The Emotional Landscape of American Television News: 2000-2020

by

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DEDICATION

To Doris, Helen, Jane, and Tabitha

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ABSTRACT

Public opinion is often shaped by elite discourse, with most Americans receiving elite opinions via the media: newspapers, television, and now the Internet. All teach citizens about the world and the preferences and attitudes of political leaders and pundits. Since the mid 1990s, in an increasingly varied and crowded media landscape, these elite cues no longer produce the kind of cross-party political consensus that characterized much of the 20th century. Citizens choose information environments that provide news which is congenial to their political identities and more easily avoid ideas and news in conflict with them. Knowing that Americans opt into congenial news environments, I theorize that the current polarized and energized electorate is the result of differing emotional environments among partisan and nonpartisan news sources. I argue that the emotionality of partisan news media likely drives current upward trends in both political polarization and participation. Anger-driven political behavior, observed in greater voter turnout and out-partisan hostility, is the likely result of exposure to far more anger cues in partisan media than are typically expressed in nonpartisan news media. I find that partisan news is angrier, less anxious, and less enthusiastic than nonpartisan news, because partisan anchors construct an emotional context for politics by expressing anger, assigning blame, and motivating copartisan action. This dissertation explores how media institutions construct the emotional context of politics, focusing on how the partisan identities of news outlets are associated with variation in the emotional landscape of news. This variation is not unique to the contemporary period: the partisan press of the 19th century dominated the pages of political newspapers, where partisan editors and publishers expressed anger, assigned blame, and galvanized copartisans during elections. I theorize that the same emotionality of the 19th century partisan press has reemerged with the rise of cable television news programming over the first two decades of the 21st century. Elite cues from partisan news anchors are likely mobilizing and enraging the American public through increased expressions of anger to their television news audiences. I establish this by mapping emotional landscape of contemporary American news, focusing on two distinct time periods: 2000-2008, in which I analyze the early partisan cable news environment with the establishment of both Fox News and MSNBC alongside the more established CNN; and 2010-2020, in which I test the oft-repeated theory that during the 2016 presidential campaign Donald Trump changed the media environment. To do this, I construct and validate a methodological framework for measuring emotional cues delivered to audiences by

the hosts of news programs, enabling me to measure differences in the emotional cues that are delivered to partisan and nonpartisan news viewers. I find that nonpartisan news is more anxious and more enthusiastic than partisan news over both time periods, but that the key difference is that partisan news is more intensely and frequently angry. I also find that while expressions of anger increased in partisan news from 2000-2008 as Fox established itself as a ratings contender, there is no perceptible shift in the emotional environment from 2010-2020. Donald Trump did not cause changes to the media, but rather took advantage of a partisan press that was already conveying anger to the mass public.

CHAPTER 1

Introduction

How Americans hold their government accountable is profoundly influenced by the forces that help construct public opinion (Key, 1961), with public opinion often shaped by elite discourse (Zaller, 1992). Most Americans receive elite opinions via media: newspapers, television, and now the Internet all potentially teach citizens about the world and the preferences or views of political elites. Elite opinions about welfare (Schneider and Jacoby, 2005), climate change (Tesler, 2018), and the sexist attitudes of elites (Valentino et al., 2018) have all galvanized public opinion on policy topics and during elections. Within this framework, emotions are critical to how elite cues both shape public opinion and galvanize people for political action. Citizens who feel anxious may be less supportive of military interventions (Huddy et al., 2005) or more opposed to immigration (Brader et al., 2008). Those that are angry are prone to taking risks (Lerner and Keltner, 2001), such as leaving the European Union (Vasilopoulou and Wagner, 2017), or taking action against policies that they perceive as unjust, such as more restrictive voting laws (Valentino and Neuner, 2017). The framework for how these emotions impact politics is usually described as citizen emotions occurring after receiving information about the state of the world.

However, citizens perceive not just their own emotional states, but also those of other people (Schneider et al., 1979). When conveying preferences to the public, elites are often expressing emotions along with information, such as outrage (Berry and Sobieraj, 2013), incivility (Mutz, 2015), and even happiness (Sullivan and Masters, 1988). The perception of these emotional expressions have downstream effects on behavior and how citizens think about politics, with uncivil and angry displays increasing opposition to candidates (Mutz, 2015) and politicians expressing happiness being seen in a more positive light (Sullivan and Masters, 1988). If the emotions of elites influence the public, then the emotional signals from those that provide news to Americans likely also influences public opinion and political behavior.

This dissertation examines how media institutions construct the emotional context of politics, focusing on how the partisan identities of cable news networks are associated with variation in the emotional landscape of television news over the the first two decades of the 21st century. Elite cues from partisan news anchors are mobilizing and enraging the American public, specifically through increased expressions of anger to their television news audiences. In this dissertation, I construct and validate a methodological framework for measuring emotional cues provided to audiences by the hosts of news programs, and this framework enables me to measure changes in the emotional cues the news has been providing to audiences during national election years from 2000 to 2020. These changes correspond with the segmentation of television news into cable news programming and network news. Important in this segmentation are the journalistic philosophies that permeate these networks. Network news continues to adhere to the norms of objective and balanced reporting that characterized the professionalization of journalism in the 20th century (Schudson, 1995), while cable news takes a distinctly partisan perspectives on the news of the day. This perspective taking ultimately accounts for variation in the emotional environment of television news, with cable news infusing its coverage with anger due to partisan perspective taking, while network news' objectivity emits anxiety because of its balanced coverage of events and threats. These differences in the emotional environment likely account for the polarized and participatory American public that has occurred over the last few presidential election cycles.

To analyze the relationship between news exposure and political emotions, I examined the associations between self-reported news watching on either partisan or nonpartisan networks and how citizens feel about contemporary politics. If there are differences in the emotional environments created partisan, cable news and nonpartisan, network news, watching these different types of programming should result in differences in the associations between respondents' feelings about politics. Similar to how viewing happy candidates results in audiences perceiving candidates as more likeable (Sullivan and Masters, 1988), viewing news that is angrier or more anxious should result in differing evaluations of political candidates.

1.1 Evidence for the Influence of News on Political Emotions

I examined how viewing partisan or nonpartisan news may be associated with emotional changes among the American public using the 2016 and 2020 ANES. Both ANES studies asked respondents to report their television watching habits during the campaign and their emotional reactions to presidential candidates and the state of the nation, respectively. Since partisans will opt into news environments that are congruent with their political beliefs (Iyengar and Hahn, 2009), I explore how partisans who report watching cable or network news feel about two emotional targets: outpartisan presidential candidates in 2016 and the state of the nation in 2020.

Through my analysis of the 2016 and 2020 ANES data sets, I test associations between self-reported partisan news viewing and anger as well as anxiety. If the emotional cues in partisan and nonpartisan news environments are individual citizens watching partisan news should be correlated with greater anger. Of course, partisans who report consuming more partisan news will be angrier at opposition candidates than those who report viewing network news. This follows from work that indicates partisan polarization increases when partisans view politically congruent news (Levendusky, 2013) and that the type of negativity that matters for polarization is negative candidate evaluations (Ahn and Mutz, 2023).

Similarly I expect that the consumption of partisan news will be correlated with anger about the state of the nation. However, since emotions towards the state of the nation are closely correlated with how respondents feel towards Trump (Brader et al., 2019), anger about the state of the nation should be higher for Democrats than Republicans.

H_1: Partisan news exposure should be positively correlated with anger towards the opposition candidate/state of the nation.

H_{2a}: Partisan news viewing will be positively correlated with anger towards the opposition candidate/state of the nation than viewing nonpartisan news.

H_{2b}: For the state of the nation, partisan news viewing should boost anger for Democrats than Republicans.

I also expect that there will be variation in the emotions associated within partisan and nonpartisan news. The association for partisan news with anger will be greater than the association of partisan news with anxiety, since I theorize that the main influence of partisan news is an increased amount of anger cues. The converse should also be true for nonpartisan news: nonpartisan news should be more highly correlated with anxiety than anger.

H_3: Partisan news exposure will be associated more strongly with public anger than anxiety.

H_4: Nonpartisan news exposure will be more strongly associated with anxiety than anger.

1.1.1 Methods

The two main variables of interest are the amount of nonpartisan, network news that respondents report viewing and the amount of partisan, cable news that respondents report viewing to find out about a presidential election.[1] I constructed these variables based on weeknight network or cable news programming that was included in the survey. The number of network or cable news programs that a respondent reported watching were respectively summed to create the *Partisan News* and *Nonpartisan News* variables. Table 6.1 displays the news programs for network and cable news that were included for the 2016 ANES and Table 6.2 displays the cable and network news programs that were included for the 2020 ANES.

[1] While self-reports are not the ideal measure since respondents often have a difficult time accurately reporting their own news exposure, it does provide a starting point for examining this relationship. See the debate between Dilliplane et al. (2013) and Prior (2013) for more information.

Table 1.1: News Programs In the Network and Cable News Categories in the 2016 ANES

	Television Programming	
	Nonpartisan Network News	**Partisan Cable News**
ABC	World News Tonight with David Muir	
	20/20	
CBS	Evening News with Scott Pelley	
	60 Minutes	
NBC	Nightly News with Lester Holt	
	Dateline	
PBS	NewsHour	
CNN		Erin Burnett OutFront
		Anderson Cooper 360
Fox		The O'Reilly Factor
		On The Record with Greta Van Susteren
		The Kelly File
		Hannity
MSNBC		Hardball with Chirs Matthews
		The Rachel Maddow Show
		All In with Chris Hayes

Table 1.2: News Programs In the Nonpartisan and Cable News Categories in the 2020 ANES

	Television Programming	
	Nonpartisan Network News	**Partisan Cable News**
ABC	World News Tonight with David Muir	
	20/20	
CBS	Evening News with Norah O'Donnell	
	60 Minutes	
NBC	Nightly News with Lester Holt	
	Dateline	
PBS	NewsHour	
CNN		Erin Burnett OutFront
		Anderson Cooper 360
		Cuomo Prime Time
Fox		Tucker Carlson Tonight
		The Ingraham Angle
		Special Report with Bret Baier
		Hannity
MSNBC		The Last Word w/ Lawrence O'Donnell
		The Rachel Maddow Show
		All In with Chris Hayes
		11^{th} Hour with Brian Williams

The construction of the dependent variable for the emotions of anxiety and anger differs for the 2016 ANES compared to the 2020 ANES. In 2016 the ANES asked respondents to "think about [the presidential candidate]. How often would you say you've felt [a specific emotion] because of the kind of person [the presidential candidate] is or because of something [they have] done?" The respondent is asked to score each candidate on the emotions of *angry, afraid, hopeful*, and *proud*. The response options are *never*, *some of the time*, *about half the time*, *most of the time*, or *always*. The dependent variables for anger and anxiety in the analysis for 2016 are the variables of *angry* and *afraid*, respectively.

In the 2020 ANES emotions about the state of the nation compose six survey items that tap the three emotional categories of anxiety, enthusiasm, and anger. This analysis targets feelings of anger and anxiety, with respondents feeling *afraid* and *worried* about the nation forming the scale for anxiety, and respondents feeling *outraged* and *angry* about the nation forming the scale for anger.

For the analysis, modeling of Democrats and Republicans occurs separately, since they are most likely opting in to partisan news environments that agree with their partisan dispositions. All models include demographic controls for age, sex, strength of party identification, if the respondent is employed, ideology, and whether or not the respondent identified as white. Demographic information about the 2016 and 2020 ANES samples can be found in the appendix.

1.1.2 Results

For all models I report the coefficients of interest for partisan and nonpartisan news. Full results which report the models with demographic controls can be found in the appendix. All variables in all models are scaled to be between 0 and 1.

1.1.2.1 2016 ANES and Feelings Towards Presidential Candidates

Table 1.3 displays self-reported partisan or nonpartisan news habits regressed on partisans' feelings of anxiety or anger about the opposition party's 2016 presidential candidate. I expected that when partisans view partisan news, anger towards the opposition candidate would increase. While increases in anger are positive for both Democrats and Republicans, I am only able to reject the null hypothesis that there is no effect for partisan news for Republicans ($p < 0.001$), where increased viewing of partisan news results in an increase of anger by 32 points. This increase in anger is also significantly different than for Republicans who view nonpartisan news. Viewing nonpartisan news is associated with a *decrease* in anger of 8 points towards Candidate Clinton ($p < 0.05$) and the difference between the coefficients for partisan and nonpartisan news is statistically significant at the $p < 0.001$ level (as confirmed by Wald tests, since I am comparing coefficients within the same model).

Democrats who view nonpartisan news have levels of anger (0.02) that are not distinct from the anger associated with viewing partisan news. There are also not differences between the associations of anxiety and anger and when Democrats view partisan news ($p > 0.05$) or when they view nonpartisan news ($p > 0.05$, as confirmed by z-test, since I am comparing coefficients between different models).

Of note in the models are also the baseline levels of anxiety and anger towards the outpartisan candidate (Table 1.3). For Democrats, feelings of anxiety (0.58, $p < 0.001$) and anger (0.63, $p < 0.001$) are quite high without the addition of news whereas the baseline for Republicans' is much lower. Republican's negative feelings about Clinton greatly increased when they watch partisan news. Watching partisan news increases Republican anxiety by 15 points, moving respondents from the baseline of .13 ($p < .05$) to .28 when they watch partisan news. Whereas watching partisan news increases anger towards Clinton by 32 points, moving from a constant of .19 ($p < 0.001$) and increasing anger towards Clinton to .51 when respondents watch partisan news. While Democrats appear to have a stable baseline for their feelings about Trump, Republicans feelings about Clinton are heavily influenced by whether or not they are watching partisan cable news.

Table 1.3: Feelings of Anxiety and Anger Towards Out Partisan Presidential Candidates for Partisans in the 2016 ANES

	Democrats' Feelings Towards Trump		Republicans' Feelings Towards Clinton	
	Anxiety	**Anger**	**Anxiety**	**Anger**
	Model 1	**Model 2**	**Model 3**	**Model 4**
Nonpartisan News	0.03	0.02	-0.06	-0.08^{*}
	(0.04)	(0.04)	(0.04)	(0.04)
Partisan News	0.04	0.03	0.15^{**}	0.32^{***}
	(0.06)	(0.06)	(0.06)	(0.05)
Constant	0.58^{***}	0.63^{***}	0.13^{*}	0.19^{***}
	(0.05)	(0.04)	(0.06)	(0.05)
N	1251	1254	1286	1284
R-squared	0.07	0.11	0.12	0.15
Adj. R-squared	0.06	0.11	0.11	0.15
Residual Std. Error	0.31 (df = 1241)	0.28 (df = 1244)	0.33 (df = 1276)	0.29 (df = 1274)
F Statistic	10.16^{***} (df = 9; 1241)	17.36^{***} (df = 9; 1244)	19.06^{***} (df = 9; 1276)	25.62^{***} (df = 9; 1274)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

1.1.2.2 2020 ANES and Feelings About the Nation

The results for the 2020 ANES data are similar. I hypothesized that viewing partisan news would be correlated with increasingly angry feelings about the nation. From the results in Table 1.4, partisan news viewing results in increased anger for both Democrats (Model 2, $p < 0.001$) and Republicans (Model 4, $p < 0.001$). Because evaluations about the state of the nation are closely tied to evaluations about President Trump, I anticipated that partisan news viewing would result in higher levels of anger for Democrats than Republicans. The models bear this out. Viewing partisan news increases anger by 32 points for Democrats and by 14 points for Republicans, with the difference between them being statistically significant at $p < 0.001$ (as confirmed by z-test).

However, the effect of viewing partisan news is similar for anxiety and anger. When comes to increases in anxiety and anger, both are increasing at a similar rate for Democrats and Republicans, respectively. Partisan news increases anger more than anxiety, but the increase is not statistically significant at $p = 0.05$ level both either set of partisans. The constant term for both Democrats and Republicans in all models is also quite large (Table 1.4). Both parties appear to have a high baseline of either anxiety or anger about the state of the nation, but since evaluations about the nation are closely correlated with feelings about President Trump (Brader et al., 2019), the baseline is lower for Republicans. In addition, the 2020 election and the fielding of the 2020 ANES took place during the COVID-19 pandemic, prior to vaccines becoming available to the public. So it is not surprising that negative feelings about the state of the nation, particularly anxiety, were high for both Democrats and Republicans during this time.

While the results for the 2016 and 2020 ANES show a strong relationship for between the self-reported consumption of partisan news and increased anger among partisans, with the exception of Democrats in 2016 who already had a high baseline of anger towards then-candidate Trump, there is a not a case to be made that watching partisan news provokes stronger associations with anger than anxiety. Nor that watching nonpartisan news has stronger associations with anxiety rather than anger. However, when comparing partisan and nonpartisan news consumption, anger is prominently associated with the self-reported viewing of partisan news. My ANES analysis

Table 1.4: Partisan Feelings of Anxiety and Anger about the Nation in the 2020 ANES

	Democrats		Republicans	
	Anxiety	**Anger**	**Anxiety**	**Anger**
	Model 1	**Model 2**	**Model 3**	**Model 4**
Nonpartisan News	0.07*	0.05	0.05	0.02
	(0.03)	(0.03)	(0.04)	(0.04)
Partisan News	0.29***	0.32***	0.04	0.14*
	(0.04)	(0.04)	(0.06)	(0.06)
Constant	0.67***	0.75***	0.50***	0.50***
	(0.02)	(0.02)	(0.03)	(0.03)
N	2500	2501	2311	2309
R^2	0.11	0.12	0.02	0.02
Adj. R^2	0.11	0.11	0.02	0.01
Res. Std. Error	0.21 (df = 2490)	0.20 (df = 2491)	0.25 (df = 2301)	0.26 (df = 2299)
F Statistic	33.94*** (df = 9; 2490)	35.99*** (df = 9; 2491)	5.07*** (df = 9; 2301)	4.41*** (df = 9; 2299)

***$p < .001$; **$p < .01$; *$p < .05$

shows that partisan news is associated with increased anger, both towards opposition candidates and about the state of the United States. A potential reason for this may be because the emotional environments that viewers are in when they watch partisan cable news is angrier than that of non-partisan, network news. Anger cues from partisan networks may be producing greater anger among the American public, since Americans are opting in to partisan news that is congruent with their political identities (Levendusky, 2013). By mapping the emotional landscape of partisan and non-partisan news, I show that the main difference between these media environments is the infusion of anger into the news by partisan anchors.

1.2 Dissertation Road Map

In the next chapter of the dissertation I lay out my theory for why I expect partisan news to be infused with anger compared to the anxious emotions I anticipate are prominent in nonpartisan, network news. Partisan news, of course, is no unprecedented in American history. The Antebellum press of the early 19$^{\text{th}}$ was replete with vitriol and anger, with partisan on either side frequently lashing out at the opposition. The same anger that characterized news in that era is also present in contemporary politics, and I argue the rise of cable and the advent of competition in the cable news space created angry, partisan journalism in evening cable news programming. Finally, I lay out my theoretical expectations for how the media landscape should look and change over time, first providing expectations for 2000-2008, the early era of partisan cable news competition, and then for how the emotional landscape may have changed from 2010-2020—a period during which conventional wisdom suggests Donald Trump changed the American media environment during his 2016 presidential campaign.

In Chapter 3 I lay out the methodological framework for testing my theoretical expectations. For the emotional landscape of news to matter in American politics, members of the public must be able to perceive the emotional cues in the news. To determine whether the public can perceive the emotional cues from those reporting the news, I use public opinion surveys to test potential threats to inference, ultimately providing a methodological framework for surveying public perceptions of emotions in news programming using news transcripts as stimuli. I also discuss my sampling strategies, both the compilation and creation of news text stimuli and the sampling frame for my surveys.

Chapter 4 tests my theoretical expectations for the early days of partisan cable news, examining both the intensity and frequency of emotional cues in the partisan and nonpartisan news environment. This chapter focuses on the changes in the emotional landscape of television news after the entry of the explicitly partisan Fox News as a cable competitor for CNN who, prior to 1996, was the premier 24-hour cable news network. Here I examine both changes in partisan news and nonpartisan news and changes between the partisan news competitors: CNN, Fox, and MSNBC.

Chapter 5 tests my theoretical expectations for partisan and nonpartisan news from 2010 to 2020. Over this time frame Donald Trump rose to prominence on the national political scene and eventually won the presidency in 2016. After Trump's win, many news outlets and pundits suggested that he had fundamentally changed the news environment, which helped him win the election (Adams, 2016; Ferullo, 2020). Here I test whether it is possible that Trump actually changed the news over this time period, or whether the partisan news environment was instead continuing on an angry trajectory that was established earlier in the 2000s.

Chapter 6 concludes by summarizing findings and discussing the implications of my research. I then discuss future work that will further test the relationship between the emotional landscape of American news and the American public.

CHAPTER 2

Political Emotions and the News

2.1 Contemporary Politics, Media, and Emotions

One of the most powerful correlates of American political participation is socioeconomic status. Who is involved in politics is often defined by their level of education, income, and employment status. But over time there has also been variation in election turnout and political participation in ways that defy this pattern. Theories of political behavior have identified a number of reasons for participatory decline and increase. A lack of mobilization by political elites may explain declines in American political participation from the 1960s to the 1980s, for example (Rosenstone and Hansen, 1993). Voters are highly influenced by being asked to participate, and when they are not activated via political appeals, they stay home (Rosenstone and Hansen, 1993). Voters are also motivated to go to the polls when they believe that their private behavior will be held to public account. Citizens who believe that their friends and neighbors will know if they have voted are more likely to vote due to external pressures to perform civic duties /citeGerber Green. Habits also explain a great deal of variation in participation across individuals: having participated in a previous election positively correlates with future participation (Gerber et al., 2003).

