Media and Political Polarity in the United States

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Introduction

In a world increasingly more dependent on technology and media, with younger populations being inundated with tik-toks and an entire online culture unlike anything older generations have experienced, it is a well accepted fact that media use influences our very personalities and opinions. These opinions are not only about celebrities and fashion trends, but also are fundamental political opinions, usually shaped by public information. In the past, an individual's political opinion was largely dependent on the media they consumed, and when the world was predominantly word-of-mouth and newspaper, the opinionated media available to them was limited in perspective. However, as media becomes more diverse and begins to cater to several different viewpoints at the same time —fostering multiple communities of varying opinion within a single platform—we are interested in the relationship between media consumption and political polarity. Logicially, the increase in available opinions should reduce polarity, resulting in political neutrality. However, many may assume that those who are very involved in communities that promote a specific political viewpoint are going to self-identify as more polar— a positive reinforcement of ideas cultivating more extreme opinions— rather than the availability of opinions promoting understanding. This is why in this paper, the research question we will be exploring is: Is media use associated with ideological political polarization?

Finding evidence that supports or disproves a positive relation between social media use and increased polarity would be invaluable in understanding how media use and form– social media, newspaper, television news, etc— can contribute to extremism in America. This is a constantly developing sphere of influence as new forms of media become more popular, so it is important to continue to investigate it and update it for the existing literature.

In the following sections we start with a review of the current understandings of political polarity and how it has been measured in previous research. From this we concluded that there is mixed messaging when talking about political polarity in general. Based on this literature, we found the clearest definition possible to move forward with, which was the idea of ideological political polarity. This is the type of polarity we used to form our hypotheses. Following these inconsistencies, we also had a range of literature with conflicting opinions on political polarity and media. Based on this, we split the term 'media' up into separate categories based on the literature we found. This meant that our hypotheses tested the relationship between ideological political polarity and social media, specific television news stations, as well as local and national television news. The reasoning and specific hypotheses are outlined in our literature review as well as the theoretical framework. The general sentiment was the more active you are with media, particularly partisan leaning media, the more likely you are to be polarized. In the case of polarization vs national and local TV news, we consider national news to be more polarizing than local news. We then tried to substantiate these hypotheses with both linear and logistic models, using data from the CCES 2020. Overall, we found that people who watch polarized news stations are more likely to be polarized themselves, which aligns with our overall hypothesis. One specific finding we had was that contrary to our hypothesis, national news had a less polarizing effect than local news. We were also able to see there was evidence that social media had a slight positive association with polarization, but not significant enough to make a claim about. We believe the lack of substantial results we had relating to our hypotheses is in part due to some difficulties we had with our data sample sizes, and we highlight this in our results section as well.

Literature Review

There has been significant research into the relationship between political polarization and media consumption, particularly in the last decade. While this research is consistent in finding increased polarization in media content and in its consumers, there is a lack of consistency in regards to the type of polarization being analyzed. We use the following definitions to note the differences in types of polarization and how the lack of consistent measures limits the existing literature:

1) Ideological polarization is the divergence of political opinions, beliefs, attitudes, and stances of political adversaries (Dalton)

2.) Affective polarization is the extent to which people like (or feel warmth towards) their political allies and dislike (or feel lack of warmth towards) their political opponents (Finkel et al).

3) "Approximately two-thirds of the articles do not provide a definition of political polarization. Many do not explicitly state whether they are assessing ideological or affective polarization, rather just using the term 'political polarization'"(Kubin & Von Sikorski).

These discrepancies do not provide sufficient evidence on the topic despite the large amount of research. For the sake of our paper, we are looking into ideological political polarization, and conceptualizing it using the same definition as Dalton above. We do however take a novel approach to measuring ideological polarization through party self-identification. This method is taken based on the general consensus among researchers that there has been a cultural phenomenon in which party identity has become aligned with political ideology. Yphtach Lelkes notes that the correlation between the 7-point party identity measure and the ideological self-placement measure has doubled in forty years leading up to 2012, while additionally referencing notes of several other researchers that the average correlation between party identification and a variety of issues increases by .05 each decade. Through this novel approach we hope to provide consistency in findings toward ideological polarization in media, and by doing so create additional supporting evidence for the increasing phenomenon of political ideology becoming sorted by party-identification.

