

Effects of news media bias and social media algorithms on political polarization

by

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A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF ARTS

Major: Political Science

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Iowa State University

Ames, Iowa

2019

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ACKNOWLEDGMENTS

I am beyond grateful for the assistance provided by my committee members Dr. Mack Shelley, Dr. Kelly Winfrey, and Dr. Kelly Shaw in the writing of this thesis. Without the help of my committee, this research and writing would have been nearly impossible. The guidance and wisdom provided by these members has been an incredible benefit.

In addition, I reflect upon my time at Iowa State with incredible memories. Peers, mentors, and professors have all helped shape my adventure and mold my journey. The educational experience I have had at Iowa State University is second to none and I am beyond grateful for all who have contributed to my success over the last four years.

ABSTRACT

This thesis makes use of existing research and data to create a clearer understanding of the impact that bias in news media reporting as well as biased social media algorithms can have on political polarization within the United States. Data is used to highlight the fact that the United States is in a state of polarization that has not been seen before with individuals moving further right and left every year. Furthermore, sharing scores of United States congressmen and women are used to show this news media bias and which major party is most closely aligned with a number of news sources. Furthermore, an examination of existing literature on social media algorithms is used to understand whether social media algorithms are shaping the beliefs of individuals within the United States subconsciously.

Based on the results, this thesis was able to accept one of the hypotheses that biased news reporting has contributed to the increase in polarization of the United States. It appears as though partisan individuals are watching news sources that are biased and becoming even more polarized. A microcosm of this is noted and discussed as the Fox News Effect. The other hypothesis in this thesis is about whether social media algorithms impact polarization. This is a relatively new area of research and the data indicated a picture that was not clear, therefore a conclusion was not reached. However, multiple Pew Research Center studies provided impactful information about the current state and potential power of social media platforms.

This thesis advances existing literature in multiple ways. First, it operates under the premise of the news media and social media algorithms being related. Most research has separated the two as independent topics yet, the lines are consistently being blurred on how to separate the two domains. Additionally, it shows the great power and extent to which the news

media and social media algorithms can impact polarization within the nation. Finally, this thesis combines multiple studies in one central location which allows for readers to form a more clear picture of the existing environment of the news media and social media algorithms.

CHAPTER 1. INTRODUCTION

The current status of American politics has led to a greater focus on and scrutiny of how media consumption may impact beliefs and ideological leanings of the public. In turn, this situation can have a direct impact on who is elected to office and directly shape public policy within the country. With the rise of digital media and increased platforms for news to be shared, there has been greater news consumption but also greater variance in framing political issues (Budak, Goel, & Rao, 2016) and increased impact on agenda-setting (Soukup, 2014). Concurrent with this proliferation of platforms, it appears many news organizations have also taken an ideological slant to how they deliver the news. A potential explanation for this is that they may be tailoring their message to a specific audience (Hyun & Moon, 2016) in an effort to drive up their ratings and increase viewership among subgroups.

Along with this shift in the orientation of news media, the rise of social media has had a great impact on news media consumption and policy. It has added another medium for information to be dispersed to viewers at a rapid pace with little oversight (Ressa, 2019). In addition to providing more people with voices to share thoughts and information, social media has provided the opportunity for current political leaders to take their message directly to the public. This can be seen directly through the Twitter account of President Donald Trump. The Trump presidency has been one of great polarization among people in regards to both his personality and policies. Trump's outspoken nature on Twitter has sparked many discussions on what is considered presidential and whether his social media use has been beneficial to his presidency. Trump's unique approach to social media has largely been attributed to his troublesome relationship with what is considered by many to be the "mainstream media." He has continuously attacked the media for bias and claimed they treat him extremely unfairly.

This leads to a greater philosophical question of whether President Trump is correct in asserting that the media have been biased in their reporting about him. If so, is it reasonable to expect news networks to be 100% free of any and all bias? Another important question to be asked is what is the impact of biased news coverage? Could partisanship or polarization be impacted by bias? This paper intends to address these questions with two research hypotheses:

H1: Social media algorithms play a role in increasing polarization and partisanship

H2: The news media play a role in increasing polarization and partisanship

The American general public certainly appears to believe the news media favor one side over the other. According to Pew Research Center data from 2018, 68% of Americans say the news media favors one side. Moreover, 86% of Republicans feel this way compared to only 52% of Democrats (Gottfried, Stocking, & Grieco, 2018), which indicates a much greater distrust of unbiased reporting coming from conservatives. Furthermore, the general public does not have great trust in their national news organizations. In the same study, only 21% of people indicate they have a lot of trust in the information they get from national news organizations and only 4% have the same trust in social media (Gottfried, Stocking, & Grieco, 2018). These statistics are significant for understanding the current relationship between the public's belief in the news they receive and the sources of news through political journalism and reporting. There are severe potential negative ramifications of having a general public that widely distrusts the news and information it receives.

Sources of Bias

While it is clear that a majority of Americans feel there is some form of bias at play in the news media, there are also a couple explanations as to why these biases occur and why

Americans go to different sources for their news. One theory is Partisan Selective Exposure (PSE), defined as, “the propensity of an individual to select information in a way that is congenial to his or her existing beliefs and partisan predisposition,” (Hyunjn Song, 2016). PSE suggests that people seek out biased news sources, intentionally or unintentionally, because the issue framing aligns with their prior beliefs. This selectivity can occur for multiple reasons (Metzger, Hartsell, & Flanigin, 2015), but this is the most important overarching aspect of the theory. Confirmation bias, a second theory of what motivates the potential filtering is closely related to PSE. Confirmation bias is defined as, “The tendency to seek, favor, or recall information that confirms what one already believes to be true. This may be achieved by the selective way in which data is collected (focusing on collecting evidence that supports one’s ideas, rather than collecting all relevant evidence),” (Jeanes, 2019) An application of this would be individuals making decisions on how they feel regarding a political issue and then seeking out news sources that support their thoughts on the topic rather than a news source that may provide an objective perspective or information that challenges the person’s prior belief. These two theories are closely related but have stark differences that separate them as will be discussed later.

Moreover, there are multiple ways to see bias and potential partisanship in the news media and social media. First, bias could be seen in topics discussed by the news media or in the stories they post. This potential source of bias lies at the intersection of the news media roles of agenda-setting and framing. A second potential place for bias to exist is in online search results (Epstein & Robertson, 2015). This can occur on any social media platform or search engine. The algorithms behind organizing news stories and search results can have a tremendous impact on how people see the world (Timmermans, 2017). A biased algorithm could promote some

stories more than others in an effort to sway the thoughts of the general public to be more aligned with an organization's desires. Finally, it is possible to see partisanship and bias on social media through sharing and discussing content. Individuals and news organizations providing only information that is conservative or liberal and interact with individuals who support their thoughts can create an echo chamber in which polarization increases. This could be seen on Twitter through retweets (An et. al) and Facebook through sharing select posts.

Social Media and Media Consumption

While the rise of the Internet and smartphones has brought endless options for people to decide how to get their news, there are various media trends that must be examined and explained. First, it is important to draw a distinction between the news media and social media. Social media platforms are more widely used by teens, although they are also used by adults for news consumption and leisure (Gramich, 2019). A 2019 Pew Research Center study found that 43% of adults use Facebook for news, 12% use Twitter for news, and 8% rely on Instagram (Gramich, 2019). These numbers indicate that there are tens of millions of adults in the United States who use social media every day for news consumption. Adults use Facebook at a higher rate than teens even though teens are more likely to use social media in general (Gramich, 2019).

We can examine 2016 presidential election voter preference and news sources to evaluate news consumption related to political ideology. Trump voters overwhelmingly supported Fox News as 40%, indicated that this was the main source for their news (Mitchell, Gottfriend, & Barthel, 2017). CNN came in second place at a distant 8% and Facebook was third with 7% of Trump voters indicating it was their main source of news. Clinton voters were much more dispersed in their sources, but CNN was the clear leader at 18% claiming it was their main

source (Mitchell, Gottfried, & Barthel, 2017). MSNBC was the main source for 9% of Clinton voters, and Facebook was at 8%.

These data indicate that the only consistent social media source voters in the two major political parties visited at a similar rate was Facebook. On average, only 23% of the average Facebook user's friends are of an opposing political affiliation (Manjoo, 2015). With a wide variety of friend ideologies, partisan compositions, and general connections, no two people will ever see the same Facebook, yet it is important to be aware that Facebook is as capable as traditional news sources of swaying public perception (PBS, 2016). In the context of the discussion about "fake news," having the ability to decipher what is factual and what is not can be rather valuable in addressing the use of Facebook as a news source. Additionally, the Facebook algorithms tabulate interests and traits of users (Gramich, 2019) with 51% of users assigned a political "affinity" (Hitlin & Rainie, 2019). This algorithmic approach goes one step further in individualizing each user's Facebook experience. All of this is done in an effort to increase engagement but also leads to great variance in each user's Facebook experience.