A citizen's civic skills can also help them overcome hurdles to political participation. Those skills may develop through formal education, helping explain why education is so highly correlated with participation (Brady et al., 1995). Involvement in civic organizations, such as church attendance or volunteer work, also correlates with political participation (Verba et al., 1995). But involvement in organizations, like involvement in politics more broadly, is also predicated on citizens having time to participate (Verba et al., 1995). Family life also plays a role in political socialization, with families passing on habits of participation (Verba et al., 1995) and partisan identities to their children (Campbell et al., 1960). In low-income households without strong ties to the US political system, children who take on adult responsibilities may defy the expected voting behavior correlated with a lack of socioeconomic resources (Carlos, 2021). Carlos (2021) argues that Latinx immigrant children who help mediate communication for their immigrant families via translation or who take on household responsibilities like chores or an outside job learn skills that aid them in political participation.

Research regarding the increasingly segmented media environment suggests that we are living in an era where it is more difficult for citizens to become politically activated. Increased media choice means that citizens are far less likely to acquire political information by simply turning on the TV and watching the end of the evening news while they wait for their favorite sitcom to begin on one of the major networks (Prior, 2007). In fact, cable and streaming choices mean that they can opt out of political content altogether. This lack of consistent exposure to political information via network television reinforces another factor in low turnout: citizens who do not have high levels of political interest are no longer exposed to media that politically activates them, and so they are staying home (Prior, 2007). Growing media consumption is also thought to be detrimental to civic life (Putnam, 2000), reducing sociability and perhaps foreclosing opportunities to acquire skills that would help them overcome other resource deficits to participation. According to these theories, we should expect declining political participation, as Americans have less shared exposure to the elite cues that politically activate citizens and fewer of the civic skills that might overcome some barriers to participation.

Despite a more fragmented media, participation in American politics is on the rise. The 2020 presidential election saw increases in voter turnout in every state compared to 2016 (Desilver, 2021). On average, voter turnout has increased since the early 2000s (Desilver, 2021). At the same time, Americans also increasingly report strong dislike of partisan opponents. Recent polling from Pew shows increasing partisan hostility between 2016 and 2022, with large segments of self-identified Democrats and Republicans rating members of the opposing party more negatively than most other groups in America (Nadeem, 2022). This increasing hostility is not the result of policy differences or disputes, but partisanship (Iyengar et al., 2012). Political partisanship and identification as either a Republican or a Democrat are major social identities in American politics (Campbell et al., 1960) even as the parties have become more homogeneous over time (Mason, 2018). This, coupled with increased social sorting, in which partisans are more likely to interact with copartisans than the opposition, has led to greater partisan animosity (Mason, 2018). Iyengar et al. (2012) speculate that the cause of this partisan animosity is increasing exposure to campaign messages which attack the opposition. Partisans also report becoming more hostile towards their political opponents over the course of a campaign (Sood and Iyengar, 2016). Along with direct messages from campaigns, Iyengar et al. (2012) argue that campaign advertising is but a small part of modern campaigns and that "voters are more likely to encounter campaign messages through news coverage" (p. 426). And partisan news does seem to polarize Americans. In experiments, citizens with prior strong political attitudes who watch like-minded media become more polarized, with the effect lasting for several days (Levendusky, 2013). This can create a feedback loop in which those with strong political attitudes are further polarized after watching news that is congruent with their politics (Levendusky, 2013). Negative evaluations of opponents also occur within the online news environment: access to faster Internet increases partisan reliance on politically congenial media and increases partisan hostility (Lelkes et al., 2017).

These effects may be compounded by citizens' natural inclination to pay attention to and seek negative information, which reinforces not only negative media content (Trussler and Soroka, 2014; Soroka et al., 2019), but likely negative partisan content. Closeups of news hosts and incivility in exchanges between guests (Mutz, 2015), outrage (Berry and Sobieraj, 2013), and partisan frames (Jamieson and Cappella, 2008) are problematic for how Americans receive information and have been shown to increase political polarization, but are also prevalent in contemporary media. Political talk shows that traffic in negativity are characterized by extreme closeups and incivility, which in turn encourage negative views of political opposition and also increases viewer recall of political arguments (Mutz, 2015). And negativity is also an important tool that alerts people to novelty: negative news coverage performs better because citizens pay attention to and seek negative information (Trussler and Soroka, 2014; Soroka and McAdams, 2015).

Alongside the polarization produced by negative news are the problems of misinformation and disinformation: false and potentially harmful information which, in the latter case, is deliberately used to sew confusion (Freelon and Wells, 2020). The prevalence of dis- and misinformation within campaign messaging may have minor consequences, since campaign persuasion appears to have minimal effects (Kalla and Broockman, 2018) and fake news does not seem to impact political behaviors or beliefs (Lazer et al., 2018). However, the political media environment impacts public opinion not only through primary news exposure, but through two-step information flows: those who do not view partisan news themselves are often politically persuaded by those who do (Druckman et al., 2018). Yet policy positions do not seem to be the cause of partisan polarization (Iyengar et al., 2012).

One job of the news is to direct citizens to what information is important and to which issues viewers should pay attention (Iyengar and Kinder, 1987). In theory, the news can produce broad political consensus, but partisan media may only further fracture public opinion. The media's capacity to foster national political consensus may be diminished in the face of a highly segmented media environment (Iyengar and Kinder, 1987), but here partisan agenda setting flourishes. In June 2022, around seventy percent of Republicans believed that the 2020 election was stolen from Donald Trump, despite the nearly complete lack of evidence to support the claim (Greenberg, 2022). While the election was not stolen, Republican citizens who seek out partisan news sources are still being told that it was and that it remains an important issue to which they should pay attention. The fact of differing information environments likely means that partisans are exposed to different assessments of the recent political past (Fiorina, 1978; Healy and Malhotra, 2013) or economic conditions (Kinder and Kiewiet, 1981), which in turn produces sharply different assessments of the state of the world: in 2022, a majority of Democrats (96%) said that the attack on the US

Capital on January 6, 2021 was a major problem or crisis, while only 36% of Republicans saw that event as concerning (Agiesta, 2022).

Further complicating the relationship between polarization, caused by partisan isolation in social and media environments, and participation, which should decline if citizens are able to opt out of campaign cues by elites, is that the type of polarization has specific consequences for political behavior (Ahn and Mutz, 2023). Ahn and Mutz (2023) examine the differences between negative feelings about the opposition *party* and negative feelings about the opposition *candidate*. They find that increased negative feelings about opposition candidates appear to drive political participation at a greater rate than negative feelings about the party (Ahn and Mutz, 2023). But inherent in these conceptions about campaign cues and polarization is a focus on general negativity—about partisans (Iyengar and Westwood, 2015; Mason, 2018) and about candidates (Ahn and Mutz, 2023), and as cues in the news (Mutz, 2015). Here, emotions in politics are conceptualized as being either positive or negative along a single dimension, with negative emotions described as *negativity*, *hostility*, or *incivility*. This is in line with contemporary media environment analyses that focus on general negativity in the news, which, again, alerts people to novelty, important events, and situations in the United States and around the world (Young and Soroka, 2012; Soroka and McAdams, 2015).

But research that focuses on the differentiation between two conceptions of emotions that are both negative—fear and anger—shows that emotions in the negative space have opposing cognitive and behavioral influences on politics (e.g. Marcus et al., 2007; Valentino et al., 2011) and arise from different contextual evaluations (Smith and Ellsworth, 1985; Roseman and Smith, 2001; Lazarus, 1991). Short-term emotional forces can push people substantially off their baseline likelihood of voting and of participating in politics (Marcus et al., 2007; Vasilopoulou and Wagner, 2017; Valentino and Neuner, 2017). I contend that emotions from partisan media—not just negativity in news—are driving participation and polarization. In particular, an increase in anger cues in the American news environment over the last 30 years, particularly emotional cues from partisan news anchors, is mobilizing and enraging the American public and producing greater political engagement, which flies in the face of prior research that correlates increasing media environment segmentation with decreasing political engagement (Prior, 2007; Putnam, 2000).

First, anger is likely the primary emotion driving engagement, because it is a negative emotion that encourages action and participation (Valentino et al., 2011) while also reinforcing social polarization (Webster and Albertson, 2022) and idealizing partisan loyalty (Webster, 2020). Angry citizens are not only more likely to participate than those who are anxious, but they are also more likely to participate in costly ways, such as volunteering for a campaign or attending a political event (Valentino et al., 2011). The polarizing effects of anger include less interaction with members of the partisan opposition, even when citizens feel angry about a nonpolitical topic (Webster and Albertson, 2022). Anger also makes it less likely that citizens defect in elections: even when citizens do not like the candidate their political party has on the ballot: anger at the out-party increases partisan loyalties (Webster, 2020).

Anxiety, on the other hand, induces a voter to look for information that can be applied to the current situation (Marcus et al., 2000; Brader, 2005). Citizens who received political advertisements with fear appeals, which were manipulated by altering the music and context, but not the content, of the messages, were more likely to search for information to rely more on contemporary considerations rather than habits (Brader, 2005, 2006). Anxiety can also cause citizens to be more deliberative, more considerate of information that opposes their prior beliefs, and more likely to compromise (MacKuen et al., 2010). By manipulating a web page about affirmative action, not only were the effects of anxiety made clear, but anger (which the authors call ”aversion”) has the opposite effects: citizens who reacted with anger were less likely to compromise with their political opponents MacKuen et al. (2010). While citizens are more deliberative when they are anxious, they are less participatory: thoughtful citizens do not seem to be politically active citizens (Mutz, 2006).

Enthusiasm can also drive political participation (Brader, 2005), but the behavioral consequences of an enthusiastic electorate would likely not emerge amid the partisan animosity that we see in current US politics. The emotions the electorate feels are linked to their dispositional and surveillance systems (Marcus et al., 2007). The *dispositional system* is responsible for reliance on habit—if circumstances are familiar, human beings can rely on prior knowledge, dispositions, and beliefs to carry them through a situation (Marcus et al., 2000). Enthusiasm and anger form the two poles of this system, which prepares people for action towards *known* people and objects, but enthusiasm and anger differ in effect. When familiar stimuli are liked it triggers enthusiasm; when they are disliked, it triggers anger (Huddy et al., 2013). Enthusiasm arises when people encounter stimuli that they like, which is incongruent with an environment of partisan animosity produced by negative stimuli in media environments. Enthusiasm would produce an electorate that is participatory but not nearly as confrontational. Meanwhile, the *surveillance system* alerts people to novelty and threat—precursors for anxiety—and prepares them to cope with novel stimuli (Huddy et al., 2013).

Appraisal theory also argues that the antecedents to enthusiasm and anger differ. According to appraisal theorists, variations in social contexts influence the construction of emotional responses to conditions and stimuli (Lazarus, 1991; Frijda, 1993). While often called cognitive appraisal theory, *cognitive* refers not to higher-order thinking, but to the automatic, precocious evaluations and responses that occur in a person's brain (Moors, 2010). A person's relationship to a political object helps rapidly form evaluations and determines subsequent emotional and behavioral conditions, often based on the amount of control and blame a person perceives in a given situation (Smith and Ellsworth, 1985; Ellsworth, 2013). The work of Smith and Ellsworth (1985) maps control and blame to the emotions of fear and anger: fear arises when an individual does not feel in control of a situation and cannot determine who or what is responsible. Anger arises when citizens have some control over threats that obstruct them and can clearly assign blame to someone or something (Ellsworth, 2013).

Critical to emotional appraisals is the ability to detect others' behavior *and* their emotions, as they inform the context in which appraisals arise. Being confronted with an angry co-partisan may produce different emotions than a confrontation with an angry member of the political opposition, depending on how one's automatic processes evaluate the situation (Roseman and Smith, 2001;

Van Kleef, 2009). But along with blame and control, Marcus et al. (2007) also include *norm violations* and *attacks on cherished groups* as sources of anger among the electorate (Marcus et al., 2000). Emotions are important because they produce political actions, but the activation of political emotions is dependent on context. And while previous research has examined how context in the news can influence citizens' perceptions of politics, this context is often linked to information rather than emotions.

The news environment was shaped by the development of new professional norms in the 1920s (Schudson, 1981). Engaged citizenship was increasingly thought to arise from access to objective information, rather than loyalty to political groups (Schudson, 2018). In 1923, the American Society of Newspaper Editors' code of ethics called for nonpartisan reporting of the news (Schudson, 2018). Around the same time Lippmann (1922) argued for the importance of objectivity in journalism when forces outside a newsroom might seek to manipulate the news to sway the public. As journalism professionalized, objectivity required reporting multiple sides to news stories. Schudson (2018) calls this "contextualizing" the news, which he describes as offering interpretation and analysis of a story without partisanship. More information is provided to audiences, but control and blame are not assigned: readers are given more in-depth analysis, but they are not given didactic conclusions about what they read (Schudson, 2018).

One example of how contextualizing the news influences citizens is how the framing of the news is key to citizens assigning blame for newsworthy events. When the news focuses on individual actions as the source of events and fails to connect these actions with other events or circumstances in the news, it results in weaker political accountability (Iyengar, 1994). The "portrayal of recurring issues as unrelated events prevents the public from culminating the evidence toward any logical, ultimate consequence. . . ", (Iyengar, 1994, p.143) obscuring blame, and thus anger, in nonpartisan news contexts. While this news environment may not lead citizens to connect similar events, negative and partisan news may be making these connections more explicit. Other work has shown how the context of news also effects political behaviors and attitudes and causes citizens to hold others, particularly out-partisans, responsible (Mutz, 2015).

The advent of the television age also introduced new vectors of political influence in media. Sullivan and Masters (1988) found that the visual medium gave citizens new information about political candidates: viewers assessed candidates' facial expressions. How citizens react to facial displays is contingent on their predispositions and identities: seeing distress in a person one dislikes produces happy opponents, while detecting anxiety in a preferred candidate is stressful for copartisans (Way and Masters, 1996).

Partisan perspective-taking necessitates evaluations of political objects and people that emphasize group membership and values. Group norms and values produce an environment in which the opposition is blamed, attacked, and scolded, while copartisans are cheered and praised. Partisan news operations use the particular appraisals that drive anger—blame, norm adherence, and defending cherished groups (Smith and Ellsworth, 1985; Ellsworth and Smith, 1988)—against the opposition and drive copartisan anger. The professionalized journalism corps of the 20$^{\text{th}}$ century reified an objective style of reporting that did not assign blame and addressed audiences in non-partisan terms (Schudson, 1981). Reporters instead focused on alerting viewers to stories and topics that might be of interest and on providing them with a set of facts, akin to the scientific method (Starr, 2004). The infusion of anger into the news environment happens when the press is partisan, as the stories and items viewers or readers are alerted to is predicated on the outlet's political party. This sharpens the public's anger, as partisans blame the opposition for political outcomes and norm violations and also cheer copartisan politicians, attempting to rally citizens to support the party.

In this chapter, I examine how politics, emotions, and media are intertwined in American politics, focusing on the case of contemporary cable television. I argue that the fragmentation of the media environment and the rise of partisan news create the conditions for anger to thrive. And anger may be responsible for both the rise in partisan animosity *and* recent increases in electoral participation. This is partly due to the ideological conditions that gave rise to contemporary news models.

But the simmering anger that pervades our body politic in fact echoes that of early 19$^{\text{th}}$ century

America—a time when political machines used media to lash out at political opponents and promote their candidates. The partisan press in the 19th century was an angry press—one that blamed the opposition, used *ad hominem* attacks, and defended cherished in-groups. These same factors are once again occurring in present-day partisan media, and the early partisan press era provides a foundation for understanding the angry media environment in which we now live.

2.2 The Roots of Emotional News

At the beginning of the 19th century, newspapers in the United States were highly partisan. News production was dominated by political patronage systems (Schudson, 1981; Starr, 2004), as parties competed for government printing contracts that required newspapers to inform citizens of laws, policies, and other public notices (Smith, 1982). The owners of local papers, often political leaders and close allies of sitting elected officials, were ready to print party positions and direct political attacks at the behest of office holders (Doll, 1959; Smith 1982). Newspapers also recirculated stories from other papers (Schudson, 1981), often written by copartisans (Lerche, 1948), and special postal privileges allowed newspaper editors to send copies to other editors free of charge (Henkin, 2008).

Early 19th century papers were typically four-page weeklies. The first page of the paper typically contained information about how to subscribe; notices on behalf of national, state, or local government; and other miscellaneous items. Page 4 included personal and business notices; notices of divorce, artisans for hire, and advertisements for local businesses were common. Pages 2 and 3 were generally where the editorial and political action was located. Attacks against political rivals were often coordinated affairs within these pages of a partisan paper, which might feature commentary by the editor, guest editorials from pseudonymous sources, letters to the editor selected for their partisan zeal, and writings from other copartisan publications (Lerche, 1948). Editors were not shy about publishing their partisan affiliations and opinions. Often the names of papers indicated their political slant—like the *Arkansas Whig*, in Little Rock, Arkansas, or the

True Democrat, in Ann Arbor, Michigan. Similar to Fox News, papers were often, though not always, founded with the intention of providing a partisan perspective to local audiences. From July 16 through September 17, 1829, three men advertised for a printer in the Detroit Gazette, hoping to establish an Antimasonic paper in the "village of Ann Arbour," Michigan (Doll, 1959). In the October 26, 1837 issue of the *Baltimore Sun,* a "distinguished editor from the West" advertised a new paper to be started in Washington whose "political complexion [was] to be whig" (p.2).

Along with this partisan content came emotion: cheering preferred candidates and maligning the opposition though personal attacks, blame, and moral outrage. Because political norms of the day discouraged candidates from directly campaigning, proxy contests were conducted in these pages (Bensel, 2004). The vitriol and anger of the partisan press was expressed in charges of disloyalty and intimations of revolutionary violence. During the presidential contest between Thomas Jefferson and John Adams in 1800, "the Federalists' newspapers printed any anti-Jefferson smear they could obtain," often in editorials or guest editorials (Lerche, 1948, p/471). A well-known attacker went by the pen name "Burleigh" in the *Connecticut Courant* (Lerche, 1948). He declared in an October 6, 1800 article that "Mr. Jefferson is an enemy to the constitution of the United States" (p.1) and raised the specter of the French Revolution: Jefferson, Burleigh wrote, would enrich himself as had the Jacobins in France (Lerche, 1948). Burleigh warned his copartisans that a Jefferson presidency would destroy "the life of society" and his antidemocratic, French sentiments would "deprave the minds of children" (Burleigh, 1800, p.1). These attacks were clearly intended to inspire anger—how dare Jefferson violate the norms of the United States and the family unit?—and came with calls for action; Burleigh stated with certainty that Adams supporters could beat Jefferson at the ballot box (Burleigh, 1800).

Jefferson's supporters returned fire with the same enmity. The most well-known anti-Jefferson screed came in a three-volume handbill entitled "The Prospect Before Us," printed by *Richmond Recorder* writer James Callender (Durey, 2013). In volume two, Callender (1800) described Adams's "hideous hermaphroditical character" (p.57), smearing the candidate with *ad hominem* attacks that included barbs about his wife's appearance. Callendar was subsequently jailed for

“The Prospect Before Us,” but upon his release continued in the newspaper business, launching partisan attacks with great zeal until his death in 1803 (Durey, 2013).

Angry partisan papers played a significant role in political communication until the Civil War. The election of 1828 was particularly notable for the extent of partisan rage expressed in newspapers. The election was particularly bitter because it was a rematch between the incumbent John Quincy Adams and Andrew Jackson. The election of 1824, in which Jackson won the popular vote but failed to secure a majority of the Electoral College in a field of four candidates, had produced what Jacksonians called ”the corrupt bargain.” When it fell on the House of Representatives to declare the next president (Copeland, 2003), Adams loyalists struck a deal with supporters of Henry Clay in order to secure the presidency (Copeland, 2003; Smith, 1982). The election of 1824 marked the last moments of the so-called ”Era of Good Feelings,” fracturing the Democratic-Republican Party and giving birth to the Second Party System. By 1828, Jackson and Adams, now a Democrat and a Republican, respectively, had partisan papers poised to do their dirty work. Adams’s executive printing patronage was bestowed upon the *National Journal* in Washington; the *National Intelligencer* also aligned itself with Adams’s administration in the hopes of receiving government printing contracts (Copeland, 2003). To combat Adams’s partisan papers in Washington, supporters of Jackson purchased their own DC paper, which they dubbed the *United States Telegraph* (Copeland, 2003).