A major interest in polarization stems from the emergence of social media, and thus most research focuses on whether social media is contributing to rising polarization rates. Some pitfalls with the current research come with a hyper-focus on specific social media platforms coupled with the varying definitions of political polarization. Hutchens and Hmielowski measure affective polarization and find that social media is actually depolarizing, contrary to the majority of other research. "Taken as a whole, our study indicates that news on Facebook, social media filter bubbles, and echo chambers may not be the culprit for rising citizen polarization"(Hutchens and Hmielowski). Alternatively, another study testing a twitter bot that posted opposing political views concluded with very different findings. "We find that Republicans who followed a liberal Twitter bot became substantially more conservative post treatment. Democrats exhibited slight increases in liberal attitudes after following a conservative Twitter bot"(Bail & Brown). These two conflicting results certainly are attributed to the methods of study. However, it is noticeable that both research put a stronger emphasis on specific social media outlets. Hutchens and Hmielowski focused more on Facebook(a.k.a Meta) while Bail and Brown focused more on Twitter.

Before analyzing specific media outlets and their correlation with polarization, it is important to understand where specific media outlets currently stand in regards to political affiliation. Within the United States, some of the most popularized media outlets include FOX news, CNN, and NBC. These particular outlets are commonly regarded as being "politically biased" towards their respective political affiliations. Recognizing potential bias in these networks is necessary as they are subsets of the broader media outlet of televised media. Since most consumers tend to have loyalties toward specific television networks, it is not common to group the networks together and therefore we must recognize their political affiliations and potential bias to understand the context of any resulting insights. It is reasonable to assume that a political bias would be inherently present in specific television networks in an attempt to retain viewers. “As media increasingly fragment and strive to control niche markets, it seems probable that at least some news organizations might choose to overtly market their ideological viewpoint as a means of attracting a reliable audience” (Tim Groeling). With this being said we look further into Groeling’s analysis of major television networks in the United States to determine partisanship within them. “In every case, the differences found were consistent with the partisan's stereotypes: ABC, CBS, and NBC all appeared to favor good news for Clinton and bad news for Bush, while Fox appeared to favor the reverse (even in the aggressively controlled fully specified model)” (Tim Groeling). With these results, we establish the understanding that ABC, CBS, and NBC will have a more democratic bias, and Fox will have a more republican bias. We will carry this over to our hypotheses about news stations and polarization.

Furthermore, we wished to expand the scope of our analysis beyond simply visual media like large television channels and social media, both of which are nationally and internationally more cohesive to print media, which has a long and rich history and tends to vary more regionally. Researchers Joshua Darr, Matthew Hiit, and Johanna Dunaway have conducted research on the relationship between local newspapers and polarization for several years. In 2021 they conducted a quasi experiment by surveying members of Palm Springs before and after a local newspaper stopped covering national news for a month long period of time. The results showed those who relied on the newspaper for politics became less polarized. The same research team also discovered that when 110 newspaper companies closed in various cities, the respective polarization of these places increased. These two results indicate that there is a correlation between local news (in the form of newspapers) and lower polarization. However, these authors also examine it with broad, undisclosed measures of polarization. It would be valuable to examine these different outlets all through the same operationalized measure of political polarity.

Theoretical Framework

Our core hypothesis is:

> At a state level of analysis, the percentage of respondents that have had an interaction with media will be more ideologically politically polarized than the percentage of respondents who have less interaction with media .