Recent Trends

Various current trends shape the relationship of the general public with social media platforms and news media. One important trend is how members of each party feel regarding the role of the media as a watchdog. The Pew Research Center has been tracking such survey responses since 1985. In 2016, more GOP members than Democrats believed the media had a role to operate as a "watchdog" (Gottfried, Stocking, & Grieco, 2018). By 2019, that pattern was almost entirely flipped, as 89% of Democrats supported the role of the media as a watchdog compared to only 42% of Republicans (Gottfried, Stocking, & Grieco, 2018). While this finding may have something to do with the polarizing presidency of Donald Trump, the 47 percentage

point difference is the largest gap between the two parties since the data began being recorded. This dramatic gap could indicate a growing trend of partisanship and polarization of the media and among the general public.

A second trend is viewership of news programs. While CNN historically has the largest viewership, that has not been the case recently. According to a Nielsen Media Report in 2018, Fox News is the most-watched cable news network and MSNBC finished second in overall viewership but had the fastest-growing viewership (Joyela, 2018). CNN, which is considered less partisan by many measures such as sharing score (Messing, Van Kessel, & Hughes, 2017), had the third-highest viewership but overall their average audience is shrinking (Joyela, 2018). Using sharing scores to rank MSNBC and Fox News, it appears that these two sources are consistently liberal and consistently conservative respectively. This result, along with other data, indicate that overall partisan news sources appear to be gaining viewership while more neutral or less partisan sources are either maintaining viewership or shrinking.

Additionally, social media use in the United States is growing so it is important to understand how this is occurring overall and where the most growth is occurring. Currently, Facebook has the largest online user base (Gramich, 2019) which would indicate that it potentially is the most powerful social media platform. However, it is important to note that Twitter appears to be growing at a rapid pace (Narayanan, 2018), which may indicate that researchers should continue to pay attention to the role Twitter may play going forward. A far greater number of people interact with social media platforms regularly than rely on social media for news. According to Pew Research Center Data from 2019, 69% of adults use Facebook, 37% use Instagram and 22% use Twitter. Furthermore, the median American uses three social media platforms (Hitlin & Rainie, 2019). This context leads to a more complete picture of the power of

social media sites. Any apparent bias in the algorithms each of these platforms uses for content or search results, it could have a large effect on the information people receive generally and potentially could impact overall feelings on topics of societal and political importance.

How can an algorithm be biased and have such a large impact? Currently, today's social media platforms can be described as a Filter Bubble Landscape (Pariser, 2018). This filter bubble can occur in a couple of ways. The algorithm designed by each social media platform, can guess a users' specific beliefs and interests and show information they are projected to want to see. However, users do not know how algorithms judge them. There is a large chance the algorithm may not have correctly judged each individual user (Pariser, 2018). However, if users are inundated with a large amount of information and social media posts that support their feelings, this can lead to potential confirmation bias as described earlier.

Algorithm Impact

While understanding the Filter Bubble Landscape can provide value and context to understanding social media, each platform has different goals and ideas for engagement, leading to drastically different algorithm designs. Facebook and Instagram have the most closely related algorithms, as Facebook is the owner of Instagram (Hubspot, 2018). This algorithm appears to be based almost solely on engagement as compared to algorithms for sites like Twitter and Google (Hitlin & Rainie, 2019). Facebook and Instagram's algorithm is purely content-based and is designed for users to spend as much time as possible on the platform (Wheeler, 2017). This means that on Facebook and Instagram, based on the interests and demographics the algorithm assigned to each user, posts are ranked and shown in order of what Facebook believes will create the most engagement. Moreover, Facebook tracks the activity of users even when they are not on the website through the Facebook Pixel (Hitlin & Rainie, 2019), which allows the

platform to record activity of users on websites outside of Facebook and pass the data back to Facebook. This process allows for more targeted advertising and greater understanding of a user's interests and behavior (Hitlin & Rainie, 2019).

This activity raises many philosophical questions and overall the general public lacks knowledge of the algorithms and the behavior of social media platforms. A majority (53%) of users do not understand why certain Facebook posts are included or omitted (Gramich, 2019), which indicates they do not understand how algorithms operate overall. Furthermore, 74% of Facebook users are unaware that the site is recording their information, but once aware that this is happening 51% reported that they are not comfortable with this activity taking place (Gramich, 2019). The overarching theme among all of this is the desire for Facebook to generate corporate revenue. The best way to generate revenue from advertisements and through users is to increase engagement. This linkage indicates that social media platforms have a direct interest in increasing engagement so they can increase profits (Warner, 2018; Hubspot, 2018; Ressa, 2019).

While this context provides the best explanation for the behavior of Facebook and Instagram, it does not in any way address how Google's or Twitter's algorithms operate. Google's search results are done through attempting to decipher information based on what is deemed most relevant. While this is a rather challenging task, it certainly provides a great opportunity for bias to occur. If the engineers who designed the algorithms decide to give priority to certain words, topics, or websites, this would simply automate human biases (Bellovia, 2019) rather than remove them entirely. The algorithm that decides what appears on Twitter timelines appears to be multi-faceted. First, Twitter users have the ability to see their content in chronological order, which would eliminate many aspects of bias that could be present. However, the featured tweets could be biased as those are more likely to get interactions

(Warner, 2018). In addition, the search results for Twitter are designed to increase engagement, increase time on Twitter, and lead to users being more active (Warner, 2018). This circumstance creates an environment where bias could occur as certain tweets and ideologies could be promoted earlier in search results than opposing thoughts.

There is substantial evidence people are interested in opinion-reinforcing political information (Garrett, 2009), which would create an environment in which it would make sense to promote information Twitter users are most likely to agree with and support increased engagement and Twitter use. This is not to say that deliberate bias occurs, but the potential for biased search results to appear is possible. Twitter CEO Jack Dorsey has also acknowledged a left-leaning bias among Twitter employees but claims it does not translate into the algorithms or search queries (Pyrinis, 2018). Yet, if algorithms simply automate human processes, there is certainly the potential for bias among employees of any social media platform to construct the algorithms that impact users' experiences.

It is important to note that not much direct knowledge is available on the details or specifics of how each algorithm works for each platform. Each company designs their algorithm in a unique way that shapes their platform. If they allowed complete knowledge of their algorithm they would essentially be giving away their entire platform and allow someone else to create the exact same thing, so there is a strong desire to keep most aspects private. However, based on what has been discovered, it appears that almost all algorithms at their core are designed to increase engagement. This can be done in multiple ways.

First, companies will use users' personal activity to determine what they like to see. Instagram uses personal activity to shape what users see in their searches (Warner, 2018). Depending on what a user likes, shares, or spends a large amount of time observing, the

algorithm may attempt to show those things more frequently. Second, the Facebook model is also common, wherein a profile is created based on decisions made and actions taken by a user. This is where interests and traits are assigned to individuals and social media platforms begin tailoring information to the profile. Finally, social media platforms want to keep users on their site for as long as possible so they will provide posts that have the highest engagement. This process can occur in posts a user is most likely to agree with or will bring the user a more intense emotional reaction of happiness, sadness, or anger (Hubspot, 2018). These emotions can greatly affect engagement among users and increase time spent on the platform.

Social media algorithms and the news media certainly have a strong relationship with people and politics. However, they differ greatly in how users seek them out. In news networks, individuals have the ability to select what channel they will watch and potentially what slant their news will have. When they are cognitively aware of this, the impact or affect may be different than if they are not aware. Social media platforms are similar in the aspect that users can choose who they would like to connect with, but if the algorithm is based on engagement it may decide what information is shared and what users see on their homepage users then no longer have a cognitive decision to make regarding what information they are given. If there is bias in that information or bias in how much of a certain type of information is shared, that slant could have a great impact on users who may unconsciously follow this information and use it as a reflection of what others believe.

CHAPTER 2. LITERATURE REVIEW

Research into the use of social media and news media for political purposes has grown at a rapid pace. With the rising influence and use of social media platforms in concurrence with attacks on the news media, this research is valuable as it can provide important information and dispel myths. A majority of the research is rather recent, partially due to the recent formation of social media companies and increased Internet accessibility. Overall, the main takeaway from research on social media and the news media impact on politics is two-fold. First, it does appear polarization is increasing. This can be seen in many measures but it appears the divisiveness of campaigns and the commentary on candidates may be a major factor as it furthers stereotypes of the outgroup (Iyengar, Sood, & Lelkes, 2012). Furthermore, party affiliation is becoming an increasingly important demographic as partisanship is now as divisive as race and religion within the United States (Iyengar, Sood, & Lelkes, 2012). Second, this increase in polarization does appear to have a relationship with social media and news media coverage. While that does not directly answer the hypotheses of this thesis, it provides support for further research and indicates the hypotheses are very relevant in the current political landscape. Using a chart from the Pew Research Center, it can be seen that among United States residents, polarization has increased dramatically in the last 25 years (Figure 1):

