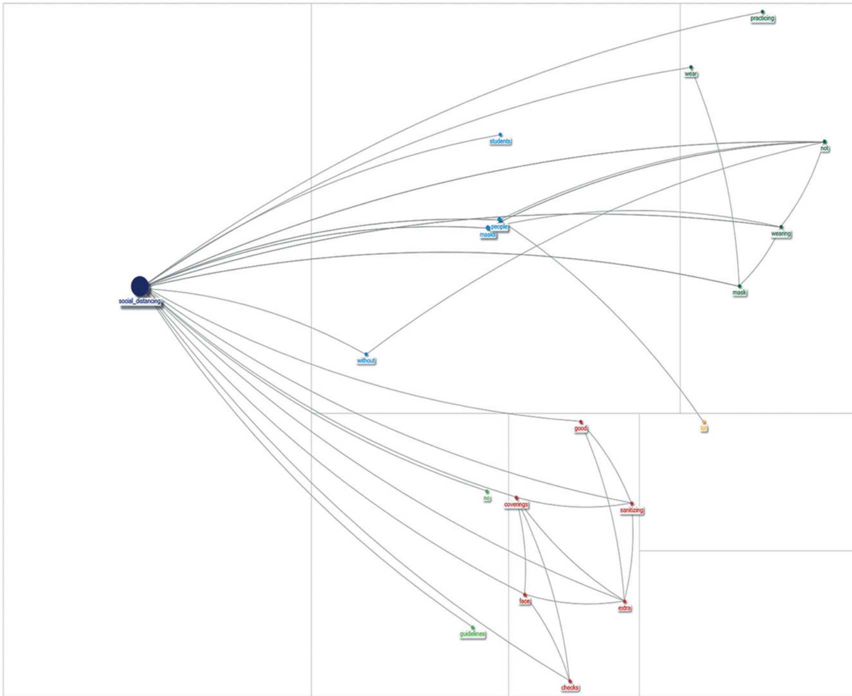

FIGURE 4.4 (cont.)

algorithm (Clauset et al., 2004). This method identifies communities by finding the node cluster that produces the largest increase in modularity, or the relative density of edges within communities to those outside communities. There are other faster clustering algorithms, such as the Louvain method (Blondel et al., 2008). The reason we chose the Clauset-Newman-Moore algorithm is that it is available in NodeXL, which we used to generate the networks.

The word groups in CNN's August 2020 coverage, containing at least three words, numbered 24. Table 4.4 lists the seven largest groups, including the top ten most central words in each. Table 4.5 shows the word groups for Fox News. It had only seven groups, and they occur at considerably lower frequencies. The order of groups reflects their size. For comparison purposes, the top seven largest groups are shown for CNN. Because our interest is not in mapping all the meanings for social distancing on CNN, but only to contrast the main differences between CNN and Fox News, we list the top seven largest groups for CNN, rather than all 24.

CNN's largest word group is about people not wearing masks or social distancing, while Fox News reinforces guidelines for it. So, while CNN is pointing out violations, Fox News is promoting social distancing. In downplaying lack of compliance, Fox News exhibits conservative ideology, yet at the same time encourages social

TABLE 4.4 CNN August word groups

1	*2*	*3*	*4*	*5*	*6*	*7*
possible	avoid	people	Reopening	really	health	day
masks	large	risk	States	president	dont	visit
not	gatherings	putting	Seeing	event	defying	pay
enforced	crowds	taking	new	heads	state	daughter
no	socialdistancing	sick	coronavirus	mt	officials	kids
wearing	mandatory	trying	cases	trumps	experts	back
think	steps	attend	today	trump	public	school
wash	practices	thousands	ways	supporters	system	youre
mask	making	expected	jersey	rally	care	time
wear	way	gathered	yorkers	donald	safety	put