Critical to the election was the new practice of he printing of special weekly “extras,” which advanced the parties’ “mud-slinging, name-calling, and the less genteel type of publicity” (Smith, 1982, p.70). One publication, *Truth’s Advocate and Monthly Anti-Jackson Expositor*, lashed out at Jackson’s moral failings in order to stoke outrage (Smith, 1982; Basch, 1993). Created by Charles Hammond, the editor of the *Cincinnati Gazette*, *Truth’s Advocate* portrayed Jackson’s wife as a bigamist and declared him unfit to hold the office of the presidency. “When, then, in our country,” he wrote, “a man is suggested as a candidate for the Presidency, the fathers and husbands, the matrons and the maidens of the land, have a deep stake in knowing the character of his wife; and if she be a weak and vulgar woman, for that reason alone, his pretensions should be passed by" (Hammond, 1828, p.2). The moral violation of adultery cast upon Jackson and his wife, defaming their character, was part and parcel of partisan newspapers' opposition rhetoric: even the suggestion of moral decline, regardless of the truth, led to charges of subversion and disloyalty.

It was through these "extras," and not in the pages of the daily papers, that false accusations against Jackson were primarily circulated. The rancor of these personal attacks was matched with outrage from papers friendly to his candidacy. The *United States Telegraph*, in a tone familiar to anyone who has watched contemporary partisan television, angrily decried the accusations, saying that they had "become a mania, and his calumniators manifest a rapidness in their desperate vocation, that better qualifies them for a mad-house, than the Cabinet" (Green and Jarvis, 1828, p.2). The accusations of blame, moral outrage, and personal attacks continued in the partisan press throughout the election cycle.

The anger in partisan news was not limited to papers published on the more populated East Coast. Papers in communities that were part of America's westward expansion also took on a partisan flair. Ann Arbor supported both a Republican paper, the *Ann Arbor Journal*, and a Democratic paper, the *Michigan Argus*, in the lead up to the Civil War (Doll, 1959). While the country had four nominees for President in 1860—Lincoln, the Republican; Douglas, the Democrat; Breckinridge, the Southern Democrat; and Bell of the Constitutional Union party—the *Argus* conveyed partisan anger and acted as a cheerleader for Democratic candidates in a way that may feel familiar to modern news audiences. In its November 2, 1860 issue the paper called upon its readers to not "not be induced by personal friendship or appeals to your sympathies" and give their votes to the Republican candidate for Michigan Representative and suggested that such a result would be clear evidence of cheating (Pond, 1860b, p. 2). They invoked the norm violation of illegal voting, warning that Republicans might attempt to change votes by "smuggling" the names of their candidates onto ballots, in order to galvanize anger and electoral action (Pond, 1860b, p. 2). After Lincoln won the election, the paper again accused Republicans of trickery in a turn analogous to Republican complaints about the 2020 election, writing that "the victory was bought and paid for" by the Republicans (Pond, 1860a, p. 2).

Absent from these papers was the discussion of elections in uncertain terms: all threats were attributed to the partisan opposition. There was no doubt about who is to blame for the Democrats loss to Lincoln in 1860. There was no postmortem about how time will tell what went wrong. Obviously it was the partisan opposition, violating norms of free and fair elections, who caused the loss! Absent were cues of uncertainty, which would stoke anxiety and information seeking (Frijda, 1986; Moors et al., 2013). Instead of uncertainty the *Argus* conveyed with certainty and blame—appraisals central for feelings of anger (Ellsworth, 2013)—that they and their copartisans were wronged by the Republicans.

Doubt is also absent in the aspersions cast upon Jackson and his wife in the 1828 election. Hammond (1828) is not only certain about Jackson's marriage to his wife, Rachel, violating the norms of the day regarding marriage. Hammond and Adams's supporters were certain that violations of marital norms would translate to national problems if Jackson was elected (Basch, 1993). The anger in these papers was not tempered with doubt or inquiry: the partisan press knew the opposition was to blame, that their bad moral character was clearly demonstrated in their norm violations, and that clear and obvious action needed to be taken to prevent the partisan opposition from succeeding. Partisan perspective taking in news, present in the angry, aggressive political newspapers of the 19^{th} century, is likely what is responsible for increased animosity in contemporary American politics.

2.3 The Rise of Cable and Partisan News

The rise of cable television in the 20th century changed the structure of news delivery. Cable news began to take shape in the 1980s, after several decades in which the news industry was dominated by an objective and professionalized press corps (Ladd, 2012).

The Cable News Network (CNN), founded by Ted Turner in 1980, was, for almost two decades, *the* place for 24-hour news for many Americans. Turner's interest in the news was not a matter of civics, but of economics: Turner wanted to capitalize on the new revenue streams from advertisers and the subscription fees of basic cable packages (Ponce de Leon, 2015). Specialized channels, like ESPN for sports, HBO for movies, and C-SPAN for continuous coverage of Congress, were already on the scene, but a channel that specialized in news (and one with a focus on breaking news in particular) was absent from the cable television market.

From its launch, Turner's CNN relied primarily on videotape technology, working with Reese Schonfeld's Independent Television News Association, an exchange for taped news between US and international news stations (Schonfeld, 2001). Buying content from the ITNA exchange allowed the company to obtain footage without hiring a significant in-house journalistic staff or bearing the costs of multiple domestic bureaus (Ponce de Leon, 2015). Tape technology also facilitated CNN's ability to deliver breaking news—the channel could "go live" when new and significant events occurred and provide immediate coverage to viewers, because its own newsroom was not tied up producing scheduled coverage. This model was enabled by the structure of cable news and the economic incentives that drove the it. Relying on subscriber fees, rather than advertiser revenue, allowed them to pivot quickly to stories without worrying about angering—and losing—advertisers.(Ponce de Leon, 2015). CNN's system also relied on on-air talent, rather than on-the-ground reporters, to describe what was happening as live shots were broadcast to audiences. Desk anchors came to play a larger role in framing the news and determining what was important for viewers, with one anchor often responsible for the setting the tone and agenda of an entire block of news, rather than cutting away to a network corespondent on the ground.

By the end of 1989, CNN had nearly 54 million subscribers and had generated hundreds of millions of dollars in annual revenue (Collins, 2004). In 1990, the first Gulf War further propelled CNN into the spotlight. Not only was the channel able to capitalize on its ability to immediately shift to breaking news, but CNN was eventually the only U.S. television network with an on-the-ground presence in Iraq (Diamond, 1991). The bombing of Baghdad knocked out communication lines within the country, but CNN's satellite audio linkages allowed it to stay on air even after other networks' coverage was completely interrupted (Zelizer, 1992). Shortly after that, citing concerns over water and energy levels, Iraq expelled all journalists—except for CNN correspondent Peter

Arnett and a small news team (Kurtz, 1991). CNN was allowed to stay because it was an international network and a known quantity to Iraqi authorities—and because the network agreed to allow Iraqi minders to supervise its embedded reporters (Diamond, 1991).

With a small news team and satellite infrastructure already in place, the combination of exclusive coverage and nimble reporting (Zelizer, 1992) allowed CNN to set the agenda for coverage of the war. CNN's production decisions, which included upbeat music, flashy graphics, and stories that emphasized fear and danger, (Kellner, 2019) created evocative coverage. CNN also heightened the emotional stakes of its broadcasts by centering American fears (Kellner, 2019) and focusing on bombings and their aftermaths (Ponce de Leon, 2015) over coverage of diplomatic and political engagement. This translated into must-watch television for Americans.

CNN's success made others want a piece of the cable news market. Legacy network NBC had already had success with its cable business news channel, CNBC, founded in 1989, and led by Roger Ailes, a former Republican party operative who made his name by getting Nixon to take television much more seriously ((Ponce de Leon, 2015). NBC initially tapped Ailes to head a new network called America's Talking, which combined news with the talk-radio style of reporting that Ailes used to make CNBC appealing to a wider range of viewers (Ponce de Leon, 2015). In 1995, when NBC joined forces with Microsoft and scrapped America's Talking, Ailes left the network. The partnership with Microsoft was meant to take advantage of the rise of the Internet, allowing the television programming to direct audiences to "go online" to get more information and reaping advertising dollars both via television viewership and online engagement (Collins, 2004). NBC launched MSNBC in July of 1996, and it initially represented CNN's biggest competition. At the same moment, however, Australian media mogul Rupert Murdoch entered the fray.

After trying for a number of years to launch a cable venture in the United States, Murdoch tapped Ailes to head Fox's new network, the Fox News Channel (Fox). Murdoch and Ailes sought to create a station that would provide a different, decidedly partisan perspective to the American news consumer. Though Turner emphasized objective news and hired news analysts with a wide variety of political perspectives for CNN's programming, there were still complaints that CNN was ”too liberal” and that a conservative perspective was missing from the news. Murdoch’s other media ventures leaned right, and Fox was meant to supply news to those who felt disconnected from the mainstream media, which Murdoch was on record as calling “too liberal” (McKnight, 2010). Fox launched in October 1996, setting the stage for cable news competition. The presence of Fox and MSNBC meant that CNN no longer exercised unilateral judgement within the cable market about what news to cover—and, more importantly, they now had to respond to new partisan market forces (Ponce de Leon, 2015).

Both MSNBC and Fox tapped existing talent to lead their cable programming, but went in different directions regarding objectivity. NBC signaled that it would continue its objective news approach at MSNBC by taking anchors Tom Brokaw and Brian Williams along to the new network. NBC executives saw this as a way to tie a known audience base to a 24-hour cable channel: if news broke during NBC’s evening news, they could direct viewers to flip to MSNBC, where coverage of the story would continue (Collins, 2004). Executives also raided the video archives of NBC, producing inexpensive programming with “video time capsules” of previous news events (Collins, 2004). MSNBC drew upon NBC’s extensive archives and recirculated its previous coverage to save money that might have been spent on new reporting. If it was not providing viewers with live objective reporting, MSNBC was going to provide them with footage of their professionalized journalists objectively reporting significant news events.

Ailes took a very different tack at Fox. The goal was to mix in-depth reporting with opinionated prime time talk programs, essentially bringing the “expressive edginess of [Don] Imus and [Rush] Limbaugh to cable tv” (Ponce de Leon, 2015, p.228-229) and engaging those who were already politicized by conservative talk radio. Ailes did not choose an exclusively professionalized journalistic corps for Fox’s anchor roles. He allegedly watched shows with the sound off in his hotel room, looking for great performances that would cause “cause him to get up and turn the sound on” (Collins, 2004, p.140) because of the star quality of the reporter or host. This meant hiring bombastic personalities like Bill O’Reilly, who joined Fox in 1996 from his previous position as a tabloid news reporter, and radio personalities Sean Hannity and Alan Colmes, who anchored a point-counterpoint show with a conservative and liberal voice.

By 2000, it was clear that MSNBC was in trouble and that Fox's star was on the rise (Collins, 2004). In the hopes of improving ratings, MSNBC ventured into more opinion-style broadcasting, moving Chris Matthew's *Hardball* over from CNBC and debuting Keith Olbermann's *Countdown*. This new competition within cable news had begun to shift the broader media environment away from the "objective" reporting that Turner and other journalists of the 20th century had favored and towards a more entertaining style of news that brought with it explicitly partisan viewpoints and more potent emotional cues.

2.3.1 The Early Cable News Era

The first decade of cable television news saw changing lineups for both partisan and nonpartisan networks. Nonpartisan broadcast network ABC's flagship *World News Tonight* was anchored by Peter Jennings from the 1980s until his death in 2005. The show was anchored briefly by Bob Woodruff and Elizabeth Vargas before they were replaced with Charles Gibson in June 2006. All of these hosts were "traditional" journalists who embodied the journalistic philosophies of Walter Lippman—they were understood to be politically independent experts who transmit the news of the day to the public objectively (Lippmann, 1922; Schudson, 1981).

Journalistic objectivity was also the philosophy at NBC's *Nightly News*. Anchored by Tom Brokaw from the 1980s until 2004, and then by Brian Williams until 2015, the program represented steady, politically independent voices delivering objective news. Together with ABC, they represented the professional, journalistic ideal of news production: objective reporting of facts, telling all sides of the story, and keeping their own opinions or those of the corporate owners out of their reporting (Schudson, 1981). While this reporting was professional, both programs followed the convention whereby the final segment, often referred to as a "kicker," was made up of feel-good stories about people overcoming adversity or giving back to their communities. While many are unsure sure of its origins, including journalists who currently end their programs with the happy "kicker," there appears to be a consensus that it is meant to leave viewers with a sense of optimism and connection to the news hosts (Soroka and Krupnikov, 2021).

In the cable environment, various news production philosophies were at play for CNN, Fox, and MSNBC. Fox, because of its explicit commitment to providing a conservative perspective on the news of the day, hired partisan anchors during this time period. Anchoring its prime-time programming over the course of 2000-2008 was Bill O'Reilly. *The O'Reilly Factor* attracted a large prime time audience with reporting on topics like the 2000 Presidential election (O'Reilly strenuously argued that Al Gore should not have demanded a recount in Florida) and military action in the wake of September 11, 2001 (which, he said, Americans should not have protested) (Ponce de Leon, 2015). O'Reilly and other conservative hosts channeled alleged viewer dissatisfaction with supposed liberal bias on CNN into ratings: by the summer of 2001, Fox and CNN were virtually tied for prime-time viewership (Collins, 2004).

MSNBC, however, took longer to find its prime-time partisan identity. Initially Brian Williams anchored its prime-time news program; *The News with Brian Williams* emulated NBC's evening news in style and format. This was part of a plan to use MSNBC to groom on-air talent it could later call up to NBC network news (Ponce de Leon, 2015; Collins, 2004). NBC would also extend viewership by directing audiences to breaking news on MSNBC at the end of the flagship channel's news programming (Ponce de Leon, 2015; Collins, 2004). This format did not capture ratings, however, and soon MSNBC put Chris Matthews into prime time. *Hardball* marked a shift away from professionalized journalism and towards a partisan ”talking head” model (Ponce de Leon, 2015; Collins, 2004). This was particularly ironic because Matthews had been brought into the NBC fold when Roger Ailes, who hired anchors for their bombastic and performative style, was in charge of CNBC (Collins, 2004). In 2003, *Countdown: Iraq* premiered on MSNBC. Initially anchored by Lester Holt, the network soon replaced him with Keith Olbermann, a sports journalist with a penchant for liberal commentary and lashing out at conservatives—particularly his prime time competitor Bill O'Reilly (Ponce de Leon, 2015). By 2005, MSNBC was providing a distinctly Democratic perspective on the news, framing it as a counter to Fox's Republican slant.

CNN was slower to react to the partisan changes in the cable news environment, and the early part of the decade saw the network lose ground in the ratings to its competitors. Its prime time ratings leader was *Larry King Live*, a lively interview and call-in show that offered a mix of politics, entertainment, and breaking news commentary. Larry King launched the show in 1985. *Anderson Cooper 360 Degrees*, hosted by the Vanderbilt heir and onetime American Broadcasting Corporation jack-of-all-trades, premiered in 2003. It initially ran earlier in the weekday programming lineup, at 7pm EST, but it eventually became CNN's lead prime time program. By 2006, however, CNN seemed to have at least stopped its downward ratings trajectory (Arango, 2008). (In 2008, CNN's president Jim Walton acknowledged that the network had been slow to address the competition offered by Fox and, to a lesser extent MSNBC: "the network [had] faced an identity crisis" (Arango, 2008, para. 19).)

The changes to the cable news environment in the initial years of the 21st century, driven by the success of Fox's partisan model and by greater competition within the cable market, had important implications for the emotional tenor of the macro cable news environment. According to my theory, the reemergence of partisan news in the American political environment should have brought with it a number of changes in the balance of emotional cues delivered to audiences on a daily basis. If the primary emotional signature of partisan news is anger, characterized by *ad hominem* attacks, blaming adversaries, calling out norm violations, and defending cherished partisan groups, then I expect that anger will be greater in the cable news environment than it is in the traditional news environment. This difference in anger should appear both in higher intensity and frequency compared to traditional news.

H_1: Partisan news will have more intense anger than nonpartisan news.

H_2: Partisan news will have more frequent anger than nonpartisan news.

Greater anger in cable news is also likely to create an off-set, where it coincides with lower levels of anxiety due to airtime for each program being a closed set. The more time partisan news spends cueing anger, the less time it will spend cueing anxiety. Since traditional news relies on the journalistic norm of objectivity, the standards of which include covering novel threats from both sides of the political aisle without galvanizing blame, I anticipate finding that nonpartisan news broadcasts more anxiety cues to viewers. This hypothesis is also in line with previous work that has shown that the news environment is, on balance, negative in valence (Young and Soroka, 2012), but that tenor is not produced through rhetoric of blame. I expect to find that traditional news cues more anxiety than partisan news. Partisan news will cue less anxiety than traditional news, in terms of both intensity and frequency over the time period. And within partisan news, the intensity and frequency of anxiety should be lower than that of anger.

H_3: Partisan news will have less intense anxiety than nonpartisan news.

H_4: Partisan news will have less frequent anxiety than nonpartisan news.

H_5: The frequency of anxiety will be lower than anger within partisan news.

The kickers at the end of the news programming of ABC and NBC should also produce greater enthusiasm in viewers compared to partisan news. While partisan news does cheer-lead copartisans, the broadcast norm of ending every program on a positive note should create greater enthusiasm, in both intensity and frequency, for nonpartisan news compared to partisan news.

H_6: nonpartisan news will have more intense enthusiasm than partisan news.

H_7: nonpartisan news will have more frequent enthusiasm than partisan news.

I also expect that anger, fueled by inter-network competition in the cable environment, will increase in the aggregate over time for partisan cable news compared to traditional news. Fox's success led MSNBC to add the more partisan *Countdown with Keith Olbermann* to its lineup; CNN also attempted to take market share from Fox by producing similarly partisan content. I expect this competition to coincide with increases in the intensity of anger and its frequency over time for partisan cable news and expect both CNN and MSNBC to become more partisan. And because of the anger off-set, these increases in anger should have corollary reductions in the frequency and intensity of anxiety over time for partisan news.

H_8: Anger, in both frequency and intensity, will increase for partisan news over time.

H_9: Anxiety, in both intensity and frequency, will decrease for partisan news over time.

I also hypothesize that while nonpartisan news will maintain higher levels of enthusiasm compared to partisan news over the time period, both traditional news and partisan news will remain at constant levels for the intensity and frequency of enthusiasm .

H_{10}: nonpartisan news will maintain higher levels of enthusiasm other time than partisan news.

The variation within the partisan cable networks also means that there will be movement in the emotional cues expressed by the three cable networks. Because of Fox's conservative context and its consistency in expressing partisan allegiance over 2000-2008, I anticipate that levels of anger will be higher for Fox—and, because they are imitating Fox's hyperpartisan model, for MSNBC and CNN. Anger on Fox will not increase over the time period, because it has been a consistent feature of the channel over time. Rather, the increases in anger will largely come from MSNBC and CNN, which adjusted their programming and style to compete with Fox for ratings in this period.

H_{11}: Fox will have more intense and frequent anger than CNN and MSNBC.

H_{12}: CNN and MSNBC will have increased intensity and frequency of anger over the time period.

I also anticipate that an anger offset will occur for MSNBC and CNN: the frequency of anxiety will decrease over time. I also expect relative levels of enthusiasm to remain constant for Fox and MSNBC, but because of CNN's approach to news adhering to the professional journalistic norms of the mid-20th century, I anticipate that the network's levels of enthusiasm will decrease over the time period as it moves away from traditional, nonpartisan media—and, I hypothesize, away from the enthusiastic kicker segments that often end nonpartisan news programs. H13: The frequency of anxiety over time will decrease for CNN and MSNBC H14: The frequency and intensity of enthusiasm will decrease for CNN over time.

2.4 Trends or Trump? Change in Emotions from 2010-2020

The emotional experiences of various groups are often invoked by journalists and pundits to explain electoral success or failure. Trump's 2016 victory was assumed by many in media to be results of “economic anxiety” throughout the country, particularly among white men (Adams, 2016; Casselman, 2017; Van Dam, 2019). Alternatively, the other common hypothesis was that Americans were fearful of Hillary Clinton (Beinart, 2016; Page, 2016). Yet the behavioral outcomes associated with anxiety (e.g. Marcus et al., 2000; Brader, 2005; Valentino et al., 2011)—whereby respondents rely less on predispositions and instead use contemporary considerations to make decisions—does not correlate with the increases in turnout and political participation that characterized the 2016 presidential election cycle. Rather than anxiety, it is likely feelings of anger among the electorate is driving politics. Anger drives citizen behavior that is more participatory and more vocal, confrontational, and aggressive when asserting political beliefs and identities.

Just as journalists and pundits invoke emotional experiences to describe electoral effects, a broad truism has circulated over the last several years: that changes occurring in the media around the 2016 election were the result of Donald Trump’s unique and novel media machinations, not the result of a candidate taking advantage of and exploiting a known media landscape. He has been referred to as a “catalyst” for the change in media (Ferullo, 2020, para. 8) and understood as a figure who has owned coverage in new and novel ways; some observers imply that this novelty lies in his emotional expression and public outbursts during the campaign (Kalb, 2022).

I disagree that contemporary partisan news represents a novel model, but it is possible to identify whether the changes that people perceived in the media around the 2016 campaign were actually part of broader changes in the emotional output of the news over the 2010-2020 time period. This chapter examines the emotional differences in partisan cable news and nonpartisan broadcast news in election years from 2010—2020 in order to determine the extent to which changes in the emotionality of the news coincide with the political rise of Donald Trump. Finding such a change would comport with the general sense that ”something happened” with the media during the 2016 campaign; it could also explain the current participatory, angry electorate.