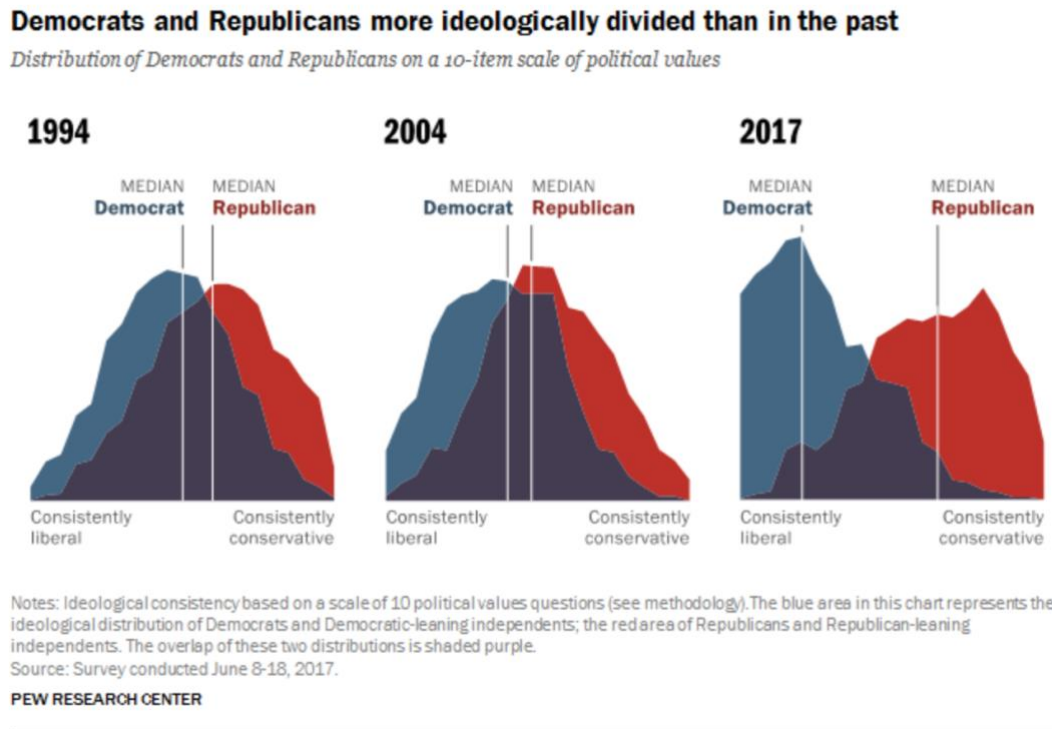


Figure 1. Increased Political Polarization among the General Public in the United States, 1994-2017

As can be seen in Figure 1, the beliefs of the median Democrat and the median Republican were fairly closely aligned in 1994 and there wasn't the same dramatic difference in ideology as can be seen in the 2017 data. Additionally, in Figure 1, the purple area in the middle is where respondents tended to overlap in their beliefs and as expected this has also shrunk in size. Perhaps one of the most interesting items of note, is the apparent intensification of this trend between 2004 and 2017 (Pew Research, 2017). The data from 1994 and 2004 appear to show a rather similar picture, but the data in 2017 show a radical departure from this. While multiple variables could be related to this trend, between 2004 and 2017 Internet accessibility and social media platforms grew immensely. Correlation cannot be confused with

causation, but the increase in polarization deserves attention and media could be a plausible explanation for what is occurring. Moreover, while this trend is occurring among individuals living in the United States, it appears to lag behind the pattern of heightened polarization among members of the United States House of Representatives (Fernholz & Kopf, 2019). This can be seen in the data provided in (Figure 2):

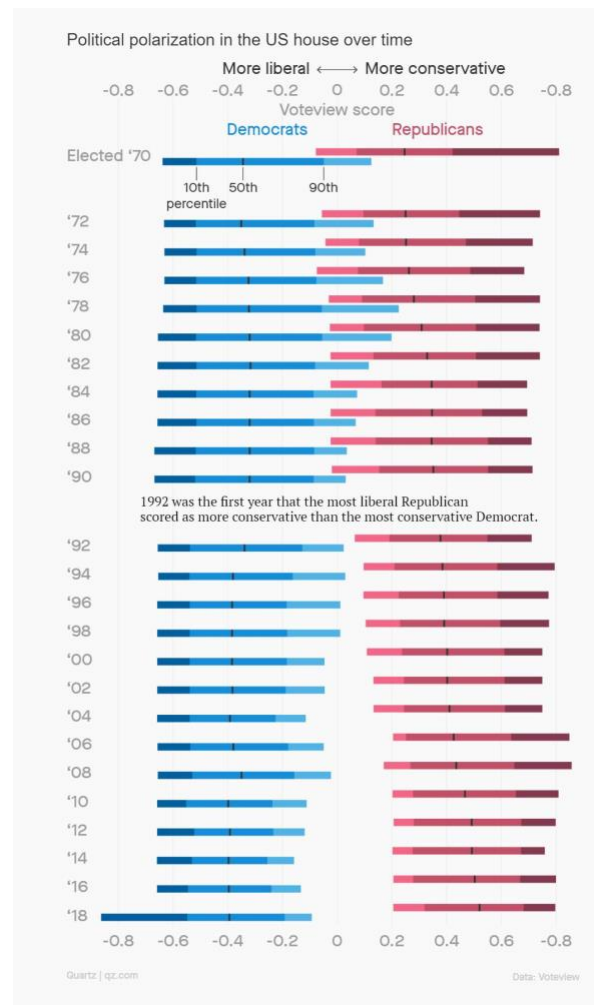


Figure 2. Increased Political Polarization among Members of the United States House of Representatives, 1970-2018

Based on the Voteview data to score members of the United States House of Representatives on polarization, there is clearly a consistent trend in the House since 1972 (Fernholz & Kopf, 2019). While there used to be some overlap between the most conservative Democrats and most liberal Republicans, after 1992 this common ground all but disappeared and members have continued to move further apart on the issues into the formation of the current political climate of hyper-partisanship. Figure 2 is not in place to necessarily indicate there is a relationship between congressional polarization and the impact the hypotheses have had. Rather, it is in place to show that polarization is occurring in multiple facets not just the news media or general population. Understanding that polarization is occurring in Congress can be just as insightful for creating a full picture of the state of polarization in the United States as understanding trends in the general population.

While data appear to show increased polarization of both Congress and the general public, it is important to ask what are the consequences of partisanship and polarization? Is it a bad thing? There is extensive literature on the topic of the effects of partisanship and polarization that helps clarify the consequences of these trends in society. First, it is important to note that polarization leads to increased political engagement among individuals (Stroud, 2016; Kim, 2013). Those who are most polarized tend to feel most strongly about their beliefs and want to do something about them. While it could be argued this is largely a positive consequence of polarization, there are also negative consequences. While polarization may increase political engagement, it also leads to a less tolerant and more fragmented society (Stroud, 2016). Under this premise as people become more polarized, they become less likely to engage with thoughts or ideas from members of the opposite political ideology. In addition,

there is a potential spiral of silence that can occur due to polarization (Slater, 2007). This relates back to a greater theoretical question of what one desires the nation to look like.

There appears to be a trade-off that occurs as polarization increases. With greater polarization, there is also greater political engagement and a less tolerant society. If one could assume in the opposite scenario that a political climate of no polarization creates a more unified society but increases political apathy and lowers engagement, would this be an overall improvement? A politically informed and engaged society seems to be desired, but is the desire for this strong enough to overcome a fragmented and less tolerant society? Individuals will fall on all places of the spectrum answering that question but the literature certainly provides evidence of a trade-off that must be confronted in what individuals seek the nation to look like. At very least, some of the negative consequences could be researched to lessen the impact of having a politically fragmented society and intolerant society.

While literature shows that polarization is increasing and is related to news media coverage, this leads to a greater question of whether it is possible to be totally free of all bias in any situation. On some level, everyone suffers from some form of unconscious bias but what does that look like when applied to social media and news media discussion of politics? Perhaps it is easiest to start this conversation by looking at algorithms. Many people believe algorithms attempt to remove human bias and just automate everything using machines and formulas. Yet, according to Cathy O’Neil, “Algorithms replace human processes, but they’re not held to the same standard” (Knight, 2017). This would indicate that algorithms still have some form of bias, and could potentially be more dangerous. If there is the assumption that bias is removed but in reality it is not, any information provided by the algorithm can be taken as fact when it is not true. Furthermore, machines and algorithms can pick up on biases by mistake (Bellovin, 2019).

If the inputs into the algorithm or machine have any bias from humans, the outputs will also suffer from the biased inputs (Bellovin, 2019). The great danger in algorithms lies in assuming that they will remove bias without understanding that algorithms are created by humans, who suffer from unconscious biases.