TABLE 4.5 Fox News August word groups

1	*2*	*3*	*4*	*5*	*6*	*7*
socialdistancing	people	practicing	health	good	safe	lot
follow	close	wearing	guidelines	extra	engaging	now
operation	together	not	no	sanitizing	really	inside
allowed	coronavirus	mask	public	checks	common	tech
protocols	masks	testing	ignoring	face	measures	campaigns
concern	things	wear	pandemic	coverings		
cases	think	house	lives			
miss	hand	sound	own			
numbers	required	doesnt	way			
outbreak	covid	situation	good			

distancing, a stance considered more liberal. This is further evidence for the failure of ideology to explain the coverage of social distancing. More consistent with the data is marketing motives. By not expressing as much negative sentiment toward lack of compliance, they avoided risking their audience loyalty for the bulk of its audience, conservatives. Yet, by encouraging social distancing, they also appeal to more liberal audience members. Fox did use the slogan "Fair and Balanced", and during daytime hours included opposing partisan commentators in panels. Thus, consistent with the findings from the comparison of ideology vs. market share growth as predictors of sentiment, here among the whole semantic networks, we found further evidence at the level of the substantive content showing the failure of ideology to explain media coverage of social distancing.

In CNN's August coverage, the first word group is about not wearing masks. The second is about the need to avoid large gatherings. Group 3 is about the Southern

California beach crowds, while Group 4 is about reopening and a surge in cases. Group 5 is about Trump rallies, while Group 6 is about defying state public health officials, and Group 7 is about schools.

The top word groups in August for Fox News appear in Table 4.5. Group 1 is about social distancing protocols and numbers of cases, while Groups 2 and 3 are about the need to wear masks, Group 4 is about the public ignoring health guidelines, Group 5 is about sanitizing and face coverings, Group 6 is about engaging in safe common measures, while Group 7 is about tech campaigns.

Table 4.6 shows the top 20 negative and positive sentiment words that appeared in CNN and Fox News's coverage in August. The values range between 0 to 8, based on the frequency weighted inverse square of the shortest paths linking with social distancing, representing the closeness and strength of the target to the sentiment words.

TABLE 4.6 CNN August social distancing sentiment word strengths

CNN				*Fox*			
NEGATIVE		*POSITIVE*		*NEGATIVE*		*POSITIVE*	
problem	8.00	celebrate	8.00	no	7.00	good	6.00
difficult	7.00	effective	8.00	not	6.00	engaging	3.00
lose	6.00	working	7.00	concern	4.00	new	3.00
hard	5.00	ready	6.00	disgusting	4.00	safe	3.00
crowded	4.00	yeah	6.00	miss	3.25	thank	3.00
infections	4.00	absolutely	5.00	ignoring	3.00	young	3.00
issue	4.00	big	5.00	outbreak	3.00	open	2.00
nonexistent	4.00	enjoy	5.00	protests	3.00	significant	1.75
nothing	4.00	great	5.00	risk	3.00	recommendations	1.50
vice	4.00	proper	5.00	cry	2.56	safely	1.50
controversy	3.00	works	5.00	suspect	1.50	rose	1.00
ill	3.00	young	5.00	worried	1.44	safe	5.00
impossible	3.00	care	4.00	no	8.00	totally	3.25
infection	3.00	clear	4.00	refused	4.00	open	2.50
partisan	3.00	early	4.00	cry	3.75	new	2.25
risk	3.00	encouraged	4.00	not	1.75	recommendations	1.50
seriously	3.00	hope	4.00	suspect	1.50	engaging	1.22
terrible	3.00	open	4.00	worried	1.22	significant	1.00
worst	3.00	significant	4.00	ignoring	1.00	young	1.00
dangerous	2.75	thank	4.00	disgusting	0.75	good	0.72

In summary, the results for August, in which the sentiment differences between CNN and Fox News became greatest, were further explored with four methods, comparing: 1) word pair's relative frequencies, 2) the overall semantic networks for the two news channels, 3) cluster analysis, and 4) sentiment analysis. The analysis comparing significant differences in the two outlets' word pair frequencies found CNN emphasizing the lack of social distancing and Fox News attending more to the health implications. CNN's overall semantic network had about six times more co-occurrence frequencies, producing a more developed network, with CNN having 24 groups, while Fox News had only seven. CNN focused more on the lack of enforcement, while Fox News encouraged social distancing. In terms of negative sentiment, CNN focused on the problems to enforce social distancing. On the positive side, it was more exuberant in celebrating the benefits of social distancing.