Speaking to multiple television outlets in 2011, Donald Trump accused then-President Barack Obama of lying about his birthplace—and therefore ineligible for the executive office that he held (Parker and Eder, 2016). This was the beginning of Trump’s foray into the national political scene, a move from reality television star to political reality. By the time he was elected president in 2016, pundits had hypothesized that Trump himself had changed American media (Kalb, 2022) by manipulating political anxieties about the economy, about race, and about his Democratic rival, Hillary Clinton (Adams, 2016; Casselman, 2017; Van Dam, 2019; Beinart, 2016). Yet the behavioral outcomes associated with anxiety —citizens becoming less reliant on predispositions and instead using contemporary considerations to make decisions (Valentino et al., 2008)—do not correlate with the increases in turnout and political participation in 2016 presidential. Anxieties typically do not provoke the shift in observed behaviors over the past decade. Participation combined with animosity among the electorate is the product of anger—and would be the expected result if anger cues are increasingly provided to viewers in the partisan cable news environment in correlation with growing participation rates. If Trump's candidacy had an impact on the emotional tenor of the media, there should be apparent changes between the 2010 midterm and his election to the presidency in 2016. Since the conventional wisdom seems to focus on the election in 2016 as the moment of decisive change, I give particular attention to the elections from 2014-2018 to determine whether the media did indeed change with Trump's election or whether Trump harnessed changes that had already begun to reshape the news environment.

2.4.1 How Might the Media (Not) Change

While changes may have occurred in the television media environment during Donald Trump's rise in national politics, the theoretical relationship between anger and anxiety should remain the same. Partisan cable news should continue to have greater intensity and frequency of anger and lower intensity and frequency of anxiety than nonpartisan news. I also anticipate that enthusiasm cues will be greater for nonpartisan network news that continues the programming norm of ending episodes with uplifting, heroic stories of community and overcoming adversity.

H_1: Partisan news will be less intensely anxious than nonpartisan news.

H_2: Partisan news will be less frequently anxious than nonpartisan news.

H_3: Partisan news is more intensely angry than nonpartisan news.

H_4: Partisan news is more frequently angry than nonpartisan news.

H_5: Nonpartisan news will be more intensely enthusiastic than partisan news.

H_6: Nonpartisan news will be more frequently enthusiastic than partisan news.

While anchors were mostly stable for all networks in this period, ABC's and NBC's anchors each changed once over the sampled time frame. Diane Sawyer anchored ABC's nightly news program from 2010-2014; David Muir became the primary anchor in 2016. Brian Williams was NBC's lead anchor from 2010-2014, when he was replaced with Lester Holt. The networks themselves did not change their reporting overall philosophy: they continue to report news in the objective and unbiased framework of the mid-twentieth century. Because of this, I do not anticipate movement in either the frequency or intensity of emotions of news over time: movement over this time period should be within and between partisan news networks.

Over the 2010-2020 period, the hosts of the most-watched partisan prime time programs were consistent. Sean Hannity's eponymous program earned the highest ratings for Fox while Rachel Maddow's self-titled program also lead the ratings for MSNBC. Meanwhile, *Anderson Cooper 360 Degrees* occupied the prime time slot for CNN. If there were changes in the media attributable to a 'Trump Effect,' the first way in which they should appear is as increasing intensity and frequency of anger in partisan cable news, both because this is the emotional signal that partisan news sends to copartisans and because of the increases in participation and partisan animosity over time.

H_7: Anger, in both frequency and intensity, will increase for partisan news over time.

Similar to 2000-2008, if anger is increasing within partisan news, there should also be an anger offset where the negative emotion of anxiety decreases. The formats for the programs did not change over this time period—each maintained the same number of segments and the same one-hour programming block in these years. Therefore, if anger is increasing and the news program is a closed set, cues for anxiety should decrease. I do not anticipate a change in enthusiasm over this time period. As with my hypotheses regarding enthusiasm in the early days of partisan cable news, while enthusiasm can generate participation (Brader, 2005), partisan hostility has continued to increase in this time period (Nadeem, 2022). Since partisan animosity only continues to have a positive relationship with participation, I do not think that enthusiasm, in either intensity or frequency, will be increasing over 2010-2020.

H_8: The intensity and frequency of anxiety in partisan news will decrease over time.

H_9: The frequency and intensity of enthusiasm for both partisan and nonpartisan networks should not change over this time period.

2.4.2 Partisan News and Zooming in on the 2016 Election

I dis-aggregate the networks of CNN, Fox, and MSNBC to further examine potential changes in the media landscape over the 2010-2020 time period. If there is movement in the intensity and frequency of emotions within the sphere of partisan cable news, it is possible that all networks may not be equally responsible for such changes. If anger is increasing in partisan media over time *and* Trump has a specific and novel effect on media, I predict that all three partisan cable networks would exhibit increases in anger, decreases in anxiety, and stable levels of enthusiasm over the time period.

H_{10}: Anger will increase over time in both intensity and frequency for CNN, MSNBC, and Fox.

H_{11}: Anxiety will decrease over time in both intensity and frequency for CNN, MSNBC, and Fox.

H_{12}: Enthusiasm will remain stable in both intensity and frequency for CNN, MNSBC, and Fox.

A Trump effect would result in a clear discontinuity in emotions around the time of the 2016 election. Trump entered the presidential race on in June of 2015 (Diamond, 2015), and allegations that he changed the media environment first appeared after the 2016 general election (Kalb, 2022). If an exceptional change in the media occurred, there should be evidence of that between the years of 2014 and 2016. The change should be rooted in the negative emotions in partisan media, specifically an increase in anger and a subsequent decrease in anxiety.

H_{13}: The frequency and intensity of anger for CNN, Fox, and MSNBC should increase between 2014 and 2016.

H_{14}: The frequency and intensity of anxiety for CNN, Fox, and MSNBC should decrease between 2014 and 2016.

I should be able to determine whether the tenor of partisan media changed through coverage of Trump or whether Trump simply harnessed a trend of angry partisanship that first appeared in the cable news environment in the early 2000s.

2.5 Conclusion

The addition of Fox News and MSNBC to the cable news environment likely changed the emotional landscape of cable news. The fragmentation of the media environment should theoretically result in lower election turnout and participation (Prior, 2007; Putnam, 2000), but the last two decades have seen an average increase in participation (Desilver, 2021). The likely reason for this increase is citizen activation via the dominance of anger in partisan news. Unlike network news, which relies on objectivity and balance, partisan news attacks opponents, directs blame, and defends copartisan norms. This framework in news is not new in American politics and echos the partisan press era of the 19$^{\text{th}}$ century, when newspapers were expressly partisan due to patronage and alliances with political parties.

In the following pages, I produce a methodological framework for measuring emotional cues in the partisan and nonpartisan news environments and then test the emotional changes in these environments over time. First I examine how the emotional landscape shifted to containing greater anger with the arrival of partisan Fox News on cable television. Then I examine election years from 2010 to 2020 to determine if the media was already emotionally segmented or if the specific candidacy and election of Donald Trump to the presidency may be associated with further changes in the emotional landscape of the American television news environment.

CHAPTER 3

Measuring Perceptions of Emotions in the American Public

I theorize that the emotional landscape of American television news has changed over time due to the reintroduction of partisan news, specifically partisan cable news programming. While traditional broadcast news typically infuses the media environment with anxiety, partisan news specifically and particularly infuses the media environment with anger. Anger cues in partisan news create a distinct emotional environment for audiences compared to nonpartisan news. To test my theory, I need to measure the emotional cues in the news environment in a way that consistently taps the emotional constructs of interest—anger and anxiety—without bias. Measures for the emotional cues being provided to audiences by news anchors and hosts must be reliable. If I am correct that there are differences in the emotional news environments between partisan and nonpartisan news, members of the public who may comprise these audiences *must* be able to identify and score the emotional cues that are being provided during news broadcasts. If respondents are unable to differentiate between the types of negative emotions, then the emotional environments are not only unlikely to be different for partisan and nonpartisan news, but any differences in specific emotions are not likely to be playing a role in American public opinion or political behavior. This would mean that the key variables of interest are not the tripartite emotions in Affective Intelligence theory but likely valence, or how positive and negative the news environment is, which has been thoroughly researched by Soroka and colleagues (e.g. Young and Soroka, 2012; Soroka and McAdams, 2015; Soroka et al., 2019).

In addition to identifying the emotions, members of the public also must perceive differences in the emotional intensity of the news. While it is possible that the main difference is the *type* of emotion that is present, the intensity also matters. Important to my theory is that I am *not* arguing that nonpartisan news lacks emotion, but rather that it is different in type and intensity than partisan news. Nonpartisan news will not have an absence of anger, but rather what anger it does have will be less intense than that displayed by partisan networks.

Further members of the public must be able to identify these emotions regardless of their partisan affiliation: the identification of emotions should be consistent regardless of partisan affiliation, since responding to in-group or out-group emotions is contingent on the accurate identification of emotions generally and not just when dealing with copartisans or out-partisans. This is particularly important because this accurate identification of the emotions is necessary for moving from perceived emotions of the anchors to felt emotions among the American public. Members of the public must be able to accurately identify the emotions of copartisans because these elite signals help create inter-group emotions, such as how Democrats or Republicans feel about a specific issue based on how other members of their group feel. But identifying how members of the opposition feel about an issue is equally important for calibrating how members of the public feel about political issues and people. When thinking of oneself as a partisan, political elites or events that may effect their partisan group elicit emotional responses (Mackie and Smith, 2018). Since how out-partisans are emotionally reacting to political news is likely to impact the copartisan group, the accurate identification of out-partisan emotions is especially important, since this is how people will calibrate how they feel about a political situation as either a Democrat or a Republican. Since my theory is not only about the emotional environments of partisan and nonpartisan news, but how these environments are potentially influencing how American feel and behave regarding politics, the accurate assessment of emotions for both co- and out-partisans is critical.

Finally, the studies in this chapter allow me to test how the mode in which I plan to provide news programming for respondents to score. My ability to efficiently map the emotional landscape of America television news necessitates using news transcript text as stimuli. Using text allows me greater control over the stimulus: I am able to mask network affiliations, anchor names, and other identifying information to ensure that the emotional ratings respondents are providing are about emotions of the anchor being conveyed via the text. This task is more difficult for video or audio presentations of the news and requires more computational power and storage capabilities. But there is a concern that using text makes the emotional cues in the news less salient, and thus making it less likely that I will be able to measure the emotional environment of the news. To ensure that I am able to test my theory of emotions in partisan news, I ensure that using text does not diminish the emotional cues in such a way as to render them undetectable to respondents via surveys.

To also ensure that I am able to test my theory, I develop a sampling strategy which takes into account two distinct samples: a systematic sample of the news environment; and the sampling frame for the selection of survey respondents to rate the emotions in partisan and nonpartisan news. I validate that citizens are able to detect emotions in the news via text. They are able to identify both emotions and variations in emotional intensity. I also test whether partisan predispositions of the audience or the mode of news stimuli create biases when asking survey respondents to rate the emotional signals from news programming.

3.0.1 Research Design and Stimuli Construction

The methodological goal of this chapter is to produce a framework for measuring emotional cues in the news based on the perceptions of respondents using a survey research design. My research interest—in both identifying emotions and the intensity of their expression—rules out some research design strategies, including complete automation and bag-of-word approaches. Using human coders is important for this project. While recent advancements in machine learning have increased the ability to categorize emotions via text analysis, the subtlety of emotions can make detection via algorithm difficult, and detecting emotions is often most effective when words that indicate emotions are explicit in text (Sailunaz et al., 2018). Additionally, most supervised or unsupervised approaches to detecting emotion approach it as a classification problem concerned with categorization, not intensity (Shivhare and Khethawat, 2012; Sailunaz et al., 2018). Because I am concerned with both the presence of an emotion and its intensity, classifiers would not allow me to fully test my theories about the differences in the frequency and intensity of emotions in partisan and nonpartisan news. Since the appraisal of an emotion is contingent on the context in which a word, person, or object is encountered (Ellsworth, 2013), a machine learning approach to detecting emotions requires supervision at some stage because emotion detection is contingent on context. This would still require human coders to classify the emotions in text so that those classifications could then supervise an algorithm. While there may be potential for data generated from this framework to be used for supervised learning, the goal of the current project is to detect the type and intensity of emotional signals in American news via human coders.[1]

The need to categorize both emotions expressed and the intensity of the expression also rules out two readily available bag-of-word approaches, the Linguistic Inquiry and Word Count (LIWC) dictionary (Tausczik and Pennebaker, 2010; Pennebaker et al., 2015) and the Lexicoder Semantic Dictionary (LSD) (Young and Soroka, 2012). Both count words in assigned categories and use the sums in each category to identify textual differences. LIWC contains categories for both anxiety and anger, but it does not assign different intensity scores to each word. LSD is focused on the valence of words: whether or not a word can be categorized as positive or negative. LSD would categorize both angry and fearful responses to words simply as negative. Because I am interested in the differentiated political behaviors provoked not simply by negative emotions, but by anger and fear specifically (Marcus et al., 2007; Valentino et al., 2011), using LSD would not allow me to adequately test my theory.

The LIWC dictionary does count words that are likely to express anger and anxiety distinctly but does not allow for the measurement of emotional intensity for these specific emotions. Words like annoyed, irritated, angry, and outraged are not differentiated by this approach —they are treated as interchangeable or equivalent. In my study, they are not. Both "annoyance" and "outrage" can be categorized as words that indicate anger, but the words each imply different emotional intensity.

[1] I discuss possible ways that this data may be used for supervised learning and how this is related to future research in the concluding chapter of this dissertation.

There may be behavioral implications for how someone who observes these emotions responds based on the intensity of the expression. The LIWC dictionary was created based on psychological health data (Tausczik and Pennebaker, 2010). Emotions are context-dependent (Giner-Sorolla, 2019), and the LIWC's categories may bias the emotional categorization of text that discusses, e.g., political news. For example, LIWC categorizes the word 'confused' as anxious - meaning that when ever the word 'confused' appears in a text it is a sign of anxiety. However, when Fox host Sean Hannity describes President Biden as being confused, as he did on his program on February 28, 2023, he is not expressing worry or anxieties about Biden. He is attacking him. Hannity began his comments saying that, similar to other elderly Americans who suffer "from a very steep, obvious cognitive decline, Biden has good days and he has bad days," and that on a recent outing Biden "seemed completely, totally lost, dazed and confused" (Hannity et al., 2023). On the program Hannity continued with "I cannot believe that man is president. Can any of you believe that?" This further contextualizes his expression as angry, rather than anxious, regarding Biden's alleged condition (Hannity et al., 2023).[2] But if LIWC were to score this section, the word 'confused' would be scored as anxious despite that in context 'confused' is clearly being used as an attack. The context in which a word is used is central to identifying emotions the word conveys. Since the LIWC was constructed based on health data and human coded to create the dictionary, using it may introduce systematic bias into the measurement of emotions in news and impact the inferences I am able to make about emotional cues from partisan and nonpartisan networks.

The extensive availability of fully transcribed cable and network news footage online allows three potential forms of stimulus construction: with video clips, with audio clips, and with written text. While other scholars have used assembly techniques to use video clips for studies examining the behavioral consequences of viewing the news (Iyengar and Kinder, 1987), this research rests on network news that was "unobtrusively altered" (p.8). Video is not used for this dissertation because the graphic conventions of cable news—chyrons with prominent network logos typically appear the bottom of the screen throughout a segment—and the high profiles and strong partisan

[2]A common attack on Biden by the Republican party is that he is in cognitive decline. There has been no medical evidence provided for this claim, only speculation as a part of a partisan attack.

identifications of cable news hosts make it difficult or impossible to alter clips to remove such identifying information. Additionally, video adds a layer of data about emotion that complicates respondents' ability to evaluate the emotions conveyed by the language they use. My study asks respondents to rate the type and intensity of the emotions expressed in text attributed to the host of the news program. Political objects can have affective tags that rapidly come to mind when they are encountered by citizens (Lodge and Taber, 2005). When respondents can see the host, they may produce ratings based on who they think the host is as a person —an angry person, a happy person, etc.—rather than evaluating the emotions conveyed in the stimuli. Altering the news host would create an obtrusive stimulus that could add further noise to the task. Similarly, unobtrusively and adequately altering audio to mask network names, host names, and other de-anonymizing indicators would be quite difficult. Not masking these characteristics could results in respondents relying on heuristics rather than content to score the emotionality of a section of news.

Audiovisual material would also be expensive to collect, alter, and store, and having coders watch or listen to hours of news would further increase costs. For practical purposes, locating, storing, and altering news transcripts is more efficient. Names of hosts and networks can be easily masked so that stimuli differ in ways that are important for the examination of my theory. Transcripts also allow respondents to identify places in the text where they may perceive specific emotions, which allows for additional analysis of differences within and between partisan and nonpartisan news.[3]

For scoring the text, I opted to use survey respondents rather than trained coders. Trained coders are often university students, who for my purposes would be presented with news items and asked to score the items based on my chosen emotional framework. Because this project covers all election years from 2000 to 2020, this would mean paying a group of undergraduate research assistants to score thousands of pages of news transcripts. From a practical standpoint, using survey respondents to crowd source ratings is a more efficient use of resources and allows each segment of text to be coded a greater number of times. Training coders also conflicts with a fundamental goal

[3]While not used in this dissertation, I discuss the potential use of scored text in the Future Work section of the conclusion.

of the project: examining how members of the public detect emotions in the news and measuring their automatic, reflexive reactions to political stimuli (Smith, 2012). Training respondents to detect emotions in the news may compromise the measure's external validity: it would be unclear whether trained coders would identify the same emotions in the stimuli that untrained members of the public did. For the emotional cues in the news to matter for public opinion and political behavior, it is necessary that members of the public be able to detect the emotional signals news are providing to viewers. Similar to the "receive, accept, sample" model (Zaller, 1992), if the public does not "receive" emotional cues from the news —if they do not perceive them —it is difficult to make the case that they matter for the study of democracy and politics in the United States.

3.0.2 Measuring Emotion

For the emotional measure, I draw on Affective Intelligence theory (Marcus et al., 2000, 2007; Valentino et al., 2011) which focuses on three emotions: anxiety, anger, and enthusiasm. Affective Intelligence measures are normally used to ask respondents about their feelings regarding politics or political objects, like Congress or the president. The method for measuring these emotions uses multiple survey question to form a scale for each emotion category of anger, anxiety, or enthusiasm. When asking respondents to rate the emotions of the hosts or anchors presenting the news, I provide them with response categories that have previously been shown to load onto the emotional factors of anger, fear, and enthusiasm, respectively, (Marcus et al., 2017) and with sliders for indicating the intensity or absence of each emotion. The slider format has been shown to be more efficient for respondents and more reliable than using survey buttons (Marcus et al., 2017). Though study literature expresses preference is for vertical sliders, survey platform and resource constraints made horizontal sliders more practical.[4] The horizontal slider still allows respondents to quickly rate their response on an intensity scale from 0-10, where 0 indicates the absence of the emotion and 10 indicates maximum intensity. Thus it allows me to capture variation in both the

[4]The quote that I was given to make vertical sliders in Qualtrics was $20,000.

categorization of news text and variation in intensity.

While the measure itself has been shown to reliably tap the latent constructs of anger, anxiety, and an enthusiasm, there are two threats to the measurement of emotions based on using human coders. The first is based on the social identities of the coders. Differences in partisan preferences may lead to differences in how the emotional cues are perceived. The scales provided to an intensity measure may be treated differently based on partisanship. While the network and identity of the anchor is masked in the text, contextual cues like approval or disapproval of certain policies or politicians may indicate the partisan affiliation of the anchor or network to the respondent. Partisans may rate negative emotions expressed by news anchors from the opposing party as more intense than they would rate those same cues when expressed by assumed copartisans. Conversely, they may rate positive emotions more intensely when expressed by assumed copartisans compared to opposing partisans because of their positive feelings towards, and political associations with, the person expressing the emotion. This would result in asymmetries in the rating of the emotions of these anchors and an inability to conduct analyses treating the manifest variables as a measure of the latent construct of emotional cues in the news.

The second threat to inference is that coders may input their own emotional responses to the news they read, rather than their perception of the emotions being felt by the anchor. This concern is based on appraisal theories of emotion and how social contexts can influence the construction of emotional responses to conditions and stimuli (Lazarus, 1991; Frijda, 1993). The construction of emotion is based on automatic responses Moors (2010), and a person's relationship to a political object will help form evaluations and determine subsequent emotional and behavioral outputs (Smith and Ellsworth, 1985; Ellsworth, 2013). Critical to this is the detection of not just the behaviors of others but also their emotions, since the emotions of others compose the political environment. This also means that being confronted with an angry co-partisan may result in different emotional reactions than if one is confronted with angry partisan opposition, depending on how one's automatic processes evaluate the situation (Roseman and Smith, 2001; Van Kleef, 2009). To guard against respondents imputing their own emotions I explicitly tell them that they are reading news transcripts and ask them tell me "the emotion or emotions that the newscaster is feeling." My concern here is that respondent might report their own emotional reactions to the text rather than the emotional cue that the communicator is intending to send. The felt emotions of the respondent are likely influenced by many factors, including the viewer's partisanship, and so there is a need to be explicit about what I am asking respondents to do when reading the text.