Biased algorithms have been addressed frequently in various recent literature. In 2016, Facebook was accused of suppressing conservative voices in their trending news section in a scandal that ultimately led to the firing of the employees who created the algorithm (Thielman, 2016). The intentionality of this act is irrelevant, as this example can be used to broadcast the larger point of human biases being able to enter in to algorithms of social media companies. In addition, further research has been able to indicate some bias in Google search results (Pyrinis, 2018; Trielli, Mussenden, & Diakopoulous, 2015). When evaluating Google's search results, it appears there is a liberal lean in news stories (Pyrinis, 2018). This bias and lean can be seen in the results that appear on the first page. On first page search results, it appears Democrats had greater favorability and a greater number of positive articles written about their candidates during the 2016 election (Trielli, Mussenden, & Diakopoulous, 2015). While this may not seem like a great effect, there is some significance to the bias provided by search results as biased search rankings can shifting voting preferences of undecided voters by 20% or more (Epstein & Robertson, 2015). Furthermore, this may occur because 70% of clicks happen on the first page of Google search results (Trielli, Mussenden, & Diakopoulous, 2015). That would indicate that the most influential page for search results is the first page. If Democratic candidates have greater favorability (Pyrinis, 2018) and more supportive sites (Trielli, Mussenden, & Diakopoulous, 2015) appearing on the first page, this could certainly be argued by conservatives as a form of bias even if it is occurring organically.

Bias in News Media

While the impact of bias has clearly been noted in social media algorithms and search results, it is important to evaluate existing literature on the impact of biased news coverage. A microcosm of the impact of biased news coverage can be seen in what has been deemed the Fox News Effect (Epstein & Robertson, 2015). The Fox News Effect is a phenomenon that occurred in the late 1990's and early 2000's. As previously discussed, Fox News has consistently been rated as a conservative news source. When Fox News was founded in 1996, it slowly began to move into new territories and markets. Whenever Fox News entered a new market, it appeared that the number of conservative voters increased (Epstein & Robertson, 2015). This provides more evidence of a link between biased news reporting and increased political participation by conservatives. However, the Fox News Effect potentially had a large impact on the direction of the United States around the turn of the century. In 1999 and 2000, Fox News moved into many new markets in Florida (Epstein & Robertson, 2015). Their conservative reporting is estimated to have shifted approximately 10,757 votes during the 2000 presidential election in favor of George W. Bush (Epstein & Robertson, 2015) which is far greater than the number of votes he actually won the state by. There are an endless number of variables that impact why George W. Bush carried the state of Florida in 2000 and ultimately won the Electoral College and presidency because of it. The fact that Fox News may have played a role in solidifying this cannot be overlooked as it potentially shaped the course of history.

Other examples may prove there is a lesser effect of biased news media coverage. In 2015 and 2016, Donald Trump faced primarily negative coverage of his campaign from the news media yet still won the presidency. However, currently, over halfway into his first term, President Trump consistently polls at a much lower favorability than a lot of his recent

counterparts at this point of their first term (Gallup, 2019) so there is the potential the news coverage still is impacting him negatively. There can be arguments made whether this negative news coverage is merited or not as Trump has consistently provoked the media as well, but that is not the topic of discussion of this thesis. The question remains as to whether the consistently negative news coverage of Donald Trump has actually negatively impacted his favorability and job approval.

While President Trump polls at a much lower rate than presidents halfway through their first term in recent memory, he also has faced far greater negative news media coverage. During his first 60 days, 62% of news coverage about the Trump presidency was negative (Mitchell et al, 2017). When this is compared to the 20% negative news coverage President Obama faced and the 28% negative news coverage President Clinton and President George W. Bush faced (Mitchell et al, 2017), it makes the 62% seem extremely high. What is unknown is whether the negative coverage is causing low favorability of Trump or whether his actions and public opinion are fueling negative coverage.

Additionally, existing literature has shown that the impact of biased news coverage is greatest when dealing with election coverage. More specifically, the tone political commentators use to describe candidates is most impactful on their campaigns (Fyengar, Sood, and Lelkes, 2012). Furthermore, this is relevant because biased media, as seen in the Fox News Effect, does influence public attitudes and vote choice (Levendusky, 2013). This literature indicates that media bias, through content or tone, can have an impact on politicians and how the general public views them.

Previous literature has spent a lot of time on different aspects of media bias. Perhaps the most difficult task has been trying to rate news sources based on credibility and partisanship due

to the fact that there are many different ways to measure each news source for neutrality or bias. It is also important to note that news sources can change over time, as they are fluid. Some may argue that CNN has moved left as Donald Trump has increased his attacks on the company. Simply because a news media outlet is conservative or liberal in 2019 does not mean it is permanent. This fluidity also increases the difficulty of rating each news source.

In today's political environment, it appears as though centrist news outlets are struggling to keep pace with partisan news outlets. This can be seen in the comparison of Fox News, MSNBC, and CNN. Fox News, the most conservative of those three outlets, had the highest-rated prime-time shows in their network history in 2018 (Joyela, 2018). MSNBC, as discussed earlier, finished second in viewers in prime-time and was the fastest growing cable news channel (Joyela, 2018). By many measures, MSNBC would be considered the most liberal of the three networks listed here. Finally, according to Nielsen Media Report data, the viewership of CNN, which appears to be the most centrist of these three news media outlets, continues to shrink (Joyela, 2018). This would indicate that the general public actually are seeking more biased news sources and leaving those that do not supply opinion-reinforcing information. In addition, due to this trend, channels are motivated to capitalize by strategically aligning news content with political predispositions of targeted audiences (Hyun & Moon, 2016).

One of the most credible ways to rank media bias is the sharing score of each major news outlet. This can include both cable news outlets as well as print media. The sharing score is a score created by how many times a post was shared on Facebook by the members of a political party in Congress (Messing, Van Kessel, & Hughes, 2017). If news sources were not biased, one would expect the sharing score to reflect the partisan composition of Congress. This means that if the House and Senate both had an equal number of Democrats and Republicans, one would

expect all news sources to be equally shared by each party so the sharing score would be 0. If there were slightly more Republicans than Democrats, one would expect the sharing score to be just above 0 to reflect this and the opposite would be true if there were more Democrats than Republicans. In 2017, there were slightly more Republicans than Democrats in Congress. More specifically, in terms of a sharing score, 0.11 would indicate no bias (Messing, Van Kessel, & Hughes, 2017). However, that is clearly not the case in (Figure 3).

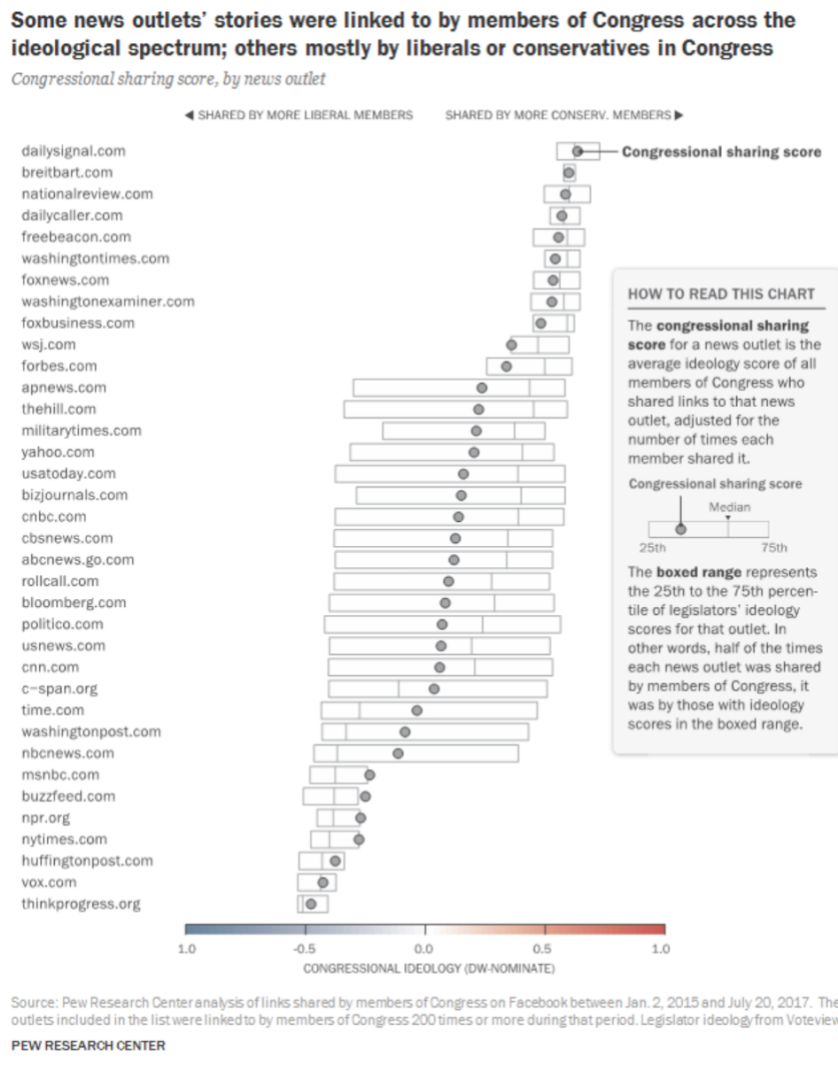


Figure 3. Sharing Scores for Liberal and Conservative Members of Congress, 2015-2017

As can be seen in Figure 3, there is clearly some form of bias in the types of media that are shared by legislators on Facebook. This is reinforced by the fact that news links are shared by just one party 48% of the time (Messing, Van Kessel, & Hughes, 2017). If there was no bias in the media, this would not be a naturally occurring trend. Additionally, it appears as though there are more conservative leaning news outlets' but a majority of them are not part of the "mainstream" media. It is also important to note that this thesis chose to rank sources based on their congressional sharing score, not the median score in this chart which certainly could have impacted the overall assessment of each source.