Our core hypothesis can then be further broken down into 3 testable hypotheses:

1) States that have a higher percentage of respondents who have recently been active about politics on social media are more likely to have a higher percentage of respondents who identify as a strong democrat or strong republican than states with a percentage of respondents who have not been active about politics on social media or don't use social media at all.
2) States that have a higher percentage of respondents who watch CNN, FOX, and MSNBC are more likely to have a higher percentage of respondents who identify as strong democrat or strong republican than states who have a lower percentage of respondents who watch CNN, FOX, and MSNBC.
3) States that have a higher percentage of respondents who watch national news are more likely to have a higher percentage of respondents who identify as strong democrat or strong republican than states with a greater percentage of respondents who use local news.

We have several concepts involved in our hypotheses. One common theme among all of them is ideological political polarization, as outlined in our main hypothesis. As stated in our literature review, the term ‘politically polarizing’ is a very broad term with many discrepancies, making it a hard topic to cover. Because of this, we will be specifically focusing on ideological political polarization. The definition given by Dalton states that ideological political polarization is the differences of opinions between those on the opposite sides of the political spectrum. To operationalize polarization, we took the most extreme sides of the political spectrum we had available to us, people who identified as a strong democrat or strong republican, and used those two political groups to identify polarity, since they would have the most opposing views of each other and would therefore be considered polarized. Therefore, the measure of ideological political polarization is done by measuring the percentage, at the state level, of respondents that identify as strong republican or strong democrat. On the other hand, the percentage at the state level of respondents that identify as anything but strong republican or strong democrat would be considered not polar. A concept in our main hypothesis that we further expand upon in our sub hypotheses is media. We have conceptualized and explored the term ‘media’ by examining the relationship between polarization and specifically social media, as well as television news media. Television news media is then further divided into individual stations, as well as local vs national stations. The specific stations we will be examining are CNN, FOX, and MSNBC. Then lastly, we had variables available to us that asked respondents, “Do you watch local or national news?”, so we personally did not conceptualize what is considered national or local news but instead used what was provided.

The literature referenced in our literature review provides evidence to support all three of our sub-hypotheses, and therefore our main hypothesis as a whole. Our first sub-hypothesis focuses on social media and the influence social media has on political opinions. Logically, an increased activity on social media concerning politics indicates a strong sense of political identity/ that an individual cares more about their political opinions than someone who is inactive. Thus, states that have a high percentage of political activity are more likely to be politically polarized. This hypothesis stems from Bail and Brown’s research about social media engagement. The more present someone is on social media, the greater the opportunity is for them to become more convinced and vocal about their opinions. This is what will likely lead to them posting about politics. This hypothesis is one that is important to examine due to the limited and conflicting literature on the topic.

Our second sub-hypothesis takes the focus to the strong political TV stations to figure out how much these stations impact the polarity of the respondents political view. Watching a lot of television that supports a particular viewpoint will consequently influence your viewpoint in the same direction. Considering CNN,FOX, and MSNBC as persuasive television, people who watch them are more likely to lean strongly in a particular political direction, thus being more polarized. We have seen in the study by Groeling that TV stations can be found to lean into partisan stereotypes. We will therefore be using and exploring this relationship in our analyses.

For our last sub-hypothesis, the comparison focuses on the differences between local news stations and national news stations and their impact on the public's political opinions. We have examined the research about the relationship between local newspapers and polarization in our literature review, and believe that it would extend to local TV news stations as well. While the explicit cause between decreased polarization and a decrease of national news in local newspapers was not defined in the article, just speculated about, we believe that those who watch national news are exposed to more issues going on in the country or even around the world that they otherwise would not have been aware of. Since they have been exposed, they have the opportunity to form an opinion, where someone in the same situation who only watches local news does not have the same opportunity. And to relate back to previous hypotheses and literature, the sources from which they get this information can greatly sway their opinion of these foreign issues and feed viewers a very specific narrative. Considering all of these factors, we will be examining the relationship between polarization and local as well as national TV news.