It is also possible the differences in the mode of the stimuli that respondents receive to evaluate the emotions of anchors results in differences in the perception and intensity of emotions. The benefit of using text is that it allows the researcher control over the stimuli that respondents are evaluating. While the control exerted here is not the same as in causal experiments, and this research is not making causal assertions, text permits the masking of network and anchor names so that respondents' judgements are less clouded by prior assumptions or affective tags about those objects (Lodge and Taber, 2005). But reading text may make emotions less salient compared to viewing or listening to a news program. This may cause variance in emotion detection and change evaluations in such a way that text is underestimating the intensity of news.

3.0.3 Testing the Use of Human Coders

In my first study *Conceptualizing Emotions: Categorization and Intensity*, I explore whether human coders are able to reliably and validly categorize emotional words using two different survey frameworks. In the first, an emotion word is presented in context and respondents are asked to categorize the word as expressing either anger or fear. In the second, respondents are presented with the categories of anger and fear and asked to place words from a list into the categories. This allows me to test two different ways that respondents might categorize emotions in text and choose the most reliable measure. This is important for testing my theory regarding the differences in emotions in partisan and nonpartisan news environments because if there are not differences in words that have previously been found to be fearful or angry, then evaluations of the news may need to rely on a valence framework. Since the context is also important for the evaluation of emotions, I also vary the context in which the words appear for both frameworks, providing both a political context and a non-political context for evaluation. In a separate task, I also examine whether coders perceive variation in emotional intensity in a transcript. This allows me to test the suitability of the bag-of words frameworks commonly used in the social sciences, specifically the LIWC and LSD; if respondents do perceive variation in intensity, the bag-of-words model is not effective, as it typically assigns equal intensity scores to different words.

The second study, *Partisan Perceptions of Emotional Signals*, analyzes whether the social identity of a coder influences their perceptions of emotions in news transcripts and whether coders are responding with their own emotional reactions to the text instead of identifying the emotions expressed by the newscaster. Building on how categorization and variation in the emotional intensity of words is detected, respondents are given short transcripts and asked to categorize and rate the intensity of the emotions of the anchor delivering the news, with the goal of examining whether there are partisan differences in the evaluation of emotions. This is particularly important for when the anchor in the transcript is assumed to be a partisan opponent of the respondent, since the accurate assessment of both copartisan and out-partisan emotions is critical for linking the emotional environment of the news to the current political environment in the United States.

Finally in the third study, *Audio vs. Text: Differences in Emotion Perception*, I am concerned with the mode in which respondents rate the news. While the first two studies focus on text, it is possible that audio changes perceptions of anchor emotions in type and/or intensity. This study addresses the question of whether the use of text stimuli results in lower estimates of emotional intensity than if respondents were asked to evaluate an anchor's emotions using audio from the same broadcast. Being able to use text is important for my goal of mapping the emotional landscape of the television news environment for practical reasons: Text is a more easily accessible and less computationally intensive than using audio or video. Methodologically, text is also easier to create consistent stimuli with because it allows me to consistently remove cues that could result in inaccurate measures, such as the names of networks or news anchors. However, if emotional cues in text are not as salient as emotional cues in audio of the same broadcast, it may not be possible to map the emotional news environment and thus test my theory regarding the differences between the emotionality of partisan and nonpartisan news.

Each of these studies support my approach to measuring emotions via human coding of text transcripts. The final section of this chapter discusses my framework for measuring emotional cues in the news and describes the sample frame for both networks and human coders that I use to measure emotions in election years from 2000 to 2020 in later chapters.

3.1 Conceptualizing Emotions: Categorization and Intensity

To understand how the public conceptualizes emotionally laden words and how these conceptions may match with current bag-of-words approaches to measurement, I selected 20 words that LIWC associates with either anger or fear/anxiety. These negative categories were selected because differentiating between them is critical: if respondents are not able to differentiate between the negative emotions of anger and anxiety then valence, rather than discrete emotion categories, should be used to examine the emotional output of news rather than discrete emotions. Using words from LIWC allows me to concurrently validate the correct categorization of words and test survey choices.

Using Amazon's Mechanical Turk, I recruited 307 respondents who reported that English is their first language in order to ensure that respondents would be able to understand tasks that involved reading and evaluating text. Participants were randomly assigned to one of four survey conditions to determine if the context of emotional words and the way in which words are sorted influences accuracy. The conditions involved either a political or non-political context for evaluating words, which measured whether small contextual changes influence the interpretation of emotion; and one of two methods for respondents to sort emotional words. In the text selection conditions, respondents were either asked to place one of the 40 LIWC words into the categories of anger, fear, or the text-entry category of other (hereafter referred to as the Category condition), or were presented with the word anger or fear and then asked to select all words in a random subset of the 40 LIWC words that correspond with each word (hereafter the Word Choice condition).

For all conditions, respondents read about a speaker identified as 'Carl,' who expressed his feeling about what was going on in one of two types of rooms: a classroom (non-political context) or a city council meeting (political context). These contexts involve similar norms when speaking, e.g., waiting for a turn, talking when called upon, not interrupting, but a city council meeting is political in nature and a classroom is not necessarily so.

Respondents were able to select more than one option for each question in each condition, so that accuracy and completion could be examined based on whether or not participants placed an emotion into a superset (anger, fear, or other) or selected emotion terms that might be subsets of the target emotion. Examples of the Categorization and Word Choice conditions are available in the appendix. No additional information was given about Carl, e.g., where he lives, his political beliefs, in order to avoid evaluations of Carl as a member of an in-group (out group) that respondents (do not) identify with in their personal lives (Mackie and Smith, 2018).

After completing the categorization task, all participants then rated the 40 words they had previously encountered on an emotional intensity scale for either fear or anger. Participants viewed a set of 5 of the 40 words at a time in a question block, where word assignment and block order was randomized.

3.1.1 Results

The sample was collected in March 2019. The majority of the sample population were women (57%, n=175), identified as white (82%, n=251), and had a college education (91%, n=278). Additional demographic information is available in the Appendix. Random assignment into the text selection and context stimuli was roughly even. Table 3.1 displays the number of participants assigned to each text selection and context category. Full tables for all results are available in the Appendix.

Table 3.1: Number of Participants in Each Condition Context and Text Selection Condition

Context	Text Selection	
	Category	**Word Choice**
Non-Political	76	78
Political	72	81

3.1.2 Categorization vs. Word Choice Task

To concurrently validate how respondents perceived the emotional value of words, I compared how closely their assignment of words, either through categorization or word choice, matched the LIWC's assignment of those words. Respondents in the categorization condition were almost twice as accurate as those in the text selection condition, correctly categorizing the words according to LIWC about 68% (sd = 0.47) of the time compared to the 39% (sd = 0.49) accuracy of those in the text selection task. This difference is statistically significant ($p < .001$)[5]: respondents are much better at placing a word into an overarching emotional category than being presented with an emotional category and selecting words that belong in the category.

3.1.3 Political vs. Non-Political Context

Since the LIWC dictionary is based on psychological emotions and not emotions in a political context, I analyzed whether a political or non-political context affected how accurately respondents placed a word into the correct LIWC category. Those assigned to the political context correctly categorized the words 52% (sd =0.50) of the time, while those in the non-political context correctly categorized the word 54% (sd = 0.50) of the time. While the difference in categorization based on context is statistically significant ($p < .001$), we might expect these results given the LIWC dictionary was compiled based on the usage of words in a physical and psychological health context - a non-political context - (Tausczik and Pennebaker, 2010) and not a political context. What these results indicate is that context matters—though likely at the margins substantively—when

[5]Results obtained via t-test. A full reporting of the results can be found in the Appendix

identifying emotions.

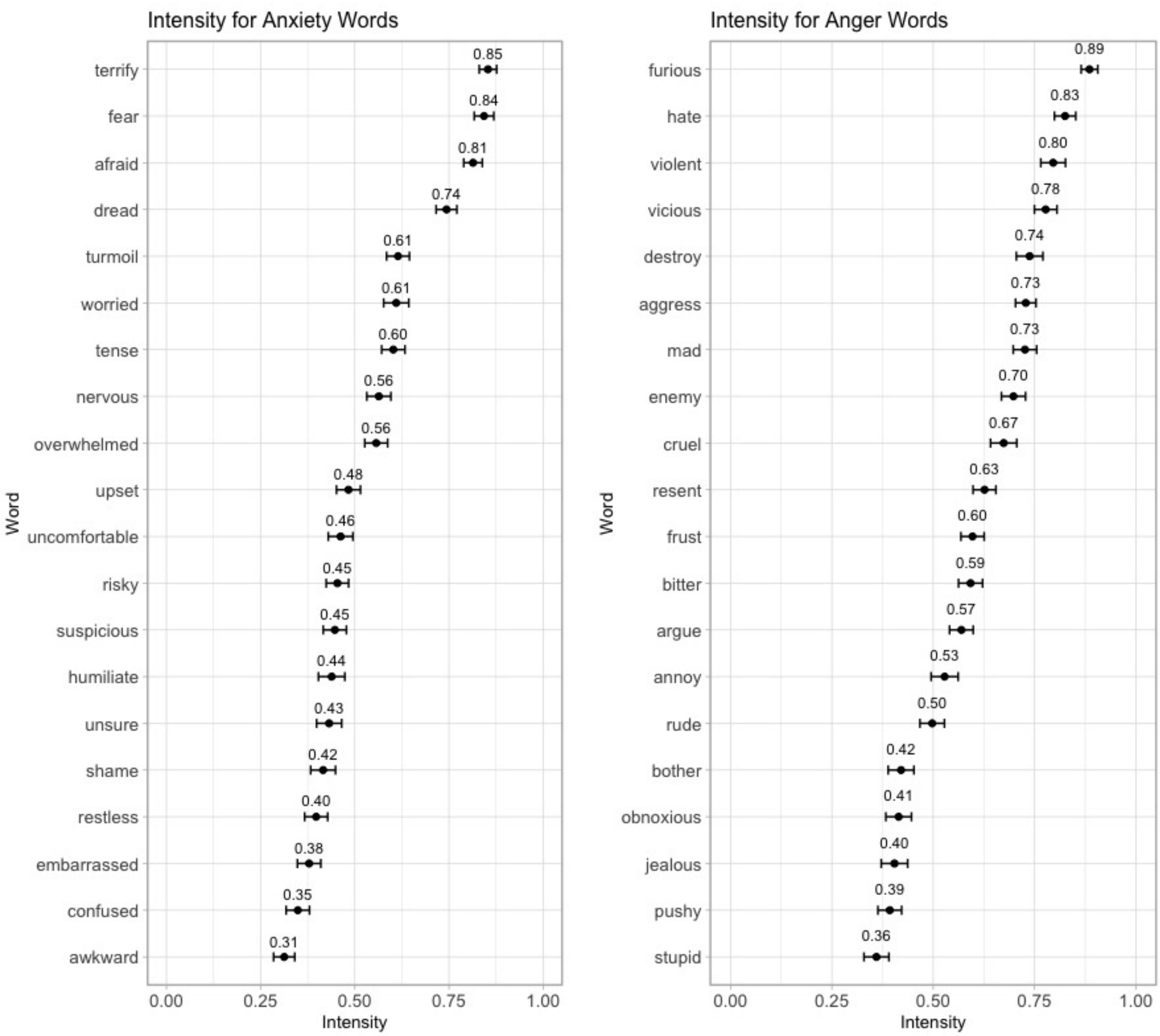
Since the categorization task had a higher level of accuracy compared to the word choice task, I also evaluated whether the influence of context was reduced if I restricted the analysis to only those respondents who completed the categorization task. Those who were assigned the non-political, categorization correctly sorted words into the LIWC categories 70% (sd = 0.46) of the time while those in the political categorization task were accurate 65% (sd = 0.48) of the time.

3.1.4 Intensity Measures

I used the final task to determine whether respondents perceive the words in the anger and fear sets as indicative of different emotional intensities. Respondents were told to rate each anger or anxiety word on a scale from 0-100, with 0 being the least intense and 100 being the most intense. The ratings were then re-scaled to be between 0-1. Figure 2.1 displays the mean intensity ratings for anxiety (a) and anger (b).[6] The most intense anxiety word is terrify, with a mean of 0.85 (sd = 0.21) while the least intense anxiety word is awkward (m=0.31, sd = 0.25). The means of the intensity of the anger words also vary substantially (Figure 2.1 a) from the highest intensity word being furious, with an intensity rating of 0.89 (sd = 0.18), least the least intense word being stupid (m = 0.36, sd = 0.27).

[6]A table of the intensity ratings is also provided in the Appendix

Figure 3.1: Ratings of Word Intensity for Anxiety and Anger



(a) Anxiety

(b) Anger

3.1.5 Conceptualizing Emotions Discussion

This initial study suggests that respondents are able to do a fairly good job of accurately placing emotional words into LIWC categories so long as they are selecting the overarching emotional category in which a word belongs. As anticipated, accuracy is enhanced when the context of the more closely matches the original training texts that were used to construct the bag-of-words dictionary. Here, this means that non-political context allows for greater categorization accuracy than the political context. However, while the differences are statistically significant, respondents receiving the political context scenario only perform 5 percentage points worse: those in the political context were still able to correctly categorize emotion words.

The intensity of emotion expressed in different words also varies within both the anxiety and anger sets. Respondents do perceive variation in emotional intensity, making the words not interchangeable. This should not be thought of as a blow against bag-of-words, but, an indicator that reducing variation in measurement may hide important emotional findings, particularly when researchers are concerned about discrete emotions rather than valence.

3.2 Partisan Perceptions of Emotional Signals

To analyze how respondents might rate various news shows, I sampled the highest rated weeknight evening news show for ABC, MSNBC, and Fox from August 1, 2018 until the end of January 2019.[7] These networks were selected because they represent non-partisan news (ABC) and the respective Republican (Fox) and Democratic (MSNBC) partisan networks. This allows me to analyze how co-partisans or oppositional partisans rate emotional cues from out/copartisans cable anchors and from non-partisan news sources and whethere there are differences in perception of the emotional cues of news based on respondents' partisan social identities.

The highest rated news programs were selected because they have the most viewers; progams with larger audiences may have greater impacts on political behavior than lesser watched program-

[7]This sample encompasses the six months prior to and during a shutdown of the United States government.

ming. The three news programs analyzed are *World News Tonight* with David Muir on ABC, *The Rachel Maddow Show* on MSNBC, and *Hannity* on Fox and all transcripts were retrieved from Lexis Nexis; hereafter the shows will be referred to by their respective network names.

To ensure thorough coverage of news content, I constructed a week of weeknight news for each program via random sampling without replacement. Each show consists of multiple segments, my unit of analysis, which are defined as sections of a show that are either between commercial breaks or start or end the news program. Each show under examination has a different number of segments per episode—ABC, 4; Fox, 5; and MSNBC, 6. To construct the sample, the number of segments in each respective show was multiplied by 5 (i.e., five weeknights), resulting 20 segments for ABC, 25 segments for Fox, and 30 segments for MSNBC. The number of episode transcripts equal to the number of segments was randomly drawn from the set of shows for each network during the six-month period; each transcript was assigned to a segment. This created a total of 75 segments for respondents to rate. For consistency, the text used as the segment frame was limited to 125 words or less; some frames contained the host uttering as few as 14 words before a guest or another host began speaking. Each transcript had identifiers such as host and network redacted, to reduce the possibility that respondents would assess the texts on the basis of prior ideas about the host or network, and was edited for clarity.

Respondents were each randomly assigned 4 of the 75 segments; the target of each survey question was the emotional intensity of the speaker, the news anchor who had read the news text with which respondents were provided. Ratings were accomplished with horizontal sliders from 0-100, with 0 indicating that the host is did not feel the emotion listed and 100 indicated the host was intensely feeling that emotion. Respondents rated how *Angry/Frustrated*, *Anxious/Concerned*, or *Enthusiastic/Hopeful* the anchor was feelings. (Hereafter, these emotion pairs will be referred to as Anger, Anxiety, and Enthusiasm). After they rated the transcripts, respondents were asked to provide their party identification, ideology, age, race, gender, and level of education.

3.2.1 Results

To test how partisan identification may influence emotional perceptions, 150 respondents recruited through Amazon's Mechanical Turk were surveyed using TurkPrime in July 2019. The sample stratified evenly by Democratic and Republican party identity. Of the 150 respondents that completed the survey, 110 were kept based on length of time to complete the survey: respondents in the lowest quartile in terms of time, those who took approximately 7 minutes (420 seconds) or less, were dropped from the sample. This resulted in a sample that is 44% Democrat (n=49), 50% Republican (n=55), and 5% Independent (n=6). Ideologically, 44% of respondents identify as liberal (n=49), 47% identify as conservative (n=52), and 8% identify as moderate (n=8). The average age of respondents is 43, with a median age of 41. A majority of the sample has a college degree (53% , n=58) and identifies as white (73%, n=82). Men and women each compose 50% (n=55) of the sample. Additional demographic information can be found in the Appendix.

3.2.2 Pooled Partisan Analysis

Figure 3.2: Partisan Pilot Study on Text and Emotions

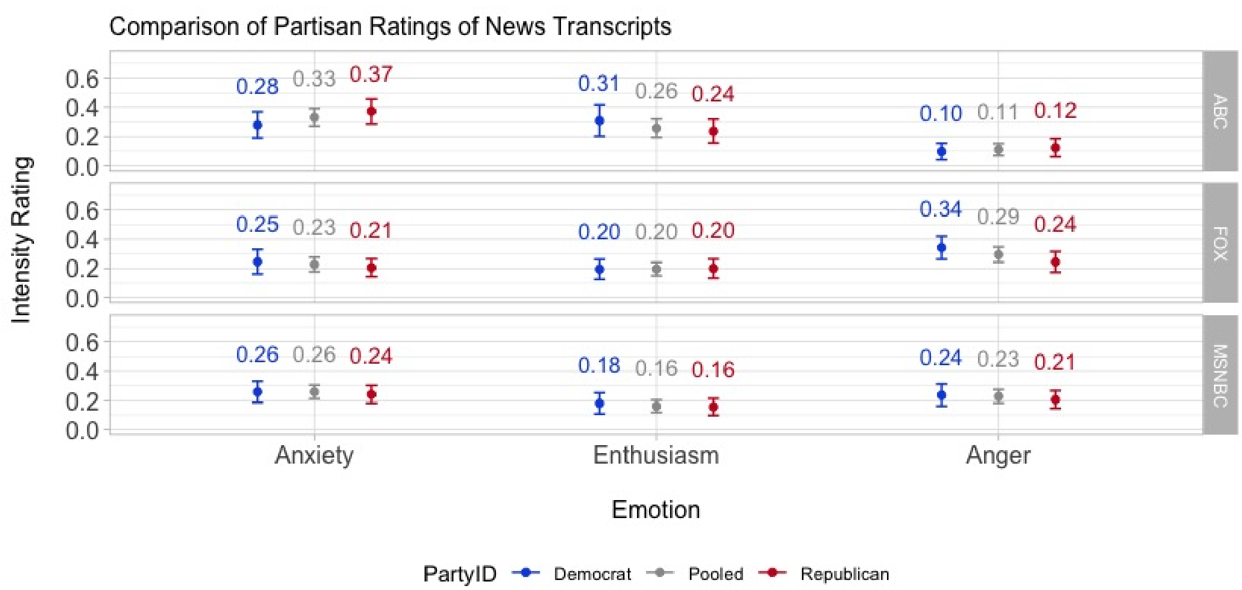


Figure 3.2 presents the results of the perceptions of emotions for partisan respondents and the

pooled, overall results, with error bars representing 95% confidence intervals. The point estimates for the means are also listed in Figure 3.2. Starting with the leftmost column of Figure 3.2, difference in means tests reveals no statistically significant differences between partisan groups in the perception of anxiety. While the point estimates for ABC have the largest partisan difference in the intensity of anxiety, the means are not statistically distinct between Democrats (m=0.28) and Republicans (m=0.37) ($p = 0.13$).[8] The main concern this study addresses is that partisans may read transcripts from networks associated with the partisan opposition and have differences in perceptions of emotional intensity, particularly with regard to emotions that are subsequent to the perception of threat. Anxiety fits that bill —and there was the possibility that when viewing partisan stimuli, respondents would either use different parts of the scale based on their feelings about the stimuli or respond with their own emotional evaluations. In measures of anxiety detected in text from Fox, Democrats and Republicans do not differ in their assessment ($p = 0.43$). They also do not differ when perceiving anxiety in text from MSNBC ($p = 0.72$).

Evaluations of enthusiasm among the three networks also do not differ for partisans. Democrats (m=0.31, sd=0.38) and Republicans (m=0.24) do not differ in their evaluations for ABC ($p = 0.29$); Democrats (m=0.20) and Republicans (m=0.20) do not differ in their evaluations for Fox ($p = 0.92$); nor do Democrats (m=0.18) and Republicans (m=0.16) differ in their evaluations of enthusiasm on MSNBC ($p = 0.61$).

Finally, the evaluations of anger do not differ among partisans. Again, the concern was that perception of threat could provoke different evaluations or that respondents might substitute their own emotional responses for the evaluations of the emotions in the news. Neither concern was an issue. Similar levels of anger were perceived by partisans when evaluating ABC ($p = 0.53$), Fox ($p = 0.07$), and MSNBC ($p = 0.54$). Of the comparisons, perceptions of anger on Fox come the closest to being separate for partisans, as it just misses statistical significance at the 0.05 level.