Partisan News Consumers

While it certainly appears there is a media bias and individuals seek out these sources, the motivations for why people seek out biased news sources has also been covered by previous literature. One motivation could be partisan selective exposure (PSE). PSE, as previously mentioned, is closely related to confirmation bias. It is defined as the, "Propensity of an individual to select information in a way that is congenial to his or her existing beliefs and partisan predisposition," (Song, 2016). It is argued that exposure to proattitudinal information may be driven by a person's subjective need to reaffirm their correctness (Song, 2016). This raises the question of whether PSE creates political echo chambers on social media.

Under this assumption, the more you hear the same perspectives from the same source, the more ideas are reinforced without being challenged (Ravenscraft, 2016). Moreover, access to partisan news is associated with declining exposure to other opinions (Garrett, 2009). There is substantial evidence people are most interested in opinion-reinforcing political information (Garrett, 2009) and it appears social media platforms may give them the opportunity to solely seek out this information. On Facebook, individuals can select their friends and on Twitter,

individuals can select who they follow. While engagement-based algorithms may shift what user's see, they still have some influence over their news feed. Contrary to this perspective, other literature has argued that exposure to counter-attitudinal information occurs when individuals have greater confidence in their views, higher interest in politics, and stronger party preference (Knoblauch-Westerwick & Meng, 2009). While this exposure to counter-attitudinal information may be beneficial, there are red flags. When people read information that is opinion-challenging, they spend more time reading it than they would spend reading information that is opinion-reinforcing (Garrett, 2009). The reason for this behavior, is that they are searching for flaws in the opinion-challenging information (Garrett, 2009). This would indicate that the motivation for viewing opinion-challenging information is disingenuous and individuals are still motivated by PSE and confirmation bias.

Within PSE, there are two primary explanations of why researchers believe it occurs. First, some believe it is related to cognitive dissonance. According to this theory, individuals seek to reduce cognitive dissonance and avoid situations where it may occur (Festinger, 1957). This interpretation may not always be supported, as there is evidence of people seeking out individual opinion-challenging information whether it is genuine or disingenuous. A second theory for why PSE occurs relates to credibility and informational utility. As individuals believe information is of greater use to them, they will be more likely to engage with it (Knoblauch-Westerwick & Kleinman, 2012). This appears to hold true for credibility as well because people want to read information they believe to be factual. It can also be assumed that people will find information they perceive to be true and supports their ideology, to be most useful to them. People process biased information in biased ways that supports their own beliefs (Metzger, Hartsell, & Flanagan, 2015). Additionally, credibility could be a source of why individuals select

their cable news networks. This appears to be closely in line with the frequent attacks from President Trump on news sources that do not support his political beliefs or may run negative pieces on him. In this scenario, he may no longer view them as credible, so he simply refers to them as “fake news” and attempts to diminish their reporting.

While there are multiple negative consequences of PSE, it appears that the Internet helps facilitate the concept (Bode, 2016). However, the Internet and use of social networking can lead to increased participation (Bode, 2016). In some sense, this relates back to a larger theoretical question of what individuals prefer from the government. Increased political participation and engagement is certainly a good thing, but is it worth it at the expense of a fragmented and less tolerant general public?

With the discussion of PSE, it is important to review the impacts of it as well. First, there is no evidence that factual knowledge is decreased because of it (Kim, 2013). While issues may be framed differently or commentary may change how individuals feel about political topics, individuals appear to maintain a baseline knowledge of the facts of a situation when it occurs. Next, it is important to be aware that it does influence stereotypic perceptions of candidates (Kim, 2013). This may again relate back to the framing of candidates in discussion of their policies or the tone used to describe them. Finally, partisan media makes citizens more convinced their views are correct (Levendusky, 2013). If individuals are not exposed to opinion-challenging information, they may be less willing to trust the other party and support compromise (Levendusky, 2013).

Other literature has focused primarily on news media influence. It appears that the two main ways the news media influences political discourse are through agenda-setting and framing (Soukup, 2014). Through agenda-setting and framing, there are two ways to influence discourse

substantially. One can choose to support the party of choice, or choose to oppose the other major party. Current trends are indicating a rise in this type of negative partisanship. Negative partisanship means that a growing numbers of Americans are voting against the party they oppose, rather than voting for a party they support (Ambramowitz & Webster, 2015). This can be seen through Pew Research Center data showing that views of opposing party have consistently grown colder and those who are politically engaged report feeling more negatively about those on the “other side.” In some ways this is related to polarization, but it can also be related to partisan media and the framing of the other party. This could also be related to the growing distrust in the news media (Gottfried, Stocking, & Grieco 2018). With only 21% of people reporting they have a lot of trust in the information they get from national news organizations and only 4% of people reporting the same thing about social media (Gottfried, Stocking, & Grieco 2018), literature shows there is a credibility crisis and potentially current news media behavior, operating in a rather partisan manner, is not the most appropriate way of reporting.

Finally, there is some debate in the research literature about whether general public polarization causes media partisanship to increase, or whether media partisanship has caused general public polarization to increase. One study concluded that mass polarization occurred before elite polarization (Rodriguez et al, 2017). While this relationship would only show a correlation, it would be damaging to H2, which states that the news media influence individual polarization. Other reports indicate that patterns of polarization in the mass public resemble elite polarization (Stroud, 2016). Moreover, other research indicates that partisan media sources take individuals who already are partisan or polarized to some degree, and makes them even more extreme (Levendusky, 2013). Regardless, previous literature provides a strong relationship and

link between news media partisanship and polarization. What remains in question is whether this is a correlative relationship and whether the public influence the media or vice versa.

CHAPTER 3. DATA AND METHODS

This thesis has made use of a variety of existing research findings and data to reach conclusions. Because of this, the data and methods section of this text operates as a literature review of the data and methods of other studies. While none of the data used may be original to this thesis, the analysis of this data done here is important but understanding how other data studies gathered their data is also valuable. At this point, it is relevant to examine how these other studies assembled their data. To begin, it may be most practical to discuss methods used for figures already in the text. Figure 1 was created as a result of a telephone survey conducted by the Princeton Data Source for the Pew Research Center. This survey asked the public 10 questions regarding their political values and has been repeated multiple times between 1994 and 2017. In 2017, the data were collected in two separate trials during the course of the year. Respondents were divided into three groups; Democrats and Independents who lean Democrat, true Independents, and Republicans and Independents who lean Republican. If respondents answered a question with a liberal position, their answer was coded as a “-1”. If a conservative answer was given, the score applied was a “+1.” This means the most liberal score possible was a -10 and the most conservative score was a 10. In total, there were 2,086 Republican respondents and 2,486 Democratic respondents. Overall, there was a total sample size of 5,009 respondents which led to an overall margin of error of $\pm 1.6\%$.

Figure 3 was created by the Pew Research Center to have a visual representation of the underlying data of sharing scores. The sharing score data came from the dataset DW_NOMINATE through Voteview. To create a full assessment, the Pew Research Center obtained a complete list set of Facebook posts created by members of the United States Senate and House of Representatives. These posts occurred on their official accounts between January

2, 2015 and July 20, 2017. For verification purposes, these accounts were only considered official if they referenced the politician's official government email. The posts were then vetted for potential duplicate postings and a machine algorithm was taught how to search through the posts and all duplicates were eliminated. The final dataset included 447,684 Facebook posts from 581 members of Congress. A regression model was then estimated to examine the sharing score and compare it to re-shares, comments, and likes of each post. The full methodology can be found in the article, "Sharing the News in a Polarized Congress" on the Pew Research Center website (<https://www.people-press.org/2017/12/18/sharing-the-news-in-a-polarized-congress/>).

The research conducted by Naomi Stroud in "Polarization & Partisan Selective Exposure" has also been useful in coming to an overall conclusion. Her study used data from the 2004 National Annenberg Election Survey (NAES). The NAES data were collected through a random-digit-dial telephone survey conducted during the campaigns for the 2004 presidential election. The design of this telephone survey was a rolling cross-sectional design where a new set of telephone numbers that had not previously been dialed were released each day of interviewing. This led to a response rate of 22%. A second research method conducted by the NAES included four different panel surveys conducted around the Democratic National Convention, Republican National Convention, the debates, and the general election. The two control variables in this study were strength of ideology and political knowledge. Polarization was measured in respondent feelings toward John Kerry and George W. Bush. Partisan Selective Exposure was measured in several ways. For newspapers, it was based on who the newspaper endorsed for the presidency. For talk radio, it was based on the self-identification of the host. For cable news, Fox was ranked consistently conservative while CNN and MSNBC were

consistently liberal based on several previous studies. Finally, coding was used to identify the partisanship of each website that individuals used for political information.