Discussion

This study used semantic network analysis and sentiment analysis to compare the discourse on social distancing in three television channels: CNN, Fox News, and MSNBC. We offered two hypotheses to explain those differences: market share growth and political ideology. Our findings indicate that market share growth is a better predictor of social distancing sentiment than ideology. This evidence supports the theory that sentiment engages audiences and accounts for increased viewership during the pandemic period studied. The market share dynamics are consistent with the critical theory. The findings suggest that media partisanship may be only a strategy for market segmentation and that ideology today is not more than a brand.

The network-based sentiment model performed as expected in quantifying positivity and negativity, enabling measurement of sentiment toward a particular target, rather than the cruder bag-of-words model that measures sentiment at the whole document level only. Previously shown to have internal and external validity, the finer-grained network approach yielded more meaningful variation and evidence, enabling testing the ideology vs. the market share growth hypothesis. In addition to positivity and negativity scores, the procedures also identified the positive and negative sentiment words that occurred and the shortest weighted paths linking them. We mapped the full semantic networks underlying sentiment and identified the significantly different elements.

The analysis shows how semantic network analysis can be used to test hypotheses even when the number of cases is small, in this case, only three news channels. Often case studies do not take advantage of the quantification and hypothesis-testing that semantic network analysis affords. Here semantic and sentiment analyses provide substantial evidence that blends two traditional approaches, qualitative and quantitative. The multi-level and multi-method semantic analysis enables the generation of more knowledge per unit of research effort. The energy no longer spent on manual coding can be directed to theory development.

Limitations included a constraint on the availability of data. While, as of this writing, the data continue to be made available. Due to a technical glitch, the social distancing snippets ceased as of October 19, 2020, so the current analysis ends with September's last full month. Another limitation was on the different time scales of the data. While snippets are available daily, the market share growth data and ideological coding for the three channels had single values for the duration, so the hypothesis test was not based on panel data.

Additionally, our choice of a monthly interval for aggregating the snippets was most appropriate for examining trends yet had sufficient amounts of text in each interval for robust semantic network and sentiment analysis. The choice of the three general 24-hour cable news channels – Fox News with the largest market share, followed by CNN, and MSNBC, was to control for the news format. We set aside the outlets with smaller audiences such as BBC, Al Jazeera, Deutsche Welle, and R.T., the more specialized channels such as Bloomberg, CNBC, and Fox Business Channel, CSPAN, and the brief news programming of the ABC, NBC, and CBS networks (PBS transcripts are not available). Future research may examine these news outlets.

Tips and lessons from the process

1. Analyzing semantic networks of television news requires access to transcripts of broadcasts. Typically, researchers use LexisNexis to obtain the texts. However, during the pandemic, GDELT provided 150-character snippets centered on keywords, such as COVID-19, social distancing, masks, testing, and several others.[8] In our research, working with the GDELT data has required extensive file management to reorganize them for semantic network analysis. Once these data are no longer available, the most likely source of television news transcripts is LexisNexis.[9] While these data are useful, the process of downloading data is cumbersome, allowing only 100 documents at a time. Nevertheless, with persistence, one can build an adequate corpus of television news texts for US outlets.
2. GDELT file sizes are large and numerous, requiring reformatting via coding in Python or another language. Transcripts from NexisUni do not need this file management.
3. Another GDELT feature is Television Explorer,[10] an easy-to-use search panel accessing television news transcripts based on keyword searches. This can help refine search terms for use in Nexis Uni. Although one cannot retrieve texts from the Television News Explorer, the tool shows curves of term frequencies over time to help decide on the time frame for analysis or to segment time in organic intervals. Other useful features are sentiment measurement (the tone of coverage), a word cloud, and thumbnails of the videos and texts. These features can help verify that the search terms are resulting in the desired outcomes.