[8]Results obtained via t-test. A full reporting of the results can be found in the Appendix

3.2.3 Discussion: Partisan Perceptions of Emotional Signals

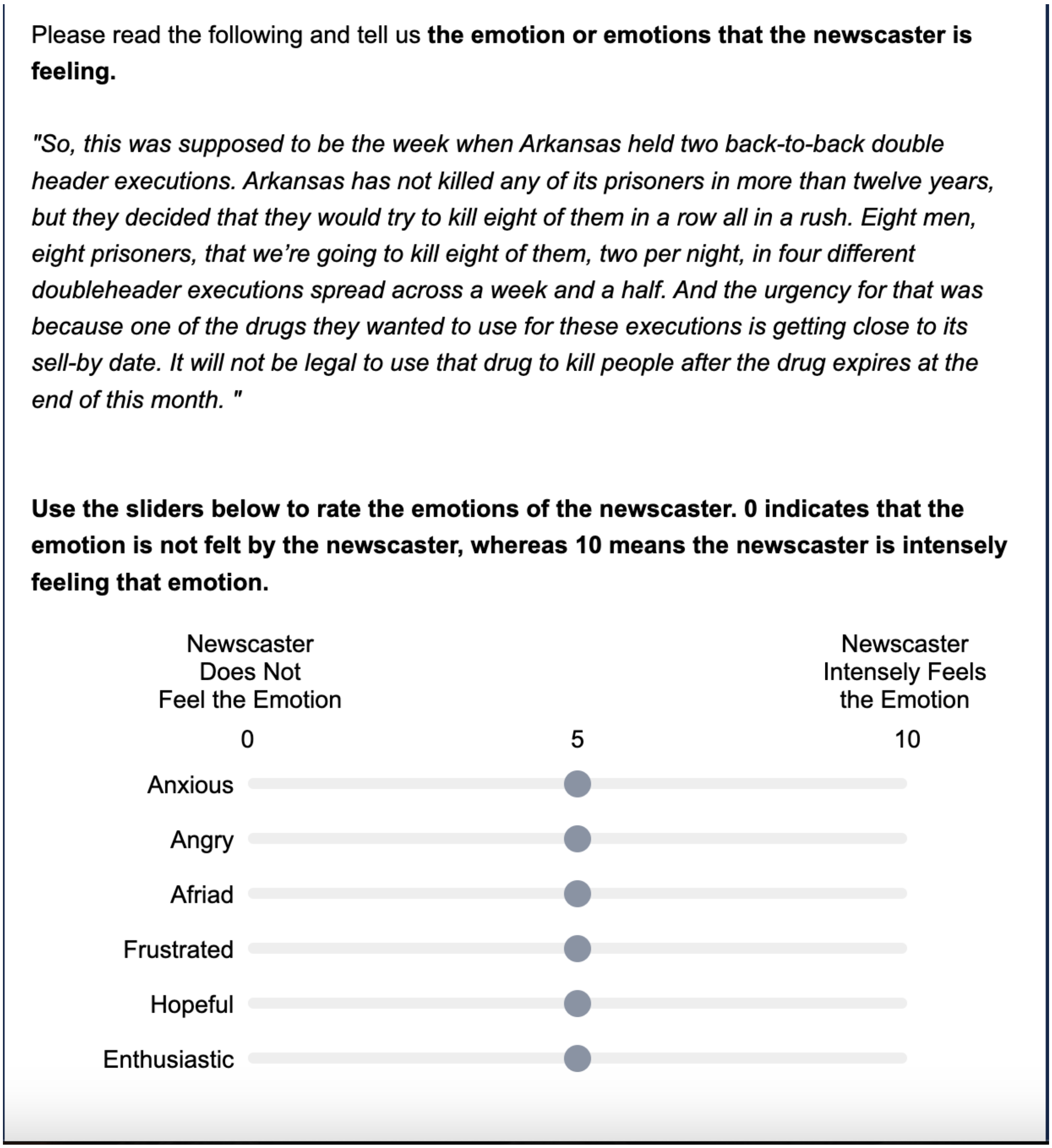
This study examined whether there are partisan differences in the emotional evaluations of news, seeking to address concerns that social identities could lead to differences in the scoring of emotions in text. This stems from a concern that respondents might either use the scales provided in different ways or may substitute their own emotional responses to the stimuli rather than providing evaluations of the anchor's emotions. This could have been especially troublesome, as social identity can affect how respondents appraise situations (Ellsworth and Smith, 1988). However, respondents' scores did not differ in a statistically significant way when evaluating the news transcripts. Across the three networks used as stimuli - ABC, Fox and MSNBC - respondents evaluated and the emotional categories of anger, anxiety, and enthusiasm, respondents were consistent in their evaluations across partisan lines. The evaluation of emotions in the news does not appear to depend on the partisanship of the respondents, even when respondents are provided with partisan stimuli. Partisans consistently rate the emotions of politically congruent and incongruent stimuli similarly, regardless of their partisan identities. If partisans were instead imputing their emotional responses to the stimuli, I would expect to see variation in how they rate the emotions in the text. Particularly when rating either Fox or MSNBC. But differences are not present in this study. Overall, partisans appear to consistently rate the emotional cues provided in text in a way that is not contingent on their paritsan identification.

3.3 Audio vs. Text: Differences in Emotion Perception

The final threat to inference when having respondents evaluate text for emotional cues is that text-only presentation, compared with audiovisual presentation, may dampen emotional evaluations. To test this, I compare audio and text from the same news programs for ABC, NBC, CNN, Fox, and MSNBC. These networks were selected because they represent a full range of partisan and non-partisan networks. ABC and NBC are representative of the non-partisan, objective news norms of the 20^{th} century. CNN, Fox, and MSNBC represent the up-start cable news, and particularly partisan news, that began in the late 1990s. Variation in partisanship is also represented in these cable networks, with Fox representing a Republican news source and MSNBC and CNN representing Democratic news sources.

To further capture variation in emotions, respondents were asked to rate the intensity of the six emotions, which are then able to be scaled into the three emotional categories that compose Affective Intelligence theory - anxiety, enthusiasm, and anger (Marcus et al., 2000; Valentino et al., 2011; Brader, 2006). Figure 3.3 is an example of the text stimuli with the response options that were presented to participants. The order of the emotions was randomized for each text and audio evaluation. The *anxious* and *afraid* responses form the scale for anxiety, the *angry* and *frustrated* options form the scale for anger, and the *hopeful* and *enthusiastic* options form the scale for enthusiasm.

Figure 3.3: Example of Stimuli and Survey Response Options for Validating Audio and Text



Please read the following and tell us **the emotion or emotions that the newscaster is feeling.**

"So, this was supposed to be the week when Arkansas held two back-to-back double header executions. Arkansas has not killed any of its prisoners in more than twelve years, but they decided that they would try to kill eight of them in a row all in a rush. Eight men, eight prisoners, that we're going to kill eight of them, two per night, in four different doubleheader executions spread across a week and a half. And the urgency for that was because one of the drugs they wanted to use for these executions is getting close to its sell-by date. It will not be legal to use that drug to kill people after the drug expires at the end of this month. "

Use the sliders below to rate the emotions of the newscaster. 0 indicates that the emotion is not felt by the newscaster, whereas 10 means the newscaster is intensely feeling that emotion.

For audio samples, SoundCloud players containing the audio for each program were embedded in the survey pages. All text and audio segments were chosen at random from content that aired on prime time news in 2017, with each network having three segments rendered in text and in the corresponding audio.

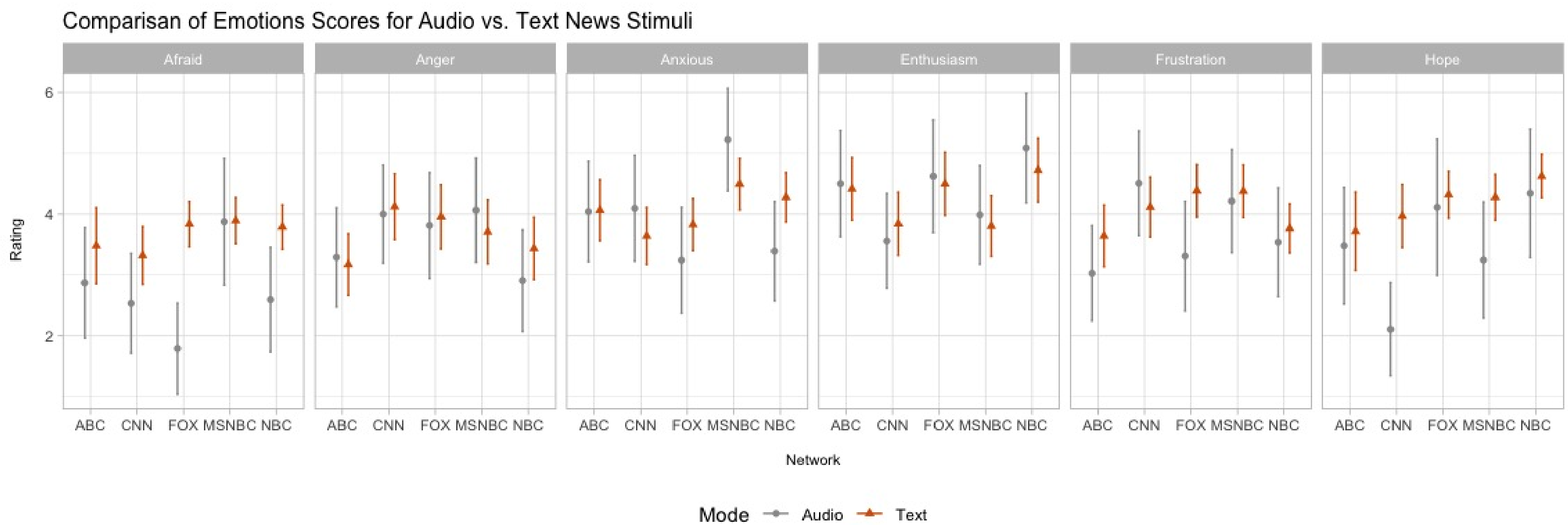
Respondents were randomly presented with five short pieces of text (max. 125 words) and three audio files that correspond to the text. The ratio for text and audio stimuli is uneven because this data collection was embedded in another pilot study; additional text stimuli that did not have corresponding audio were included in the survey. This design choice had the advantage of making it less likely that respondents would receive text stimuli that corresponded to the audio they received during the survey. Respondents rated the emotional intensity of the host on a scale from 0-10, where 0 indicates that the host was not feeling the provided emotion and 10 indicates that the host was intensely feeling that emotion.

3.3.1 Results

Data for evaluating the differences in the perception of emotions in text compared to audio was collected in Spring of 2021 using a CloudResearch sample that was split between Republicans and Democrats. Respondents who took less than five and more than sixty minutes on the survey were removed from the analysis. This resulted in a sample of 276 respondents. The majority of the sample do not identify as male (including respondents who identify as non-binary, n=151, 56%) and have attended college (n=157, 57%). The sample is almost evenly split between Democrats (n = 134, 48%) and Republicans (n=138, 50%), with a small percentage of the sample identifying as Independents (n=4, 1%). Additional demographics for this study can be found in the appendix.

While each network had three unique segments for mode comparison, I pooled results by network for ease of data presentation. Figure 3.4 presents the point estimates and 95% confidence intervals for each network and emotion based on mode, with each of the six emotions analyzed. Point estimates, standard errors, and results of Welch's t-test for each comparison can be found in the Appendix.

Figure 3.4: Comparison of Text vs. Audio News Evaluations



My initial concern that respondents might perceive much higher emotional intensity in audio than in the text transcripts appears unfounded. Of the 30 comparisons, differences between audio and text were statistically distinct at the 0.05 level only on four occasions: evaluations of expressed fear (”afraid”) on Fox and NBC and of hopefulness on CNN and MSNBC. If a Bonferroni correction is used on account of multiple testing, taking account testing within each emotion category, only the emotions of fear on Fox prior to correction, the difference was because the audio was rated as being *less* intense than the text.[9]

3.3.2 Discussion: Audio vs. Text: Differences in Emotion Perception

Initial concerns about evaluations of emotional intensity based on mode are unfounded. While there was concern that using text to measure emotions in news might lead to very different measures of emotional intensity due to salience, this was not the case. Respondents generally evaluate text and audio similarly, alleviating concerns that differences in stimuli would result in potentially biased measures of the emotional landscape. Where I do find differences, they are an inversion of my predictiction: when there is a difference, text is rated as being more emotionally intense than audio. I am not underestimating perceived emotions by evaluating text rather than audiovisual segments.

[9]This comparison falls away completely if testing is done individually for each text-audio pair and a Bonferroni correction is applied. These results are also available in the Appendix.

3.4 A Framework for Measuring Emotional Cues in the News

Human coders are able to reliably categorize emotional cues in text and perceive differences in the intensity of emotionally laden words. How people score the emotionality of text changes based on the context in which emotionally laden words are presented to them. The categorization of emotional cues is influenced by partisan predispositions: Democrats and Republicans identify similar levels of emotion. And modal differences between text and audio are not a concern. Audio does not appear to make emotional cues more salient compared to text, so text is a reliable option for measuring the emotional cues in partisan and nonpartisan news.

While this lends credibility to the process I use to have human coders rate the emotional cues in news transcripts, equally important are the sampling strategies, the construction of stimuli, and construction of the emotional measures that I use for this project.

3.4.1 Sampling Strategy for Networks, News Transcripts, and Respondents

In sampling news programming from various partisan and nonpartisan networks, I designed the samples to ensure adequate coverage of both partisan and nonpartisan news and adequate political representation for partisan news sources. I targeted weeknight news programming, since the programming format for nonpartisan weeknigh news has been consistent since prior to the rise of 24-hour news networks on cable television (Starr, 2004). The cable networks I selected are Fox, representing Republican-slanted news, MSNBC, representing Democratic-slanted news, and CNN, as it was the original 24-hour news network.

For nonpartisan networks I sampled from ABC and NBC. I sampled from ABC because it has consistently broadcast the most watched network evening news program (Johnson, 2022) and its weeknight evening news program has been on television since the 1940s (Starr, 2004). I selected NBC because its weeknight news is the second most frequently watched by American audiences (Johnson, 2022) and because the cable network MSNBC is an offshoot of NBC. This allows for comparison of the potential differences in the emotionality of partisan and non-partisan channels owned by the same corporation.

For the transcript sampling frame, I constructed two weeks of news for each network during election years from 2000 to 2020. I start in 2000 because LexisNexis begins its coverage of MSNBC transcripts with that year. To construct the two weeks of news, the number of segments in each program was multiplied by 10, representing two weeks of prime time news. Then dates were randomly drawn equal to the number of segments in a two week period per election year per show. The selected weekday calendar dates were then randomly assigned to segment numbers. This resulted in two random weeks of news per network per year. Table 3.2 displays the number of segments for each network for this analysis, as well as the total number of segments completed over the course of the project.

Human coders were sourced through CloudResearch's verified respondent pool to ensure data quality. For the collection of the 2000 to 2008 data, I used CloudResearch's Connect platform and for the 2010 to 2020 data I used CloudResearch's TurkPrime platform. Both allowed me to select coders that had been verified and to block suspicious and duplicate IP addresses. The coders that I used are not representative of the US population, as people who watch television are not representative of the US population —in 2020 about 68% of the population watched television news (Forman-Katz and Matsa, 2022), and in 2013 65% of adults watched network news and 38% of adults watched cable news (Jurkowitz and Mitchell, 2013). While partisan affiliation does not appear to affect respondents' ratings of emotional content in the news, I still split my sample evenly among Democrats and Republicans to allow for future testing of differences that might occur among coders. [10]

The large number of segments meant that collection of data was done over multiple surveys. Using the Qualtrics platform, I created 40 surveys of segments for respondents to code. The 20 surveys for segments in national election years from 2010 to 2020 were collected between March 2022 and January 2023 and the survevys for national election years from 2000 to 2008 were collected in Spring of 2023. Respondents were not initially allowed to participate as coders

[10]In the final chapter I discuss future research which focuses on further contextualizing the emotional signals in the news.

more than once, but in some later surveys respondents were allowed to participate again because of a dearth of Republican coders. Assignment of transcripts to coders was randomized within each survey to ensure that coders were not receiving transcripts from only one type of news program. Coders were also asked for demographic and news watching habits after they completed the coding tasks, both to record the demographics of the sample and to verify consistency in party and gender identification; those who were inconsistent were excluded from the analysis.

Table 3.2: Number of Segments per Program per Year Included in Sample

			Year Broadcast										
Network	Show Name	Segments	2000	’02	’04	’06	’08	’10	’12	’14	’16	’18	2020
ABC	World News Tonight with Peter Jennings	4	X	X	X								
ABC	World News with Charles Gibson	4				X	X						
ABC	ABC World News with Diane Sawyer	4						X	X				
ABC	ABC World News Tonight with David Muir	4								X	X	X	X
CNN	Larry King Live	8	X	X									
CNN	Anderson Cooper 360	5			X	X	X	X	X	X	X	X	X
Fox	The O’Reilly Factor	7	X	X	X	X	X						
Fox	Hannity	5						X	X	X	X	X	X
NBC	Nightly News	4	X	X	X	X	X	X	X	X	X	X	X
MSNBC	The News with Brian Williams	6	X										
MSNBC	Hardball	6		X									
MSNBC	Countdown with Keith Olbermann	6			X	X	X						
MSNBC	The Rachel Maddow Show	6						X	X	X	X	X	X
Total Segments From 2000-2020: 2800													

3.4.2 Construction of Stimuli

The program host's first words at the beginning of the segment were used as stimuli. Each introductory text is up to about 125 words —some texts were a few words more so that context was not lost, and some were shorter because the host stopped talking to cut to video, a guest, or a reporter in the field. This methodological choice was made because of the professional journalistic norm, first established in 19th century newspapers, that the most important information should be immediately provided to audiences (Po¨ttker, 2003). Additionally, the most important information should also co-occur with the immediate expression of emotional cues from news anchors and hosts, since the broadcasting of information and emotional cues should happen concurrently.

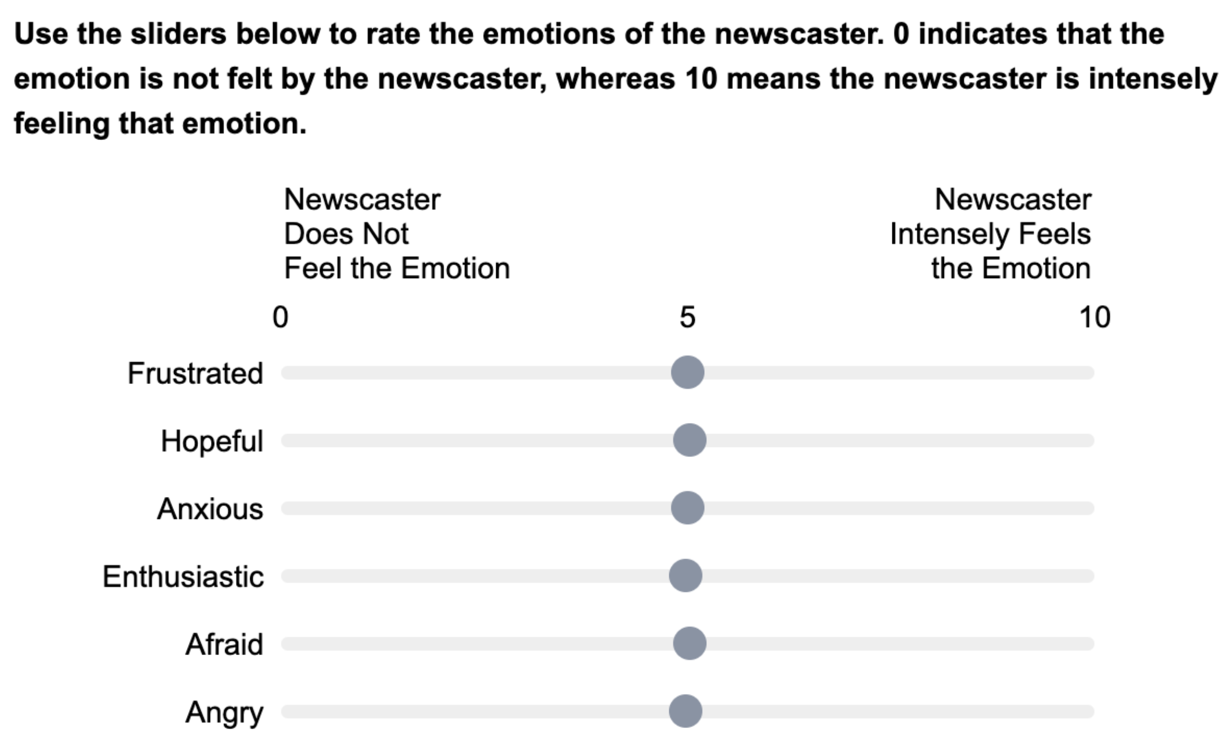
Collection of the first part of each segment varied based on the quality of the formatting of the news transcripts. Whether or not commercial breaks were explicitly identified in a transcript varied both by network and year, often requiring me or research assistants to manually insert commercial breaks into transcripts. For example, transcripts for Fox News often denoted the commercial break and included time stamps in their transcripts based on segments. If the transcripts for a single Fox were in multiple documents, the order of the documents and the location of commercials was apparent. Transcripts for ABC and NBC often did not have time stamps, and the complete transcript for a single episode was broken up into documents by topic, rather than segment. I used a variety of methods to reconstruct a program segments in the order they aired. Occasionally I could swap a poorly formatted LexisNexis transcript with one from a network's website. When this was not possible, I or research assistants used the Internet Archive to find video of news programs that aired after 2010 and match commercial breaks in the video tothe transcripts. The Vanderbilt News Archive was used to find the commercial location for news prior to 2010; it was particularly useful for ABC and NBC transcripts.