Additional data for the overall conclusion of this thesis comes from the 2008 NAES data set which was utilized by Kim (2013). The 2008 NAES survey was a rolling cross-sectional study during the 2008 U.S. presidential election. In the Kim dissertation, data from the 2008 NAES study were collected in the same way as in the 2004 NAES survey. However, the overall response rate increased by one percentage point, for an overall total of 23%. Kim chose to use data only from after the primaries and before the election, which limited the amount of data available. This led to information from May 23 and November 3, 2008 being used exclusively. Polarization was again based on how respondents felt toward the candidates of the main political parties. It was measured in 2008 based on the same question asked in 2004 with the names being updated to reflect the current election. Political participation, issue-specific political knowledge, candidate stereotypes, selective media use, demographics, ideology, and partisanship were also measured using previous studies. For evaluation of news media bias, Kim chose to use a method that relied on the perception of viewers. This method was provided by the 2008 NAES survey, where respondents were asked their perceptions of newspapers, talk radio, cable news, and the Internet. Two dichotomous variables were then created based on responses as to whether the outlet favored John McCain or Barack Obama.

While all of these data are useful for addressing H2, multiple datasets were also used in assessing H1. The impact of news media on polarization research differs greatly from the research that has been conducted on social media algorithms. Research on the news media has existed much longer and is much more thorough and comprehensive as there are stronger measures available. Due to the recent proliferation of social media use and large amount of

uncertainty regarding how algorithms operate, the research and methodology into algorithms appears to be less reliable and not as straightforward as the news media research. This could impact results and overall assessment of H1 and H2.

Data about social media algorithms also come from multiple places that previously existed and are not original to the content of this thesis. To begin, data from Bakshy et al. (2015) was used. Researchers used a dataset containing 10.1 million active Facebook users who had indicated a political party preference. This database allowed them to compare ideological diversity in news and opinions shared, compare news and opinions shared with a subset of news stories shown based on the Facebook algorithm, and observe what information individuals choose to consume. Over a six-month period from July 7, 2014 until January 7, 2015 researchers were able to report 7 million distinct URL links shared by users in the United States. Further analysis led to researchers labeling the content as hard (national news, politics, and world affairs) or soft (sports, entertainment, and travel). Only 13% of the data were found to be hard-content. The dataset was further limited to 226,000 URL links that were classified as hard-content and shared by more than 20 users who provided their party affiliation. Content alignment was then measured for hard-content by taking the average ideological affiliation of each user who shared the article. This process provided researchers with knowledge and a score of polarization among sharing of hard content.

Boxell (2017) provided the most complete dataset regarding algorithms and the Internet. In this dataset, the main source for data were the American National Election Studies (ANES) 1948-2012 Time Series Cumulative, 2008 Time Series Study, and the 2012 Time Series Study datasets. Boxell concluded that for consistency purposes it was best to include only information they believed was nationally representative and conducted in a face-to-face setting of the voting-

age population. These data were supplemented with Pew Research data from 2005-2012 to get a better picture of the growth of social media use. Overall, the main goal of the study was to measure the impact of the Internet on polarization. Formulas were created to measure the following nine variables, divided into age groups: partisan affect polarization, ideological affect polarization, partisan identity sorting, frequency of split ticket voting, issue consistency, issue divergence, partisan-ideology polarization, perceived partisan-ideology polarization, and religious polarization. The full formulas for each variable are available by reading Boxell, 2017, “Is the Internet causing Political Polarization?”. Table 1 shows the outputs of these formulas:

Table 1. Growth in Polarization 1996 to 2012

Table 1: Growth in polarization 1996 to 2012

| Measure | Overall | Age Groups | | | | | |
|-----------------------------|-----------------|-----------------|----------------|-----------------|-----------------|--------------------|--------------------|
| | | 18-39 | 40-64 | 65+ | 75+ | 65+ minus 18-39 | 75+ minus 18-39 |
| Partisan affect | 12.6 (2.4) | 4.8 (3.7) | 16.0 (4.0) | 13.5 (5.9) | 15.0 (10.0) | 8.72 (6.73) | 10.16 (10.21) |
| Ideological affect | 7.9 (3.3) | -4.7 (5.6) | 8.4 (5.5) | 21.4 (9.3) | 10.6 (12.9) | 26.10 (10.80) | 15.25 (13.63) |
| Partisan sorting | 0.03 (0.01) | -0.03 (0.02) | 0.05 (0.02) | 0.10 (0.03) | 0.13 (0.05) | 0.12 (0.03) | 0.16 (0.05) |
| Straight-ticket | 0.07 (0.02) | 0.01 (0.04) | 0.11 (0.03) | 0.06 (0.04) | 0.06 (0.06) | 0.05 (0.06) | 0.05 (0.07) |
| Issue consistency | 0.24 (0.08) | -0.08 (0.13) | 0.17 (0.12) | 1.01 (0.16) | 1.44 (0.23) | 1.09 (0.21) | 1.52 (0.27) |
| Issue divergence | 0.04 (0.02) | -0.02 (0.03) | 0.03 (0.02) | 0.14 (0.04) | 0.16 (0.06) | 0.16 (0.05) | 0.18 (0.07) |
| Partisan-ideology | 0.62 (0.13) | 0.17 (0.22) | 0.54 (0.20) | 1.34 (0.34) | 1.63 (0.56) | 1.17 (0.40) | 1.46 (0.59) |
| Perceived partisan-ideology | 0.80 (0.12) | 0.73 (0.19) | 0.74 (0.17) | 1.01 (0.26) | 0.97 (0.35) | 0.27 (0.32) | 0.24 (0.41) |
| Religious | -0.00 (0.20) | 0.15 (0.29) | 0.09 (0.32) | -0.34 (0.42) | -0.18 (0.68) | -0.49 (0.52) | -0.34 (0.76) |
| Index | 0.18 (0.05) | 0.05 (0.06) | 0.20 (0.08) | 0.32 (0.09) | 0.38 (0.16) | 0.27 (0.11) | 0.32 (0.16) |

Notes: Table shows the change in each measure, and in the index, from 1996 to 2012. The “Overall” column includes all ages. Columns “18-39,” “40-64,” “65+,” and “75+” re-calculate the measures for each age group. The last two columns show the difference in growth between the two age groups. Standard errors are in parentheses and are constructed using a nonparametric bootstrap with 100 replicates. See section 2 for definitions.

Table 1 is in place here for multiple reasons. When evaluating the table, the top two variables on the chart are of the most relevance to this thesis as they deal directly with polarization and partisanship. Within this study, Boxell sought to discover what the impact of the Internet on the general public is. Using this information to identify the impact the Internet has on the top two variables of partisan affect and ideological affect allows individuals to understand that it appears there is a greater impact of these two variables in older individuals than younger individuals. This can be seen in the values of the numbers for ages 40+ being greater than those corresponding values for the ages 18-39. Additionally, this is impactful to H1 as it is actually contrary to what would be expected considering individuals between the ages of 18-39 typically have greater access to the Internet than those over the age of 40. With greater access to the Internet, it would be expected polarization would also be higher because of the higher rate of exposure to different algorithms. Table 1 is necessary to include in this discussion because it provides background evidence about the relationship between the Internet and polarization as well as provides information that impacts the overall discussion surrounding H1.

Another important study conducted by Trielli, Mussenden, and Diakopoulos (2015) relied on a crowdsourced analysis in December 2015 to measure Google search results for Democratic and Republican presidential candidates. The data were collected using automatic gathering nonpersonalized search results and excluding all advertisements. From there, focus was then placed on the first 10 websites that appeared. Next, each website was evaluated using a crowdsourced analysis to measure favorability toward a candidate as well as opposition toward a candidate. Each website produces a unique outlook on each candidate and some may have a

mixture of support and opposition while others may have just support or just opposition. The data were then validated by comparing against their own coding to ensure accuracy.

Epstein and Robertson (2015) provided further information on algorithm manipulation and valuable data for this research. This paper used three separate studies to reach its overall conclusions. In Study 1, they conducted three laboratory-based experiments that used a double-blind control group and random assignment. Each of the experiments used 102 eligible voters recruited through online and newspaper advertisements. As a method to counter any cognitive biases, researchers used an Australian prime minister election rather than an American election. Subjects were placed into one of three groups that suggested either that they should support one of the two candidates or support neither. They then read biographical information on both candidates and were asked to assess the candidates on a 10-point Likert scale and rate how likely they were to vote for that candidate on an 11-point scale. Researchers then provided more information about the candidates using a search engine they had created. They also shifted results on each candidate to vary for each participant to simulate search engine bias and measured the effects. In Study 2, the researchers attempted to make the data more generalizable and accurate. They did this by conducting the survey with 2,100 individuals from all 50 states. The same standards from Study 1 were upheld and applied in this situation again. In Study 3, researchers measured the impact of the 2014 Indian national Lok Sabha elections. They did this by randomly assigning undecided English-speaking voters throughout India who had not yet voted. The same process used in Study 1 and Study 2 was then applied in Study 3 and effects were measured. Due to the low number of participants in each study compared to the overall population, researchers were not worried that their biased search engines and studies would influence the overall outcome.