The last thing that we need to establish before delving into our data is how our research will affect others. It is important that we really try to understand who we could be harming and who we could be helping. The potential groups that we stand to affect by releasing this information are the media companies and their users. Releasing information that could potentially damage the reputation of news outlets could not only lead to decrease in profits, but also a decrease in trust. This could lead to an environment where people distrust the sources like CNN, MSNBC, and Fox more than they already do. Our research will also affect those who watch these outlets and/or use social media. One of the potential benefits to this research is that we can potentially bring transparency to the public about how media affects us. As people who work in data, one of our responsibilities is to bring human understanding to others. We should translate data to the data illiterate public. This is one of the ethically significant benefits to working with data according to Vallor (Vallor, Shannon, 2018).

Data and Methodology

All of the data used for this project is coming from the CCES 2020 data (Schaffner et al). The CCES is a national survey done every election year by YouGov. It asks respondents to fill out a variety of demographic, social, and economic questions about themselves. We utilized a csv file of the CCES 2020 data with each row representing an individual respondent. In total there 61000 respondents.

The dependent variable in all of our analyses is political polarity. We gathered all this information from a CCES variable that asked respondents to self identify their political affiliations from weak Republican/Democrat to strong Republican/Democrat. As stated previously, we have defined ideological political polarity as a 'strong' label being attached to a political party. Therefore, this value of polarity is obtained by grouping together respondents who self identified as a strong Republican or strong Democrat. Not polar would be any other respondent that doesn't fall into the polar category.

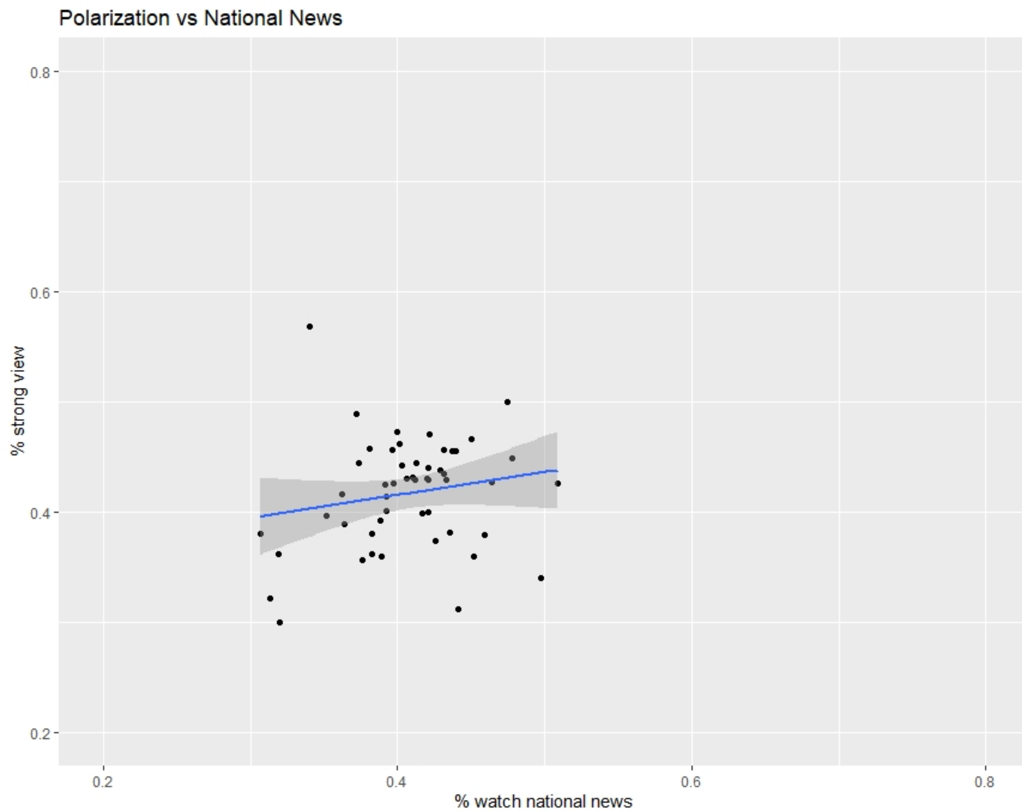
We have several independent variables that capture various types of media and media usage. The first is a variable we examined that had respondents answer whether they watch local news, national news, or both. This is broken down into a 1 for local, 2 for national, and 3 for both.