Once commercial breaks were identified for each transcript, the text of each news segment in the sample was copied and edited for length and clarity; many of the transcripts were automatically generated andcontained errors. During the editing process, identifying information, e.g., the name of the program, the host of the program, the network the program aired on, was removed from the transcript. This was completed for 2800 transcripts, which represented programming that aired between 2000 and 2020.

3.4.3 Construction of Measures of Emotions

In identifying an anchor's emotions, respondents were able to choose from a list of six: angry, enthusiastic, anxious, frustrated, afraid, and hopeful. These measures were selected based on their use and validation in previous emotions research taken from (e.g. Marcus et al., 2017; Valentino et al., 2011). The presentation of these emotions was randomized. Respondents were then able to rate the intensity of each emotion on a scale from 0 to 10, where 0 indicated that the newscaster was not feeling that particular emotion and 10 indicated that the newscaster was intensely feeling that emotion. An example of the presentation can be seen in figure 3.5.

Figure 3.5: Example Response Options Using Human Coders to Rate the Emotional Cues in News



The dependent variables of emotional intensity and frequency are formed by taking the emotional response options and scaling them into the larger categories of anxiety ($anxious + afraid$), enthusiasm ($enthusiastic + hopeful$) and anger ($anger + frustrated$). Each emotional category is then converted to range from 0 to 10. However, because 0 indicates the absence of emotion, which is qualitatively important, the measure for emotional intensity is truncated to range from .5 to 10. This allows me to measure both when an emotion is present and how intensely respondents perceive emotions that are present for each type of news. The measure for the frequency of emotion is binary. The absence of emotion is indicated by 0. If an emotion category had a value between 0.5-0.99, it was converted to a value of 1 for the emotional frequency variable, making the frequency of emotion variables indicative of whether or not the newscaster was observed to be expressing each emotion.

3.5 Conclusion

Through the testing of concurrent validity with some of the anger and anxiety words in the LIWC dictionary, and evaluation of how context makes a difference in how words are emotionally categorized, I am able to show that context does appear to make a difference in how coders evaluate the emotional categories for words. Further, words that would be considered interchangeable under a bag-of-words framework are perceived as having differing intensities by respondents. This indicates that important information about valence is missed when relying only on the frequency of words.

Additionally, partisans tend to score the same stimuli in the same way, agreeing on the intensity and categorization of emotional cues in the news. This occurs even when partisans encounter stimuli that is incongruent with their political identity. The media format does not seem to cause differences in rating the intensity of emotional cues: while I was concerned that text would decrease the salience of emotional cues from news anchors, ratings are generally similar to when respondents listened to audio of an identical newscast.

These studies inform the methodological framework for my construction of text stimuli for human coders; I redact text that would allow coders to explicitly identify which network the text came from and remind coders throughout the survey that they are to rate the emotions of the *newscaster,* rather than their own feelings. The studies also inform how I construct my measure of emotion. Rather than a binary variable for the presence of an emotion, respondents are provided with a scale that allows them to mark whether an emotion is absent (0) and to rate the intensity of an emotion if it is present. This framework allows me to capture two potential variations in the emotional cues in news over time: frequency and intensity.

I use this framework to measure the emotional cues in partisan and nonpartisan news throughout the rest of this dissertation. It is used in Chapter 4 to evaluate changes in the emotional cues in the partisan news environment after Fox and MSNBC joined CNN on cable television. I then use the framework in Chapter 5 to evaluate if the presidential candidacy of Donald Trump may have changed the emotional landscape of the news or if the emotional environment of partisan news was more likely harnessed by a unique presidential candidate.

CHAPTER 4

The Reemergence of Emotion in the American News Environment: 2000-2008

4.1 Introduction

In this chapter I analyze emotional cues in news for election years from 2000-2008 in order to interrogate both the overall differences between partisan and nonpartisan news and changes to the media landscape over that time period. This allows me to test how the entry of Fox and MSNBC in to the cable marketplace correlates with changes to the emotional landscape of the news. Fox's journalistic philosophy of providing a specific, conservative perspective on the news differed dramatically from the journalistic norms of objectivity and balanced coverage to which the professional journalists on CNN adhered (Ponce de Leon, 2015; Schonfeld, 2001). And while MSNBC started with the same news philosophy as CNN, its introduction of more partisan prime time programming in 2004 marked a shift for the network. Alongside a shifting MSNBC, and amid growing ratings competition from Fox News, CNN also become more partisan over this time. These shifting dynamics should not only result in changes in the emotional signals of partisan news, but inform my expectations for the emotional environment of nonpartisan news as well.

I argue that the emotional signature of partisan news is anger. Since the news is biased towards reporting negative information (Soroka and McAdams, 2015), a greater prevalence of anger within partisan news should also correspond with decreases in anxiety. Conversely, because nonpartisan news does not engage in certainty, blaming, or attacking the opposition, which are all appraisals for anger (Frijda, 1986; Moors et al., 2013), nonpartisan news should have higher anxiety than its partisan news counterparts. And while partisan news likely cheers on its copartisans, the nonpartisan news tradition of a happy "kicker" segment (Soroka and Krupnikov, 2021) that provides viewers with uplifting stories in the program's final segment should also result in greater enthusiasm in nonpartisan news than partisan news. I test these suppositions with three sets of hypotheses.

In the first section, I test the overall emotional differences between partisan and nonpartisan within the time period. Partisan news should have overall higher levels of anger than nonpartisan news, in both intensity and frequency. Not only will partisan news be more intensely angry, but partisan networks will signal this intense emotional anger to their audience more frequently than nonpartisan news.

H_1: Partisan news will have more intense and more frequent anger than nonpartisan news.

The overall emotional difference in anxiety between partisan and nonpartisan news will demonstrate the opposite relationship. Nonpartisan news will have much higher anxiety in both frequency and intensity than partisan news because of its commitment to objectivity and unbiased presentation of both sides of issues.

H_2: Nonpartisan news will have more intense and more frequent anxiety than nonpartisan news.

Because the time that a program is being broadcast is constant, more anger cues should also result in less anxiety cues from partisan networks. This anger offset should result in less frequent anxiety within partisan news compared to the frequency of anger.

H_3: Anxiety should be less frequent for partisan news than anger.

Additionally, the inspirational kickers for nonpartisan news should result in greater enthusiasm in nonpartisan news compared to partisan news. This should manifest both in the intensity of enthusiasm and its frequency.

H_4: Nonpartisan news will have more intense and frequent enthusiasm than partisan news.

In the second section of this chapter I test the changes in the emotional signals of partisan news from 2000 to 2008. Within cable news, I anticipate that the addition of more partisan content by MSNBC and changes to CNN's lineup should result in increasing anger for partisan news from

2000-2008. Along with this increasing anger should be reductions in anxiety: if channels are producing more anger during a program with a set airtime, this should result in reductions in the amount of anxiety that they broadcast.

H_5: Anger, in both intensity and frequency, will increase for partisan news over time.

H_6: Anxiety, in both intensity and frequency, will decrease for partisan news over time.

While I also expect that nonpartisan news will be more enthusiastic than partisan news, I expect the overall levels of enthusiasm will be maintained, since negative emotions are what engage citizens' attention with the news (Soroka et al., 2019).

H_7: Nonpartisan news will maintain higher levels of enthusiasm than partisan news over time, but the level of enthusiasm will remain constant for both partisan and nonpartisan news.

Finally I examine the changes between the partisan news networks. Because of Fox's founding philosophy of providing a conservative perspective, I anticipate that changes in the emotional intensity and frequency of anxiety and anger will occur mainly on CNN and MSNBC. Fox News should have more anger than MSNBC and CNN but maintain its levels and frequencies of anger over the time period.

H_8: Fox will have more intense and frequent anger than CNN and MSNBC in 2000.

H_9:The intensity and frequency of anger will increase for both CNN and MSNBC from 2000-2008.

Changes in anxiety should follow changes in anger. The levels of anxiety in MSNBC and CNN should decrease due to my theorized anger offset. I also anticipate that as CNN's prime time lineup changes from *Larry King Live* to Anderson Cooper's more news-focused program, the levels of enthusiasm will decrease for CNN from 2000-2008. But I anticipate that levels of enthusiasm for Fox and MSNBC will remain constant.

H_{10}: The intensity and frequency of anxiety over time will decrease for CNN and MSNBC.

H_{11}: The frequency and intensity of enthusiasm will decrease for CNN over time.

4.2 Results

Twenty survey waves were fielded in the Spring of 2023 using CloudResearch's Connect platform. Respondents were randomly assigned 6 text segments in which to rate the emotionality of the news anchor. Each segment was rated at least 9 times, and a total of 1360 segments were rated by 2314 unique respondents.[1] All respondents were asked "How often did you give a serious response to the questions on this survey?" Those that responded *Never* or *Some of the time* were dropped from the analysis. Respondents who participated more than once and who were inconsistent in their gender identification (switching from male to female or the inverse) or party affiliation (switching from Democratic to Republican or the inverse) were also dropped, with the analysis sample totaling 2278 respondents.

The sample is 53.42% ($n = 1217$) Democrats and 45.65% ($n = 1040$) Republicans. While the sample was stratified on party identification, 1% (n=21) of the sample identified as Independents. Ideologically, $47.8\%(n = 1089)$ of the sample identify as liberals, $43.59\%(n = 993)$ identify as conservatives, and $7.86\%(n = 179)$ of respondents identify as moderates.[2]

Female respondents make up $51.84\%(n = 1181)$ of the sample and the majority have attended at least some college ($76.95\%, n = 1753$), and the majority of respondents self-identify as white ($71.90\%, n = 1638$). The average age for respondents is 40 and a median age is 37, with self-

[1] Some respondents participated in the survey more than once. Demographic information is reported based on the unique IP addresses of respondents, not the total number of responses in the study.

[2] Approximately 1% or 16 respondents said they had not thought much about this.

identified ages ranging from 18-80. Additional demographic information can be found in the Appendix.

Respondents also described their media diets and identified the sources of information about what is going on in the world. A majority of respondents ($67.95\%, n = 1548$) watch some form of television to gain information about the world, and they also consider themselves either Very Much interested in the news ($29.10\%, n = 663$) or Somewhat interested in the news ($52.15\%, n = 1188$). The self-reported television news diet of respondents also varies. Table 2 displays the percentages of respondents who stated they watched news on networks included in the sample. Respondents self-report watching a variety of news types, and while they may have familiarity with programs that were in the sample, no one network appears to dominate the sample.

Table 4.1: Which Networks Respondents Watch for the News

Network	Count	Percent
ABC	663	29.10
NBC	773	32.18
CNN	936	41.09
FNC	834	36.61
MSNBC	568	24.93
No Television News	356	15.63

Note: Respondents were able to select multiple networks thus percentages do not sum to 100.

Respondents were able to rate the intensity of the newscaster on a scale from 0-10, where 0 indicates the newscaster is not feeling a particular emotion and 10 indicates they are intensely feeling it. They could choose from the emotional categories of angry, enthusiastic, anxious, frustrated, afraid, and hopeful, which were presented in a random order.

The emotional measures are formed by taking the response options and scaling them in to their respective categories for anxiety ($anxious + afraid$), enthusiasm ($enthusiastic + hopeful$) and anger ($anger + frustrated$). The scales were converted to be from 0-10, however, because 0 indicates the absence of an emotion, the intensity scale is truncated from 0.5 to 10. The frequency measure 0 indicates the absence of the emotion and all emotions with a value between 0.5-0.99 were converted to 1, creating a binary variable for whether or not the newscaster was observed to be expressing each emotion.

4.3 Overall Differences Between Partisan and Nonpartisan News: 2000-2008

Table 4.2 reports the OLS results of regressing the intensity of each emotion on network type. Figure 4.1 displays the means for the emotional intensities of anxiety, enthusiasm, and anger by network type with 95% confidence intervals. From Table 4.2, we can see that while there is a decrease in anxiety moving from the constant, which represents nonpartisan news, to partisan news (-0.12) the decrease is not statistically significant. The means of anxiety for partisan and nonpartisan news in Figure 4.1 display the result—the difference in means does not meet the threshold for statistical significance at $p < 0.05$ ($p < 0.07$) (as confirmed by t-tests).[3]

[3]Full results of all statistical tests reported in this chapter can be found in the appendix.

Table 4.2: Intensity of Anxiety, Enthusiasm, and Anger for Partisan and Nonpartisan News: 2000-2008

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Partisan News	-0.12	-0.31^{***}	0.40^{***}
	(0.07)	(0.06)	(0.07)
Constant	3.89^{***}	4.31^{***}	3.97^{***}
	(0.05)	(0.05)	(0.06)
N	6098	7774	7269
R-squared	0.001	0.003	0.005
Adj. R-squared	0.0004	0.003	0.004
Residual Std. Error	2.41 (df = 6096)	2.48 (df = 7772)	2.61 (df = 7267)
F Statistic	3.43 (df = 1; 6096)	25.79^{***} (df = 1; 7772)	33.70^{***} (df = 1; 7267)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

I do find that the enthusiasm of nonpartisan news is much greater than partisan news. Table 4.2 indicates a decrease of -0.31 in the intensity of enthusiasm for partisan news and Figure 4.1 displays the difference. The relationship between partisan and nonpartisan news regarding the intensity of enthusiasm is as I predicted: partisan news has overall less intense enthusiasm compared to nonpartisan news ($p < 0.001$).

Figure 4.1: Average Intensity of Emotion Cues for Partisan and Nonpartisan News: 2000-2008

The overall difference that I predicted for anger is also supported by the model. Partisan news has an increase of 0.40 points compared to nonpartisan news (Table 4.2). This difference is displayed in Figure 4.1 and is the largest difference in emotional intensity between network types of the three emotions, moving from an intensity of 3.97 for nonpartisan news to 4.37 for partisan news ($p < 0.001$).

Table 4.3: Logistic Regression for the Likelihood of Anxiety, Enthusiasm, and Anger for Partisan vs. Nonpartisan News

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Partisan News	-0.29^{***}	-0.05	0.20^{***}
	(0.04)	(0.04)	(0.04)
Constant	-0.16^{***}	0.12^{***}	-0.19^{***}
	(0.03)	(0.03)	(0.03)
N	14880	14876	14919
Log Likelihood	-10038.61	-10295.27	-10320.87
AIC	20081.22	20594.55	20645.74

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Table 4.3 reports the logistic regression results for the frequency of each respective emotion on news type and Figure 4.2 displays the results of the regression converted to probabilities. The results of the logistic regression for the frequency of anxiety indicate a nonzero difference between partisan and nonpartisan news (Table 4.3, Model 1). Converting the regression output, Figure 4.2 indicates that nonpartisan news is cuing anxiety 46% of the time compared to partisan news, which displays anxiety only 39% of the time. I am able to reject the null that there is no difference in the frequency of anxiety between the two network types ($p < 0.001$, as confirmed by chi-square test) and the difference is in the direction I predicted, with nonpartisan news having more frequent anxiety than partisan news.

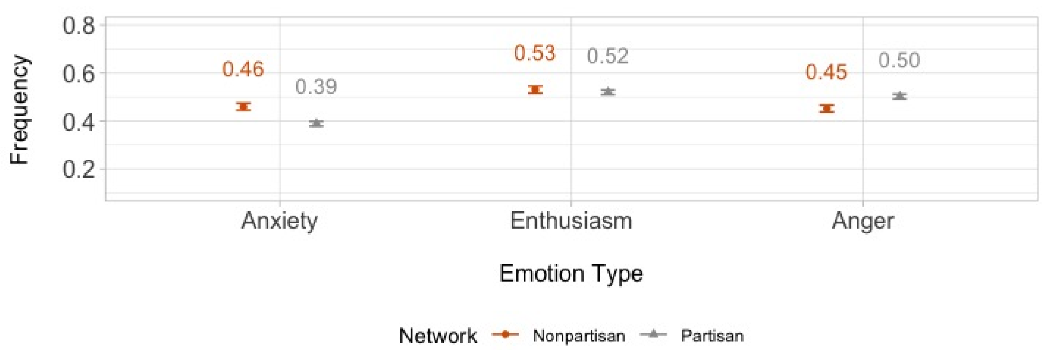
The differences in the frequency of enthusiasm between partisan and nonpartisan news are not as I predicted. Enthusiasm occurs in nonpartisan news 53% of the time and partisan news 52% of the time over the period, and these frequencies are neither statistically nor substantively distinct ($p = 0.21$). However, the frequency of anger is much greater for partisan than nonpartisan news ($p < 0.001$). Over election years from 2000 to 2008, an average of 50% of the segments for partisan news have anger cues compared to just 45% for nonpartisan news. I also predicted that the greater frequency of anger in partisan news would correspond to decreased anxiety. There is an 11 point difference between the frequency of anger and the frequency of anxiety for partisan news

($p < 0.001$). Interestingly, there is no such difference between anxiety and anger for nonpartisan news ($p = 0.3$).

My main expectations holds: partisan news has generally higher levels and frequencies of anger than nonpartisan news; partisan news had generally less anxiety. While the intensity of partisan and nonpartisan news is not different, the frequency of anxiety between the network types is; importantly, greater frequency of anger among partisan news correlates with less frequent anxiety. Nonpartisan news also displays more intense enthusiasm than partisan news, but the dosage of enthusiasm provided to the viewer is similar for partisan and nonpartisan news.

While the previous results pool the election years from 2000-2008, important to my theory are the changes in the frequency and intensity of these emotional cues over time dating to the introduction of Fox.

Figure 4.2: Average Frequency of Emotion Cues for Partisan and Nonpartisan News: 2000-2008



4.4 Changes in the Emotional Intensity and Frequency of Partisan and Nonpartisan News: 2000-2008

4.4.1 Emotional Intensity for Nonpartisan vs Partisan News from 2000-2008

The reemergence of partisan news in the late 1990s, this time in the cable television format, should also produce changes to the emotional landscape over time as cable networks adapt to a competitive news environment. To examine changes in the emotional intensity of partisan and nonpartisan news from 2000 to 2008, I regress the emotional intensity measure on news type. This model is moderated by year, a numeric variable that represents each election year in the news transcripts sampled.

$$Emotion_j = \beta_0 + \beta_1 PartisanNetwork + \beta_2 Year + \beta_3 (PartisanNetwork * Year)$$

Table 4.4 reports OLS regression results for the emotional intensity of partisan and nonpartisan news from 2000 to 2008. In each model the constant represents the estimate for the intensity of nonpartisan news in 2000. While there is a negative shift in the intensity of anxiety for partisan news (-0.13), the over-time slope for both partisan and nonpartisan networks is the same (0.01). The intensity of anxiety is also not statistically distinct: partisan and nonpartisan news have consistent and similar levels over anxiety for election years from 2000 to 2008. This trend is displayed in Figure 4.3.

My prediction concerning the difference in the intensity of enthusiasm between news types was also not correct. I anticipated that nonpartisan news would consistently have higher levels of enthusiasm than nonpartisan news. Again, the intercept shift is in the expected direction for the difference between partisan news (-0.17) and nonpartisan news, but there is no difference in the intensity between the two network types in 2000. Yet nonpartisan news has increasing levels of enthusiasm during this time period: in 2008 the level of enthusiasm is clearly higher and distinct

Table 4.4: OLS Regression for the Intensity of Anxiety, Enthusiasm, and Anger for Partisan vs. Nonpartisan News over 2000-2008

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Year	0.01	0.07^{*}	-0.01
	(0.04)	(0.04)	(0.04)
Partisan News	-0.13	-0.17	0.26^{*}
	(0.11)	(0.11)	(0.12)
Year*Partisan News	0.01	-0.07	0.07
	(0.05)	(0.04)	(0.05)
Constant	3.87^{***}	4.17^{***}	3.99^{***}
	(0.09)	(0.09)	(0.10)
N	6098	7774	7269
R-squared	0.001	0.004	0.01
Adj. R-squared	0.0001	0.003	0.01
Residual Std. Error	2.41 (df = 6094)	2.48 (df = 7770)	2.61 (df = 7265)
F Statistic	1.26 (df = 3; 6094)	9.89^{***} (df = 3; 7770)	13.23^{***} (df = 3; 7265)

***p $<$ .001; **p $<$ .01; *p $<$ .05

from the enthusiasm in partisan news (Figure 4.4).