4. Choosing the time interval for the analysis requires some exploration of the series. Plotting the frequencies of term occurrence of terms may reveal natural segments that are not chronological but based on the distributions over time. For example, over a year, one may observe a surge and subside over several months, followed by recurrent mini surges over the next year. Perhaps each of these surges becomes the organic segments for analysis. Otherwise, if calendar time is used to segment texts, the choice of monthly, weekly, or daily intervals depends on each text's distribution. If there is sufficient text volume, one can choose a daily interval, but we do not recommend this as a starting slice. We find that it is better to begin with the larger interval, for example, monthly, and decide whether this provides adequate variation across the intervals. Then, we may move to a smaller slice, such as weekly or daily. The natural limits on human processing are that if one relies on visual interpretation and presentation of results in figures and tables, most researchers could deal with up to a dozen intervals before overload occurs. Otherwise, statistically, the daily interval is preferred.
5. For sentiment analysis, the SENET software we developed is target-specific, in which the user selects a single word for which positive and negative sentiment scoring is desired. If the term is not a natural unigram but a string of words, one can edit the text file accordingly to recode the string as a unigram, for example, changing "social distancing" to "socialdistancing".

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Notes

1 https://books.google.com/ngrams
2 This section is extracted from Danowski, Yan, and Riopelle (2020).
3 Smith et al. (2010), see also http://nodexl.codeplex.com from the Social Media Research Foundation, http://www.smrfoundation.org
4 https://knightfoundation.org/reports/american-views-2020-trust-media-and-democracy/
5 https://mediabiasfactcheck.com/
6 https://www.allsides.com/unbiased-balanced-news
7 https://variety.com/2020/tv/news/network-ratings-2020-top-channels-fox-news-cnn-msnbc-cbs-1234866801/
8 https://blog.gdeltproject.org/now-live-updating-expanded-a-new-dataset-for-exploring-the-coronavirus-narrative-on-television-news/
9 https://www.lexisnexis.com/en-us/professional/academic/nexis-uni.page
10 https://blog.gdeltproject.org/now-live-updating-expanded-a-new-dataset-for-exploring-the-coronavirus-narrative-on-television-news/

References

Arapakis, I., Lalmas, M., Cambazoglu, B. B., Marcos, M. C., & Jose, J. M. (2014). User engagement in online News: Under the scope of sentiment, interest, affect, and gaze. *Journal of the Association for Information Science and Technology*, 65(10), 1988–2005.

Asghar, M. Z., Khan, A., Ahmad, S., & Kundi, F. M. (2014). A review of feature extraction in sentiment analysis. *Journal of Basic and Applied Scientific Research*, 4(3), 181–186.

Baccianella, S., Esuli, A., & Sebastiani, F. (2010, May). *Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining*. Proceedings of the Seventh Conference on International Language Resources and Evaluation (LREC) (Vol. 10, No. 2010, pp. 2200–2204). European Languages Resources Association (ELRA), Valletta, Malta .

Baughman, J. L. (2011). The rise and fall of partisan journalism. https://ethics.journalism.wisc.edu/2011/04/20/the-fall-and-rise-of-partisan-journalism/.

Becher, M., Stegmueller, D., Brouard, S., & Kerrouche, E. (2020). Comparative experimental evidence on compliance with social distancing during the COVID-19 pandemic. doi:10.2139/ssrn.3652543.

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008 (10), 10008.

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *Science*, 323(5916), 892–895.

Brandes, U. (2001). A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, 25(2), 163–177.

Campbell, A. M. (2020). An increasing risk of family violence during the Covid-19 pandemic: Strengthening community collaborations to save lives. *Forensic Science International: Reports*, 2, 100089.

Carley, K. (1993). Coding choices for textual analysis: A comparison of content analysis and map analysis. *Sociological Methodology*, 75–126.

Christensen, S. R., Pilling, E. B., Eyring, J. B., Dickerson, G., Sloan, C. D., & Magnusson, B. M. (2020). Political and personal reactions to COVID-19 during initial weeks of social distancing in the United States. *PloS One*, 15(9), e0239693.

Clauset, A., Newman, M. E., & Moore, C. (2004). Finding community structure in very large networks. *Physical Review E*, 70(6), 066111.