Next is a breakdown of what tv stations respondents watch. We have binary variables that indicate if respondents watch Fox News, CNN, and MSNBC. Each news station is measured separately, with 1 indicating that yes the respondents watch that station, and 2 meaning no.

Lastly, we have binary variables that indicate what type of social media activity respondents have engaged in in the past 24 hrs. This is made up of whether or not someone has posted a political comment, posted political links, read political articles, followed politics, or forwarded something political. Again, each type of social media usage is measured separately, with 1 being measured as yes and 2 being measured as no.

For our control variables, we utilized Race, Education, and Gender. When we were looking at Race, we decided it would be best to break it down into 5 categories in total. We used White, Black, Asian, Hispanic, and Other for our race variables. This covered all the possible race inputs that we could have seen. We then looked into education which we decided was best to separate it out into two categories. We separated it into a four year degree or more, or less than a four year degree. This allowed us to easily split up the data as we needed. Lastly, we looked into gender as another control variable. For gender, we decided it was best to split it up into just a binary variable for either Male or Female.

In order to determine the correlation of these variables and their effects on polarity, a multiple linear-regression model was used to find the coefficients of each variable. We also decided to run 2 additional linear models utilizing "Strong Republican" and "Strong Democrat" as our dependent variables respectively. In order to prepare our data for a linear model, the data was grouped by state utilizing dplyr (v0.8.0.1; Hadley Wickham, Romain François, Lionel Henry and Kirill Müller, 2019). After grouping each of our variables by state, the variables were normalized by making them a percentage of respondents in each state by dividing the variable values by the number of respondents in each state. The last thing that we did before running a model was to run basic visual analysis of our independent variables in comparison to our dependent variable. After looking at the graphs, we were satisfied with utilizing a linear model for this analysis.