CHAPTER 4. RESULTS

As the data and results apply to the hypotheses of this thesis, the information provides a mixture of support and uncertainty. First, examining the impact and influence of sharing scores could impart valuable knowledge. From Figure 3, it becomes very apparent there are trends in which each political party shares news from each source. While this does not address the hypotheses directly, it does provide some context for the environment in which they occur. Furthermore, if all news sources were completely neutral, one would expect very little variation from the 0.11 mark as that would indicate the two major parties are sharing news from these sources at an equal rate. However, due to the broad range of scores shown in Figure 3, it is apparent there is news media bias.

Also of importance on this topic is that bias occurs on both sides. There are liberal news sources and there are conservative news sources, which may refute some partisan claims that the media are always against them. Uncoincidentally, as previously discussed, it appears the major news networks that are partisan sources have higher levels of viewership than neutral sources. Joyela (2018) provided data indicating that the most watched cable news network is Fox, a consistently conservative source, and the fastest growing source is MSNBC, a consistently liberal source. At the very least, this provides a correlative relationship between media bias and polarization as individuals continue to replace sources closest to neutral with partisan sources of news. A possible underlying motivator for this is completely unconscious, as conservatives see much less bias in Fox News than liberals do (Stroud & Lee, 2013). A great topic of further discussion would be discovering what motivates people to choose a news source and to understand their unconscious biases.

While Figure 1 and Figure 2 do not answer H1 or H2, they once again provide the information necessary to understand polarization has increased dramatically within the last two decades. Previous research (Levendusky, 2013; Kim, 2013; Stroud, 2010) has linked this increasing polarization with the effects of biased news media coverage. Multiple variables may be contributing to this, but a phenomenon such as the Fox News Effect (Epstein & Robertson, 2015) indicate that the news does increase partisanship and polarization among viewers. If the Fox News Effect were indicative of the impact of the news media at the national level for all sources of news, it would provide strong support for H2. Due to limitations of this study, that information is not available. However, even with the small sample size of Florida during the 2000 presidential election, it certainly appears the Fox News Effect is a microcosm of H2. In this case, the news media bias impacted undecided voters and led more individuals to vote conservatively. In concordance with H2, this is a prime example of the news media playing a role in increasing partisanship and polarization. This cause and effect example provides anything from partial support to full support for the hypothesis depending on how generalizable the results are to the other 49 states in the country.

Further results from this research indicate that citizens' selective exposure to ideologically-slanted media outlets leads to polarized attitudes toward candidates (Kim, 2013). This result may not specifically show polarization or partisanship; however, polarized attitudes toward candidates do impact vote choice of people which then can be used to measure overall partisanship and polarization trends. Perhaps the most interesting result of these data from a similar study is that exposure to counter-attitudinal information occurs when individuals have greater confidence in their views, higher interest in politics, and stronger party preference (Knobloch-Westerwick & Meng, 2009). If this holds true, and the implication is that individuals

who do not have great confidence in their views seek out information that only supports and reinforces how they feel, this would also provide great support for H2. These same individuals who lack confidence in their views would continue to consume opinion-reinforcing information until their confidence was strong enough to engage with opinion-challenging information. By this point, individuals would already have become polarized and consistently liberal or conservative. These results again support H2. There is a direct cause and effect relationship found here as selective exposure to ideologically-slanted media outlets leads to polarized attitudes toward candidates (Kim, 2013). As data continue to support H2, the relationship between the traditional news media and polarization of the American public becomes more defined.

However, the strongest support for H2 comes from Stroud (2010), which found strong support that partisan selective exposure leads to higher levels of political polarization. This data can be seen in regression analyses from Stroud (2010) in Table 2:

Table 2. Regression Analyses Predicting Political Polarization

| | Model 1 | | Model 2 |
|---------------------------|--------------------|---------------------------|--------------------|
| Ideology/ partisanship | -0.03* (0.01) | Ideology/ partisanship | -0.03** (0.01) |
| Conservative media use | -0.02 (0.04) | Liberal media use | -0.14*** (0.04) |
| Interaction | -0.13*** (0.02) | Interaction | 0.15*** (0.02) |
| R-square | 0.21 | R-square | 0.21 |

Notes: Unstandardized coefficient (SE).

Ideology/partisanship (higher values correspond with stronger liberal Democrats) and liberal/conservative media use are mean centered. Control variables (see Appendix) are included in the model, but are not shown here. Full tables, including control variables, are available upon request. Interaction results are unchanged if ideology or partisanship is used in place of ideology/partisanship. As there is some controversy regarding whether NPR should be counted as a liberal outlet (consider that Cappella, Turow, & Jamieson, 1996, coded Diane Rehm of NPR as liberal and *Talk of the Nation* as moderate), analysis was repeated without NPR-users classified as liberal talk radio listeners. Results are unchanged. Although liberal and conservative media use are modeled separately, if they are included as independent variables in the same model, the interactions with ideology/partisanship remain significant ($p < .001$) and in the same directions.

$N = 12,840$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Stroud's table shows significant effects on ideology and partisanship liberals obtain their political information from biased media sources. For example, liberal Democrats who obtain political information from liberal news organizations tend to be more liberal than the typical Democrat (Stroud, 2010). The results in Table 2 provide support for H2 and support the notion that media bias plays a role in increasing partisanship and polarization. This is rather important to note as well because it provides the link of causation that many studies fail to provide. Table 2 provides the necessary data to conclude there is validity to H2. While most of the earlier studies have found correlative links, this study provides a causal link that traditional news media sources are increasing polarization. This shows the comprehensiveness of the Stroud (2010) study but also provides an interesting note as conservative media was not significant at increasing polarization in this study. Further research could be helpful in identifying why that was the case and whether that is the general trend or if this study was simply an anomaly at measuring the influence of conservative news sources. The finding of conservative media not being significant in this study raises some interesting questions as to why this may be the case as other studies and phenomenon, such as the Fox News Effect, have showed clear indications of a causal relationship being present.

While there appears to be extensive literature supporting H2, information regarding H1 is much more difficult to uncover. Research into algorithms and social media is relatively new as none of the social media sites examined existed before 2004. That makes all research relatively new and a wide range of knowledge unknown. Moreover, while it appears simple to test polarization among individuals based on the news they receive, it is not as straightforward when dealing with social media algorithms. As discussed previously, there is a desire among companies to keep their algorithms private. Furthermore, because no two people see the same

social media the algorithm's consistency is an issue and self-reporting of feelings among users may weaken the data. Nonetheless, some research is able to provide clarity to the picture of today's social media environment and how it relates to partisanship and polarization.

H1 states that social media algorithms play a role in increasing polarization and partisanship. Yet, when observing Table 1 from Boxell (2017), that does not seem to be the case. As can be seen in the table, older individuals experienced larger changes in polarization from 1996-2012 despite having a lower rate of Internet access (Boxell, 2017). If H1 was true, it would make more sense for younger people to experience greater levels of polarization and partisanship as they are exposed to the Internet and social media algorithms at a higher rate. This indicates some opposition to H1 as a whole because it contradicts the premise of algorithms increasing polarization. This result could also be indicative of other factors exerting a greater impact on polarization than algorithms or there may be something working to counter the impact that the algorithms have. A possible explanation could be the fact that social media algorithms do tend to show things that users like and agree with, but they are still exposed to alternative viewpoints (Barbera, 2015; Garrett, 2009). If users are continuously exposed to alternative viewpoints, albeit at a lower rate, this could perhaps be an explanation as to why extreme polarization is not caused by social media algorithms.

Further research has reached mixed results on the topic of social media algorithms' effect on polarization. An and colleagues concluded that the bias among users in sharing information on Twitter can lead to a partisan perception. However, the research does not go far enough to conclude that the sharing of information actually leads to greater partisanship or even increased polarization. The effects of this partisan perception are unknown and could be the topic of future

research. However, the data fall short of endorsing H1 fully and some even contradict what the expectation for H1 would be.

While the Twitter data cannot explain whether social media algorithms have actual bias or increase polarization, the research does seem to indicate somewhat of a trend as it relates to Google. According to Trielli, Mussenden, and Diakopoulos, (2015), Google does have a liberal bias in their search results. While this is the first result that clearly is indicative of bias, it still falls short of explaining how or if the bias found in Google algorithms actually influences partisanship. While this information is interesting and useful it also falls short of a complete endorsement of H1 and cannot lead to a firm conclusion.

Perhaps the data that come as close as possible to explaining the overall impact biased algorithms can have was presented by Epstein and Robertson (2015). Their results indicate that biased search rankings can shift voting preferences of undecided voters by as much as 20% (Epstein & Robertson, 2015). This information is extremely useful when it comes to understanding the power algorithms have and their potential impact on search rankings, but it still falls short of full support for H1. If this impact could be generalized and applied to the research done by Trielli, Mussenden, and Diakopoulos and show that Google search results have in fact altered voting preferences by 20%, then the results of these studies would be sufficient as it would provide causation. Without the causal link and merely a correlative relationship at this point, none of these datasets are sufficient to support H1 entirely.