Corman, S. R., Kuhn, T., McPhee, R. D., & Dooley, K. J. (2002). Studying complex discursive systems. Centering resonance analysis of communication. *Human Communication Research*, 28(2), 157–206.

D'Andrea, E., Ducange, P., Bechini, A., Renda, A., & Marcelloni, F. (2019). Monitoring the public opinion about the vaccination topic from tweets analysis. *Expert Systems with Applications*, 116, 209–226.

Danowski, J. A. (1982). Computer-mediated communication: A network-based content analysis using a CBBS conference. *Annals of the International Communication Association*, 6 (1), 905–924.

Danowski, J. A. (1993). Network analysis of message content. *Progress in communication Sciences*, 12, 198–221.

Danowski, J. A. (2013). *WORDij Version 3.0: Semantic Network Analysis Software*. Chicago, IL: University of Illinois at Chicago.

Danowski, J. A., & Park, H. W. (2014). Arab spring effects on meanings for Islamist web terms and on web hyperlink networks among Muslim-majority nations: a naturalistic field experiment. *Journal of Contemporary Eastern Asia*, 13(2), 15–39.

Danowski, J. A., & Riopelle, K. (2019). Scaling constructs with semantic networks. *Quality and Quantity*, 1–13. doi:10.1007/s11135-019-00879-5.

Danowski, J. A., Yan, B., & Riopelle, K. (2020). A semantic network approach to measuring sentiment. *Quality & Quantity*, 1–35.

Formisano, R. P. (2008). *For The People: American Populist Movements from the Revolution to the 1850s*. Chapel Hill, NC: University of North Carolina Press.

Fuchs, C. (2011). *Foundations of Critical Media and Information Studies* (Vol. 52). New York: Taylor & Francis.

Harper, C. A., & Rhodes, D. (2020). Ideological responses to the breaking of COVID-19 social distancing recommendations. https://scholar.google.es/citations?view_op=view_citation&hl=en&user=fYqfyJIAAAAJ&citation_for_view=fYqfyJIAAAAJ:YOwf2qJgpHMC

Hart, P. S., Chinn, S., & Soroka, S. (2020). Politicization and polarization in COVID-19 news coverage. *Science Communication*, 42(5), 679–697.

Hogan, M. J., & Hogan, M. J. (1987). *The Marshall Plan: America, Britain and the Reconstruction of Western Europe, 1947–1952*. Cambridge: Cambridge University Press.

Lipsitz, K., & Pop-Eleches, G. (2020). The partisan divide in social distancing. doi:10.2139/ssrn.3595695.

Jiang, K., Barnett, G. A., & Taylor, L. D. (2016). Dynamics of culture frames in international news coverage: A semantic network analysis. *International Journal of Communication*, 10, 27.

Jurkowitz, M., Mitchell, A., Shearer, & Walker, M. (2020). US media polarization and the 2020 election: A nation divided. https://www.journalism.org/2020/01/24/u-s-media-polarization-and-the-2020-election-a-nation-divided/.

Kharde, V., & Sonawane, P. (2016). Sentiment analysis of twitter data: A survey of techniques. *arXiv preprint*, 1601, 06971.

Khoo, C. S., & Johnkhan, S. B. (2018). Lexicon-based sentiment analysis: Comparative evaluation of six sentiment lexicons. *Journal of Information Science*, 44(4), 491–511.

Kumar, S., & Zymbler, M. (2019). A machine learning approach to analyze customer satisfaction from airline tweets. *Journal of Big Data*, 6(1), 1–16.

Kundi, F. M., Ahmad, S., Khan, A., & Asghar, M. Z. (2014). Detection and scoring of internet slangs for sentiment analysis using SentiWordNet. *Life Science Journal*, 11(9), 66–72.

Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on human Language Technologies*, 5(1), 1–167.

Liu, B., & Zhang, L. (2012). A survey of opinion mining and sentiment analysis. In *Mining Text Data* (pp. 415–463). Boston, MA: Springer.