Polarization vs National News
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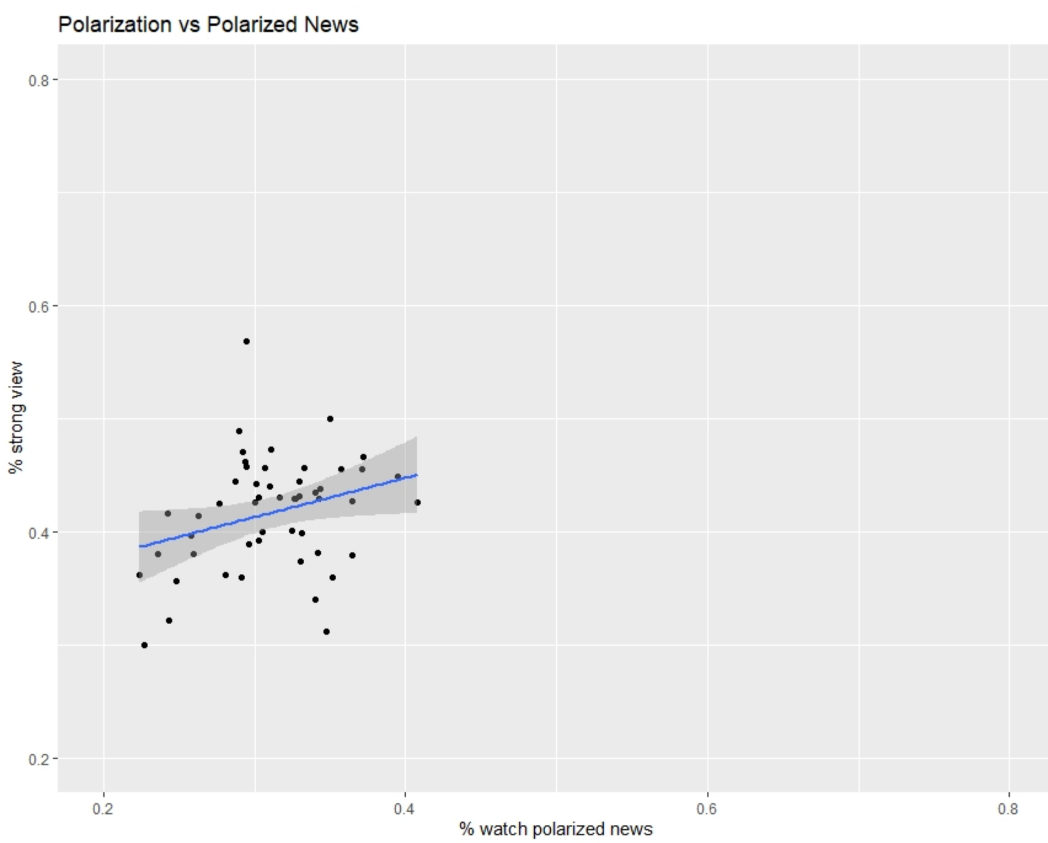
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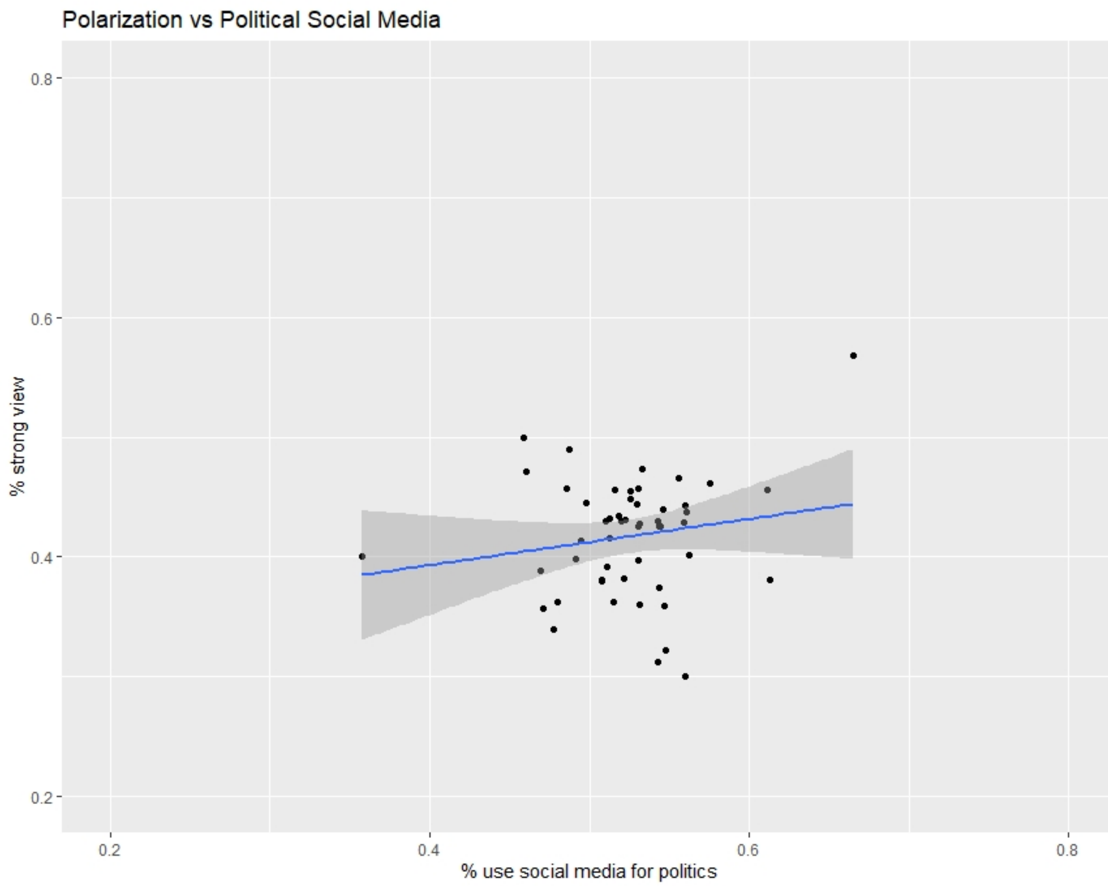