CHAPTER 5. DISCUSSION

Certainly the results of the data appear to indicate mixed support and opposition for H1. While social media algorithms may promote information users' like to increase engagement, there is evidence users also experience posts they do not like. This is an indication that users are exposed to opposing viewpoints and social media algorithms do not create echo chambers. However, the overall effect social media algorithms and the Internet have on polarization and partisanship is still unknown. There is a possibility that social media algorithms do increase polarization because a relationship appears to exist, but it is hard to determine the extent of this relationship as well as demonstrate anything beyond a correlational relationship based on when polarization increased and when social media use increased. Conversely, some data indicated trends that were the exact opposite of what would be expected if social media algorithms were driving a shift in polarization. This countertrend is seen in the Boxell (2017) data that showed older individuals are more likely to be extremely polarized despite the fact that they use the Internet and social media at a lower rate than younger individuals. As previously discussed, if social media algorithms were causing this shift in polarization, the exact opposite result would be expected.

Due to this mix of support and opposition for the hypothesis, the environment surrounding social media algorithms is still unclear and until greater information is known about them it will be difficult to have a clear understanding of their impact. Furthermore, other findings opposed the idea that social media users are exposed only to thoughts they support. A prime example of this phenomenon is the fact that on average 23% of a user's Facebook friends are of an opposing political party and 29% of news stories seen contradict the views of the user's own ideology (Manjoo, 2015). While users may not be seeing views that oppose how they feel

at the same rate that they see supportive views, they are still being shown what the opposition believes and are not operating within an echo chamber as some studies would suggest. It is important people are exposed to various messages across the political spectrum as people who are exposed to a heterogeneous message are less likely to hold polarized attitudes toward candidates (Huckfeldt, Mendez, & Osborn, 2004). There still is the potential that because an overwhelming majority of social media posts still appear to support a user's political ideology the posts of opposing viewpoints will be drowned out; however, there is no indication that this is the case. Continuing exposure to heterogeneous messages is very important to decrease polarization and partisanship within the United States. Future research could explore a larger theoretical argument and examine regarding what is best for individuals and whether algorithms should be regulated to some extent or whether social media companies have a moral obligation to change how they do business.

While the picture around H1 remains cloudy, there is much stronger evidence supporting H2. Based on the data, it appears biased news networks appear everywhere and have a great impact on what citizens think and feel. Furthermore, while this paper used sharing scores to highlight bias in the news media and partisanship, there are many different measures for bias and nearly all reach similar conclusions on how to rank news networks on ideology. Sharing scores appear to show the general picture and lay out just how partisan each news network; however, the Fox News Effect appears to be a microcosm of a larger problem.

To jump back into theory, the Fox News Effect certainly raises some overarching questions of what individuals should expect from their news media sources. Should the news media be expected to be completely free of bias? Is it possible for the news media to be free of bias? Should the government impose standards on news networks that would lead to more

comprehensive discussion of both sides of issues and ideology from both parties? While all of these news networks are owned by private corporations that are interested in their bottom line, their impact on public interest and issue-framing cannot be understated. The greatest question to be asked is whether the potential negative consequences of this coverage is enough to warrant government regulation of the content of a private entity. Government regulation of the content of news media corporations would certainly go straight to the heart of American democracy as it could be challenged constitutionally but nonetheless it is a valuable topic of interest because of the role of the news media in society. If current trends continue, society can expect partisan news sources to continue gaining viewership. It will be interesting to see the impact this has on overall partisan composition of residents of the United States as well as the potential impact partisanship can have on more centrist news sources. Without viewers, it is difficult to operate a news network which could lead to centrist news sources becoming more partisan or ceasing to exist. It would be interesting to see how this could affect individuals overall trust in the news they receive as it becomes more partisan. With the current indication being that only 21% of individuals report great trust in the information they receive from the news media (Gottfried, Stocking, & Grieco, 2018), this could cause an even greater credibility crisis as that number could potentially shrink.

Limitations

While there are a number of strengths of this thesis, there are also various limitations. First, this thesis primarily discovered correlative relationships. While these may be somewhat useful, they are not nearly as strong as relationships that demonstrate causation. When it comes to evaluating social media algorithms and H1, the exclusively correlative relationships that were found make overall applicability and generalizations very difficult. Having the ability to

demonstrate causation in many of these relationships would be much more satisfactory and provide much greater support for or against the hypothesis. Second, social media algorithm research is limited in scope and difficult to narrow down. While social media sites have existed for roughly a decade and a half, a majority of their growth has occurred more recently. Because they are relatively new, existing literature is not as detailed on the topic as it is for a lot of other political communication- and media-related topics. Finally, this thesis solely makes use of existing literature and data. It would be much stronger to create something new and conduct a study using new data. Unfortunately, extenuating circumstances did not allow for that and the overall thesis was therefore weakened.

While this may weaken the thesis, it certainly does not take away from the overall contributions this thesis makes toward the study and literature on news media bias and social media algorithms. With the rise of social media, traditional news sources have begun using these platforms to disseminate their stories. This can certainly blur the lines between social media algorithms and the news media and is a trend that should continue into the future. Most past research has viewed these two as entirely separate issues but going forward that will not be the case. This thesis combines the literature on these topics in the same place as they are examined for their potential impact on polarization. Additionally, combining the main takeaways from multiple studies allows this thesis to go further in depth and combine this knowledge in a manner that has not been seen before. When these other studies are combined in this thesis, it provides individuals with greater knowledge on the impact of news media bias and social media algorithms and provides factual information on just how powerful these domains can be on the political feelings of individuals. This allows for a greater understanding of the increasing

polarization within the nation as well as the potential relationship it may have with social media algorithms and biased news media coverage.

Furthermore, because of the challenges surrounding studying algorithms, perhaps examining the impact of the Internet as a whole would have been a better avenue of research. There has been additional time to study the Internet and the effects it has on individuals compared to that of social media algorithms. In addition, each social media algorithm appears to differ in some way that makes it difficult to generalize about all social media platforms together and all user experiences. Each individual sees their social media differently which makes generalization even tougher when algorithms are based on engagement. When this reality is combined with the fact that companies have an incentive to keep their algorithms private, it is difficult to have a full understanding of how social media algorithms operate which in turn makes it even more difficult to measure their impact on polarization. Hopefully, within the near future more will be understood about how social media platforms create their algorithms and that knowledge then can be used to study their effects.

Further research on this topic could go in multiple directions. First, finding a way to demonstrate causation in all aspects of social media algorithms has to be a primary focus. Correlation does not go far enough to determine whether social media algorithms truly impact partisan composition and polarization. Finding a way to conduct research that either convincingly confirms or disconfirms the possibility that algorithms cause polarization would provide great benefit to the dialogue on this topic.

Second, it would be beneficial to establish the underlying reason why individuals seek out partisan news sources. Cognitive dissonance, trust, and credibility all have been suggested as potential reasons why people seek out news sources that support their ideology, but there is still

some uncertainty regarding the main explanation of this behavior. If future research could identify why people seek out partisan news sources, it could help explain why there has been a great shift in polarization and why individuals are now seeking out partisan news sources over centrist ones. Furthermore, this information could explain why people seek out partisan news sources and could allow the problem to be corrected. Understanding the motivation of individuals when they choose a news source would be extremely beneficial for this research area as a whole.

Next, continuing to research the impact of algorithms is vital. Social media platforms are constantly updating and refining their algorithms in ways to increase engagement. As these changes occur, it is important for research to keep pace and discover the consequences of these decisions and the impact they may have on the general public. While it is clear search engine algorithms have the ability to influence people's vote choice, it would be extremely beneficial to understand if social media could have the same impact and to what extent it is possible.

Finally, as was seen in Epstein and Robertson (2015), the Fox News Effect had serious consequences for the 2000 presidential election as some claim it may have swayed the entire election. However, further research could go into observing whether a "CNN effect" or a "MSNBC effect" exists as well. This thesis labeled both of these sources different in ideology than Fox News so research into these other sources would potentially provide insight into whether other news sources act as a counterbalance of sorts to the Fox News Effect or if they are potentially more or less persuasive. This research could help identify which news sources are increasing polarization the most, which would be another interesting topic of discussion. This study could prove to be extremely vital as the 2020 election approaches. While the 2016 presidential election provided close results in Wisconsin, Michigan, and Pennsylvania, it would

be interesting to see if any of these news sources could sway enough votes in favor of one candidate to have a great impact on the election.

In conclusion, due to limited knowledge of social media algorithms and primarily correlative relationships, it is difficult to determine whether H1 is true or false. Continuing research into this field could prove extremely useful as social media algorithms are growing in complexity and relevancy in the everyday lives of the general public. While H1 may not be clear, there is great support and evidence that H2 is true and that the news media have an impact in increasing polarization. Continuing research on this topic and understanding why it occurs will be vital as it appears the United States is in a time period where polarization is greater than it ever has been before.

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