Mäntylä, M. V., Graziotin, D., & Kuutila, M. (2018). The evolution of sentiment analysis—A review of research topics, venues, and top cited papers. *Computer Science Review*, 27, 16–32.

Mikolov, T., Sutskever, I., Chen, K., Corrado, G., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *arXiv preprint*, 1310, 4546.

Monge, P. R., & Contractor, N. S. (2003). *Theories of Communication Networks*. New York: Oxford University Press.

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). *The Measurement of Meaning* (No. 47). Champaign, IL: University of Illinois Press.

Panchal, N., Kamal, R., Orgera, K., Cox, C., Garfield, R., Hamel, L., & Chidambaram, P. (2020). *The Implications of COVID-19 for Mental Health and Substance Use*. San Francisco, CA: Kaiser Family Foundation.

Pontiki, M., Galanis, D., Papageorgiou, H., Androutsopoulos, I., Manandhar, S., Al-Smadi, M., & Eryiğit, G. (2016, January). Semeval-2016 task 5: Aspect based sentiment analysis. In *International Workshop on Semantic Evaluation* (pp. 19–30). Beijing: Association for Computational Linguistics.

Ramos, G., Vieites, Y., Jacob, J., & Andrade, E. B. (2020). Political orientation and support for social distancing during the COVID-19 pandemic: evidence from Brazil. *Revista de Administração Pública*, 54(4), 697–713.

Rogers, E. M. (1987). Progress, problems and prospects for network research: Investigating relationships in the age of electronic communication technologies. *Social Networks*, 9(4), 285–310.

Rothgerber, H., Wilson, T., Whaley, D., Rosenfeld, D. L., Humphrey, M., Moore, A., & Bihl, A. (2020). Politicizing the covid-19 pandemic: Ideological differences in adherence to social distancing.

Rudkowsky, E., Haselmayer, M., Wastian, M., Jenny, M., Emrich, Š., & Sedlmair, M. (2018). More than bags of words: Sentiment analysis with word embeddings. *Communication Methods and Measures*, 12(2–3),140–157.

Schiller, H. I. (1991). *Culture, Inc: The Corporate Takeover of Public Expression*. Oxford: Oxford University Press on Demand.

Schiller, H. (2013). *Information Inequality*. London: Routledge.

Schneider, M. (2020, December 28). Year in review: Most-watched television networks — ranking 2020's winners and losers, *Variety*. https://variety.com/2020/tv/news/network-ratings-2020-top-channels-fox-news-cnn-msnbc-cbs-1234866801/.

Schwebel, A. I., & Cherlin, D. L. (1972). Physical and social distancing in teacher-pupil relationships. *Journal of Educational Psychology*, 63(6), 543.

Simmons, S. J. (1978). *The Fairness Doctrine and the Media*. Berkley, CA: University of California Press.

Smith, M., Ceni A., Milic-Frayling, N., Shneiderman, B., Mendes Rodrigues, E., Leskovec, J., Dunne, C. (2010). NodeXL: a free and open network overview, discovery, and exploration add-in for Excel 2007/2010/2013/2016. http://nodexl.codeplex.com/ from the Social Media Research Foundation, http://www.smrfoundation.org.

Tausczik, Y. R., & Pennebaker, J. W. (2010). The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, 29(1), 24–54.

Thakur, V., & Jain, A. (2020). COVID 2019-suicides: A global psychological pandemic. *Brain, Behavior, and Immunity*, 88, 952–953.

Thet, T. T., Na, J. C., & Khoo, C. S. (2010). Aspect-based sentiment analysis of movie reviews on discussion boards. *Journal of Information Science*, 36(6), 823–848.

Wang, B., & Liu, M. (2015). Deep learning for aspect-based sentiment analysis. *Stanford University Report*. https://cs224d.stanford.edu/reports/WangBo.pdf.

Wemple (2020, April 1). Opinion: CNN, MSNBC refused to carry full Trump coronavirus briefing. *Yay!*https://www.washingtonpost.com/opinions/2020/04/01/cnn-msnbc-refused-carry-full-trump-coronavirus-briefing-yay/.

Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8(4), e1253.