There are a couple of key data points that are important to note. On all three of our scatterplots, there is a point that hovers at 56.7% strong view. This point is Washington DC, which only has 197 respondents out of 61000. Another outlier data point is at 35.7% that use social media for politics in the last scatter plot. This point represents Wyoming, which only has 97 respondents out of 61000. The important thing to note is that the majority of our data all hovers around about 20% of each other in all of our plots. The data that doesn't do this has a smaller sample size and is more susceptible to outliers.

After this we finally built our linear model using our independent and control variables to predict the percentage of political polarization. An analysis of variance test was conducted to test if the models were useful. This test essentially just checks if at least one of the variables has an effect on the dependent variable. We also ran a correlation test for normality using the ols_test_correlation from the olsrr package(Aravind Hebbali, 2020) for each linear model.The results of these tests are found in the results section.

After running our linear models, we decided to also run logistic regression models at the individual respondent level of analysis. Logistic models make more sense for a binary dependent variable, which we can easily use for polarization. We utilized the same variables and operationalized all of them except education the same way. Education was changed to back to the scale from highschool to post grad degree that was seen in the original CCES dataset. After we ran our logistic regression we compared the direction of our predictors and their confidence to our linear model to both determine the association between the variables. To gauge how accurate logistic models were for this dataset, the cleaned data was exported to python to run train_test_split (Pedregosa *et al, 2011)* and a logistic score was calculated 20 times for each model.

Results

The tables below are utilized from the stargazer package in R (Hlavac, Marek, 2018) and show the coefficients of our models as well as certain tests and statistics about our model.

Political Polarization Linear Models

	Dependent variable:		
	Polarized Overall	Dem Democrat	Rep Republican
National	-0.004	0.089	-0.500^{***}
	(0.415)	(0.291)	(0.110)
TV	0.081		
	(0.439)		
MSNBC		0.377	
		(0.515)	
CNN		0.080	
		(0.525)	
Fox			0.956^{***}
			(0.200)
Media	0.097	0.223	-0.045
	(0.187)	(0.181)	(0.108)
edu	-0.025	0.422^{***}	-0.267^{***}
	(0.126)	(0.137)	(0.089)
Male	-0.095	-0.088	-0.415^{**}
	(0.295)	(0.251)	(0.169)
White	0.018	-0.009	-0.020
	(0.093)	(0.093)	(0.055)
Black	0.330^{**}	0.241^{**}	-0.107
	(0.131)	(0.119)	(0.084)
Hisp	0.202	0.031	0.104
	(0.166)	(0.157)	(0.097)
Asian	-35.369	-34.052	9.940
	(45.824)	(48.665)	(25.497)
Constant	0.338^{*}	-0.095	0.531^{***}
	(0.186)	(0.174)	(0.094)
Observations	51	51	51
R^2	0.480	0.720	0.817
Adjusted R^2	0.366	0.650	0.777
Residual Std. Error	0.040 (df = 41)	0.038 (df = 40)	0.023 (df = 41)
F Statistic	4.211^{***} (df = 9; 41)	10.271^{***} (df = 10; 40)	20.403^{***} (df = 9; 41)
Note:			*p<0.1; **p<0.05; ***p<0.01

The first thing of note in this table is that running an analysis of variance on our models shows that they are useful for predicting polarization, strong Democrat, and strong Republican. The adjusted r-squared for each model is also shown to give us an accuracy metric for our models. Under the test for normality our models had a score of .98 for Polarized, .98 for strong Democrat, and .99 for strong Republican. This tells us that linear models are acceptable for these features. Looking at both the F-statistic and adjusted r-squared, we can see that general polarization is our weakest model and strong Republican is our strongest. Looking at our coefficients we see that only our control variables were significant in any model other than strong Republican. This means that our hypotheses can't be accepted for both our general polarization and strong Democrat models. However, our model for strong Republican has significant predictors for both percentage that watch national news and percentage that watch Fox news. Percentage national news has a negative correlation with strong Republican which is the opposite of what we hypothesized. This could be due to Republicans having closer ties to their local community. The percentage that watch Fox news in each state has a strong, positive correlation with the percentage of strong Republicans in each state. This is the only case where we are confident in one of our hypotheses when looking at our linear models. A big reason we believe that our hypotheses are so off and our coefficients so unconfident is due to how we grouped our data. There is a large variance in the sample size for each state. For example: Wyoming had a sample size of 95 while California had 5035 respondents. Both of these states were treated as equals in our grouped data. This becomes a problem as outliers in smaller states affect our model more than outliers in large states. This problem is circumvented in our second set of models.

Political Polarization Logit Models

	Dependent variable:		
	Polar Overall	Dem Democrat	Rep Republican
National	0.068**	-0.176***	-1.359***
	(0.030)	(0.026)	(0.042)
TV	0.494***		
	(0.031)		
CNN		0.522***	
		(0.031)	
MSNBC		1.235***	
		(0.031)	
FOX			2.494***
			(0.045)
Social Media	0.144***	0.140***	0.023***
	(0.006)	(0.006)	(0.008)
Education	0.036***	0.169***	-0.161***
	(0.006)	(0.007)	(0.008)
Male	-0.251***	-0.456***	0.066***
	(0.017)	(0.021)	(0.024)
White	0.466***	0.189***	0.639***
	(0.041)	(0.050)	(0.059)
Black	0.790***	1.336***	-1.454***
	(0.047)	(0.055)	(0.091)
Hisp	0.217***	0.433***	-0.232***
	(0.050)	(0.058)	(0.075)
Asian	-0.085	0.108	-0.437***
	(0.065)	(0.075)	(0.109)
Constant	-1.130***	-2.240***	-1.550***
	(0.046)	(0.056)	(0.065)
Observations	61,000	61,000	61,000
Log Likelihood	-40,362.000	-31,517.270	-24,029.870
Akaike Inf. Crit.	80,744.000	63,056.540	48,079.740
Note:			*p<0.1; **p<0.05; ***p<0.01

Our logistic models are a much better fit for this type of question as we are doing binary classification. Since our sample size is much larger at 61000, our coefficients are more confident than our linear models. When scoring our logistic regressions with train_test_split, with a test size of .25 of our data, and logistic score from sklearn (Pedregosa *et al*, 2011), we get 60% accuracy for general polarization, 75% accuracy for strong Democrat, and 83% accuracy for strong Republican. Similarly to our linear models, general polarization is the weakest model and strong Republicans are the strongest. We also see that our confident coefficients in our linear models share the same direction as our coefficients in our logistic regression. We also see that some of our other variables have confident coefficients. However, since they were built around the state level of analysis, we can't utilize these models to confirm or refute our hypotheses. We can however say that we are confident that on the individual level of analysis, people who watch polarized news stations are more likely to be polarized themselves. We also see the same trend with national news being the opposite of what we thought it would be and social media having a slightly positive association with polarization, but not enough for it to be a great predictor.

Conclusion

After going through and analyzing all of our graphs relating to our hypothesis, we found out that some of our initial hypotheses were incorrect. When looking at our model for strong Republican relating to the percentage of national news, we notice that there is a negative correlation which was not at all what we expected. We attempted to regroup our data differently due to the sample size differences. After regrouping our samples together, we see that it backs up our earlier numbers, but can't fully justify any conclusions because it is a state level of analysis compared to a national level. The only thing we can say with confidence is that the more polarized news station viewers are more likely to be polarized. Aside from that conclusion, we are not confident to make predictions on our other hypotheses. We are also unsure of whether polarized individuals are more likely to watch polarized news or if polarized news makes individuals more likely to be ideologically politically polarized. Overall, we would need more even sampling from each individual state to be able to have a much more accurate understanding of our questions and analysis.

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