Anger over the time period also displays a clear difference between partisan and nonpartisan news (Figure 4.5). The intensity of anger for partisan news in 2000 is higher than nonpartisan news (0.26, $p < 0.05$). The slope for the intensity of anger over time for partisan news is not statistically significant in the regression model (0.07, Model 3) but by plotting the change over time from 2000 to 2008 (Figure 4.5) there is a clear difference between the intensity of anger in 2008 (average 4.5) and in 2000 (average 4.25). The intensity of anger did increase from 2000 to 2008, but the year to year increase is not distinct from zero. In contrast to partisan news, the level of anger for nonpartisan news over the time frame is essentially flat: there is neither a statistically significant change over time nor is the difference between 2000 and 2008 statistically significant at the $p < 0.05$ cutoff.

Figure 4.3: Intensity Cues for Anxiety Over 2000-2008

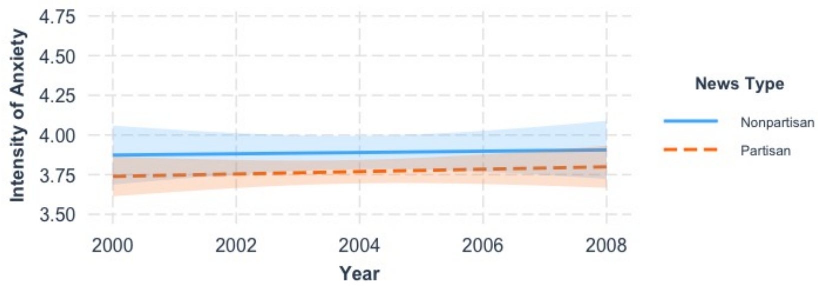


Figure 4.4: Intensity Cues for Enthusiasm Over 2000-2008

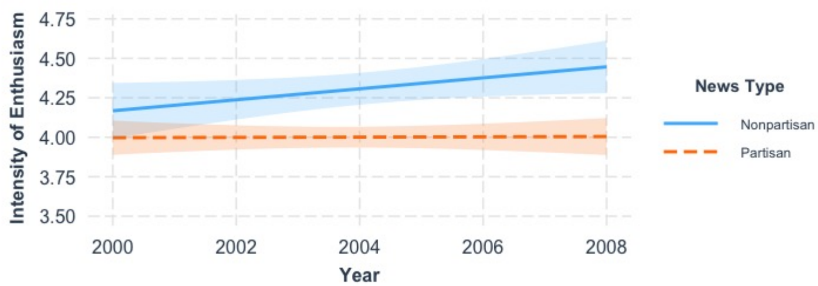
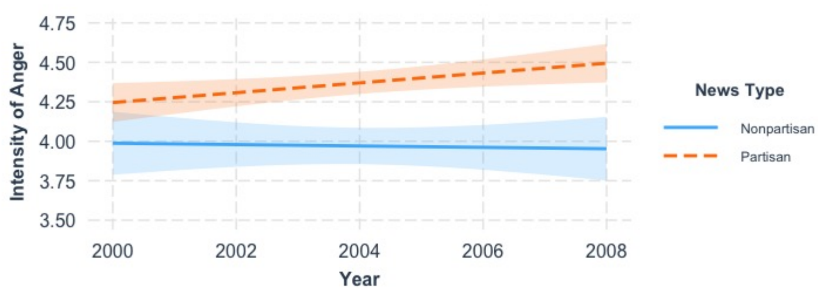


Figure 4.5: Intensity Cues for Anger Over 2000-2008



4.4.2 Emotional Frequency for Nonpartisan vs Partisan News from 2000-2008

While only some of my predictions about the intensity of emotional cues for partisan and nonpartisan news between 2000 and 2008 were correct, it is possible that major shifts occurred in the frequency with which the news outlets were producing emotional cues for their audiences. To examine the frequency of the emotional cues in the news, I again regress the type of news, moderated by year, on emotions. Because the frequency of emotion is binary, I model the relationship with logistic regression rather than OLS. Figures 4.6- 4.8 display the results of the regression for each emotion over time, with the results converted to represent the frequency of anxiety, enthusiasm, and anger, respectively.

$$Emotion_j = logit^{-1}(\beta_0 + \beta_1 NewsType + \beta_2 Year + \beta_3(NewsType * Year))$$

I hypothesized that the frequency of anxiety cues for partisan news would decrease over time, and the data do not bear this out. While the frequency of anxiety for partisan news is significantly less than that of nonpartisan news in 2000 ($p < 0.001$) the slope is quite small and not decreasing over time (Table 4.3, Model 1). There is also not an increase in anxiety cues over the time period nonpartisan news. This consistency is evident in Figure 4.6 for both partisan and nonpartisan news: while the anxiety cues for nonpartisan news are more frequent than for partisan news over the entire period, neither network type has increasing cues.

Counter to my expectations, nonpartisan news does not have a greater frequency of anxiety cues than partisan news in 2000. Partisan news begins the era with more frequent enthusiasm cues, but the log likelihood of enthusiasm decreases over time ($p < 0.001$). Nonpartisan news has the opposite trend: there is a log likelihood increase in the frequency of enthusiasm (0.08, $p < 0.001$) and by 2008 its producing more enthusiasm cues than partisan news (Figure 4.7).

The biggest change over the time period is for anger cues in partisan news. Partisan news and nonpartisan news essentially start 2000 with a similar amount of anger cues (Figure 4.8). But partisan news has a large increase in the log likelihood of anger (0.12, $p < 0.001$) while the slope for nonpartisan news is essentially flat. A viewer of partisan news in 2008 is receiving anger cues 56% of the time, while a viewer of nonpartisan news is receiving anger cues approximately 45% of the time.

Table 4.5: Logistic Regression for the Likelihood of Anxiety, Enthusiasm, and Anger for Partisan vs. Nonpartisan News Over Time

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Partisan News	-0.30^{***}	0.16^{**}	-0.02
	(0.06)	(0.06)	(0.06)
Year	0.01	0.08^{***}	-0.01
	(0.02)	(0.02)	(0.02)
Year*Partisan News	0.004	-0.11^{***}	0.12^{***}
	(0.03)	(0.03)	(0.03)
Constant	-0.19^{***}	-0.04	-0.16^{**}
	(0.05)	(0.05)	(0.05)
N	14880	14876	14919
Log Likelihood	-10037.82	-10286.43	-10293.34
AIC	20083.65	20580.85	20594.68

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Figure 4.6: Frequency of Anxiety Cues Over 2000-2008

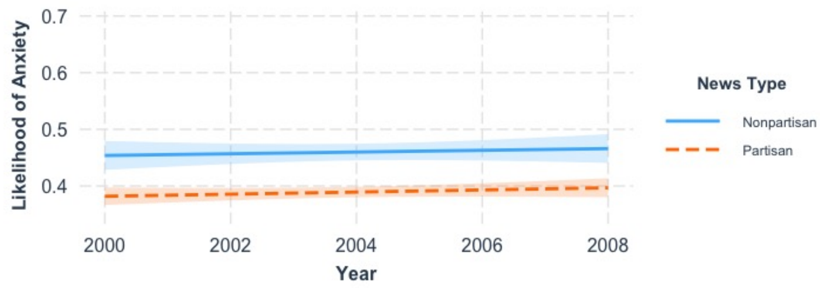


Figure 4.7: Frequency of Enthusiasm Cues Over 2000-2008

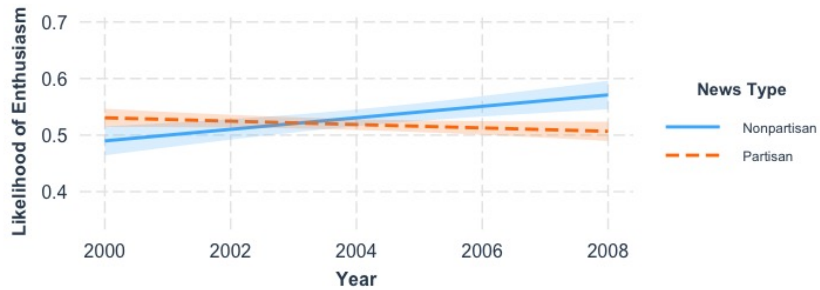
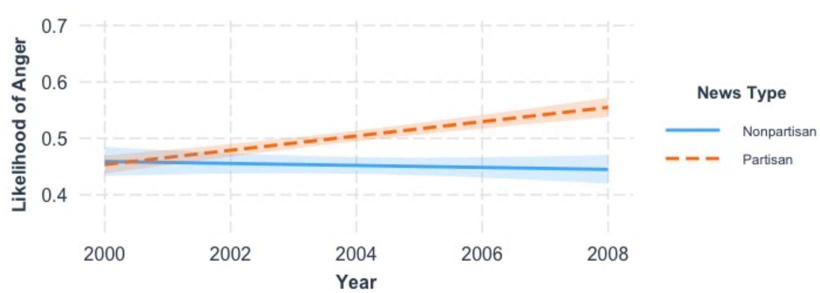


Figure 4.8: Frequency of Anger Cues Over 2000-2008



4.4.3 Discussion

The differences between partisan and nonpartisan news from 2000 to 2008 are generally in line with my predictions, though there are some surprising results. While the intensity of anxiety for nonpartisan news was slightly higher, it was not particularly distinct from the intensity of the anxiety cues in partisan news. I anticipated that there would be a greater difference in intensity between the network types, but that was not the case. The frequency of anxiety cues in nonpartisan news are consistently higher than in partisan news over the entire time period, which conforms to my general expectations. Yet partisan news did not display the decreasing frequency of anxiety that I anticipated.

By 2008, nonpartisan news does have greater enthusiasm than partisan news. But in the beginning of the era, nonpartisan news is more intensely enthusiastic, but not more frequently so, than partisan news. The frequency of enthusiasm overlaps for the network types—partisan news decreases in the frequency of enthusiasm while nonpartisan news increases the frequency of its enthusiasm cues.

However, the main focus of my theory is that the anger in partisan news will be greater because of partisan perspective taking. In 2000 the intensity of anger cues for partisan networks was greater than nonpartisan news, but not the frequency of anger cues. But by 2008, intense and frequent anger cues characterize partisan news compared to nonpartisan news. When comparing nonpartisan and partisan news, partisan news's most distinct characteristic during this time frame is intense and frequent anger cues. From 2000 to 2008 not only do the intensity and frequency of anger cues increase for partisan news, but it also results in partisan news becoming an environment that is *more* angry than nonpartisan news, since neither the frequency nor intensity of anger for nonpartisan news changes. This coupled with partisan news' lower levels of anxiety, particularly the frequency of anxiety, compared to nonpartisan news illuminates the emergence of two negative news environments that are unique with regards to the type of emotion that dominates the respective network types. Partisan news is dominated by anger while nonpartisan news is dominated by anxiety.

4.5 Changes in Emotions within Partisan Cable News: 2000-2008

4.5.0.1 Emotional Intensity For Partisan Cable Networks Over 2000-2008

My pooling of the partisan networks may hide changes that occurred over the 2000 to 2008 time period as CNN and MSNBC pursued Fox News in the ratings. To expose these changes in the data, I first analyze the changes in the intensity cues of the individual cable networks over time. I do this by regressing the network type on the intensity of emotional cues, with network type interacted with year. For the regression, CNN is the reference category for the Partisan Network variable. Table 4.4 displays the OLS regression results.

$$Emotion_j = \beta_0 + \beta_1 PartisanNetwork + \beta_2 Year + \beta_3 (PartisanNetwork * Year)$$

I hypothesized that the intensity of anxiety for CNN and MSNBC would decrease as they moved away from the journalistic norms of the 20_{th} century and became more partisan. Because Fox's founding philosophy was that the network should provide a conservative viewpoint to viewers, I did not anticipate changes to the intensity of its anxiety cues over time. My expectations were only partially correct. Figure 4.9 visualizes the intensity of anxiety cues over time for each network. Counter to my expectations, the intensity of anxiety cues for CNN increased over time (0.12, $p < 0.05$) while initially its intensity of anxiety was lower than MSNBC and similar to Fox in 2000. However, the intensity of the anxiety cues on MSNBC did decrease in the expected way. From Figure 4.9, MSNBC had higher levels of anxiety in 2000 than either CNN or Fox, and by 2008 its intensity of anxiety cues are similar to those of both CNN and Fox. The intensity of anxiety cues for Fox was essentially flat from 2000 to 2008. While there is a slight increase in intensity over time (Table 4.4, Model 1), it is not statistically significant and the confidence intervals for intensity in 2000 and 2008 overlap.

I also predicted that the intensity of enthusiasm would decrease for CNN between 2000 and 2008. While the sign on the coefficient (-0.01) for the intensity of enthusiasm for CNN is in the right direction (negative), the slope is not statistically significant. The intensity of enthusiasm cues for CNN does not decrease over the time period, nor do the intensity cues for Fox or MSNBC. Figure 4.10 visualizes the consistent nature of the intensity of enthusiasm for all of the networks and they all have essentially the level of intensity.

The results for the intensity of anger reveal that Fox had levels of intensity greater than both CNN and MSNBC in 2000, as I predicted (Table 4.4, Model 3). The intensity of anger on Fox also stays at a consistent level of intensity over the time period (Figure 4.11), even though the regression indicates that the coefficient for intensity of anger over time for Fox is negative and statistically significant (-0.17, $p < 0.05$). This is because of the additive nature of the model: this negative change is offset by the positive slope for CNN over time (0.13, $p < 0.05$), which serves as the reference category in the regression, and by summing them the slope for Fox remains stable when examining the difference between 2000 and 2008 (Figure 4.11). MSNBC's intensity of anger cues also increases over this time period: while the network begins the era in 2000 with anger levels lower than Fox, by 2008 the intensity of anger cues on MSNBC are the same level as those on Fox News (Figure 4.11).

Table 4.6: OLS Regression for the Intensity of Anxiety, Enthusiasm, and Anger for Partisan Networks from 2000 to 2008

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
FOX	0.20	−0.18	1.18***
	(0.16)	(0.13)	(0.16)
MSNBC	0.72***	−0.03	0.64***
	(0.16)	(0.13)	(0.17)
Year	0.12*	−0.01	0.13*
	(0.05)	(0.04)	(0.05)
FOX*Year	−0.08	0.04	−0.17*
	(0.07)	(0.06)	(0.07)
MSNBC*Year	−0.23***	−0.004	−0.01
	(0.07)	(0.06)	(0.07)
Constant	3.42***	4.06***	3.54***
	(0.12)	(0.09)	(0.12)
N	4084	5451	5294
R-squared	0.01	0.0005	0.02
Adj. R-squared	0.004	−0.0005	0.02
Residual Std. Error	2.38 (df = 4078)	2.44 (df = 5445)	2.64 (df = 5288)
F Statistic	4.67*** (df = 5; 4078)	0.51 (df = 5; 5445)	20.08*** (df = 5; 5288)

***p < .001; **p < .01; *p < .05

Figure 4.9: Cable News Intensity Cues for Anxiety Over 2000-2008

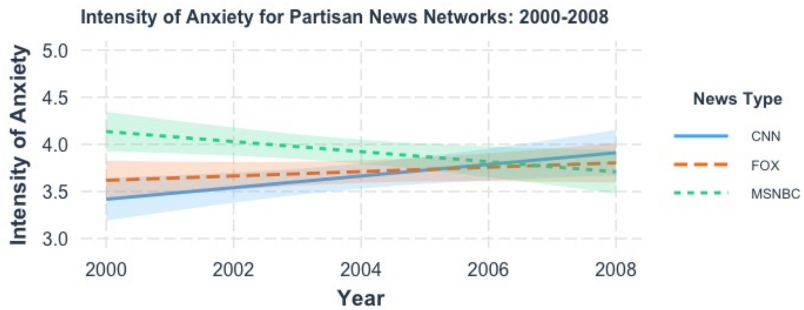


Figure 4.10: Cable News Intensity Cues for Enthusiasm Over 2000-2008

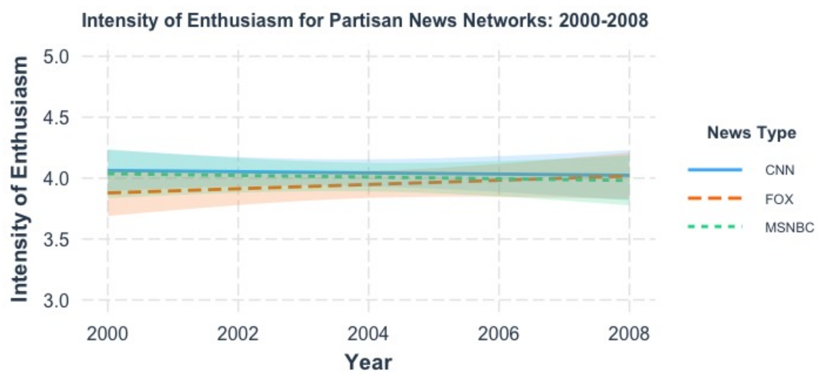
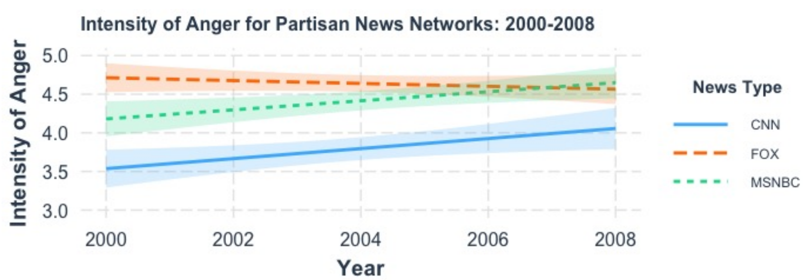


Figure 4.11: Cable News Intensity Cues for Anger Over 2000-2008



4.5.1 Emotional Frequency For Cable Networks over 2000-2008

For the frequency of emotions for partisan networks from 2000 to 2008, I regress network type onto the emotion variables, once again interacting the partisan network with year. Because frequency is binary, this relationship is modeled using logistic regression. Results of the regression are shown in Table 4.5. CNN is once again the reference category.

I predicted that the frequency of anxiety cues will decrease for both MSNBC and CNN over this time, along with increasing anger on both networks. The results for the frequency of anxiety are mixed: both Fox (0.43, $p < 0.001$) and MSNBC (0.70, $p < 0.001$) have an increased log likelihood of being anxious compared to CNN in 2000. However the slope for both Fox (-0.17, $p < 0.001$) and MSNBC (-0.27, $p < 0.001$) is negative, while the slope for CNN (0.16, $p < 0.001$) is positive. Because CNN's slope is the baseline condition, this results in a consistent rate of anger cues for Fox from 2000 to 2008 (Figure 4.12). The rate of anxiety cues for MSNBC decreases, consistent with my prediction. Interestingly, the rate of anxiety cues for CNN increases from 2000 to 2008. In 2000, CNN's rate of anxiety cues was lower than both Fox and MSNBC, but by 2008 the frequency of anxiety on CNN is greater than the other two networks.

Table 4.7: Logistic Regression for the Likelihood of Anxiety, Enthusiasm, and Anger for Partisan News From 2000-2008

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
FOX	0.43^{***}	-0.31^{***}	1.25^{***}
	(0.08)	(0.08)	(0.08)
MSNBC	0.70^{***}	-0.27^{***}	0.55^{***}
	(0.08)	(0.08)	(0.08)
Year	0.16^{***}	-0.02	0.12^{***}
	(0.03)	(0.02)	(0.03)
FOX*Year	-0.17^{***}	0.01	-0.17^{***}
	(0.03)	(0.03)	(0.03)
MSNBC*Year	-0.27^{***}	0.001	0.06
	(0.04)	(0.03)	(0.04)
Constant	-0.84^{***}	0.30^{***}	-0.77^{***}
	(0.06)	(0.05)	(0.06)
Observations	10,501	10,498	10,550
Log Likelihood	−6,979.49	−7,244.63	−7,068.36
Akaike Inf. Crit.	13,970.97	14,501.27	14,148.71
Note:	*p<0.05; **p<0.01; ***p<0.001		

Results are also contrary to my prediction about enthusiasm cues for CNN. I anticipated that the frequency of enthusiasm cues on CNN would decrease over the time period. Instead, CNN maintains a consistent rate of enthusiasm cues over the time period, and these cues occur more frequently than the enthusiasm cues on both Fox and MSNBC (Figure 4.13). Meanwhile, the frequency of enthusiasm cues for both Fox and MSNBC remain essentially the same during the time period. Similar to CNN, the rate of change for both networks is not statistically significant (Table 4.5, Model 2). There is not overall change in the frequency with which any of the cable networks broadcast enthusiasm cues between 2000 and 2008.

However, my predictions for the increasing frequency of anger for CNN and MSNBC bear out from 2000-2008 (Figure 4.14). Both Fox (1.25, $p < 0.001$) and MSNBC (0.55, $p < 0.001$) have a greater log-likelihood of anger in 2000 compared to CNN (Table 4.5, Model 3), which is also apparent in Figure 4.14. Despite the slope for Fox being negative (-0.17, $p < 0.001$) and the slope for MSNBC being positive but not statistically significant (0.06), because the slope for CNN is positive and statistically significant (0.12, $p < 0.001$) the overall slope for Fox (Figure 4.14) is essentially flat while the frequency of anger for MSNBC increases from 2000 to 2008. Overall CNN's rate of anger cues increases by roughly 10 percentage points from 2000 to 2008 while the increase for MSNBC is around 15 points.

Figure 4.12: Cable News Frequency Cues for Anxiety Over 2000-2008

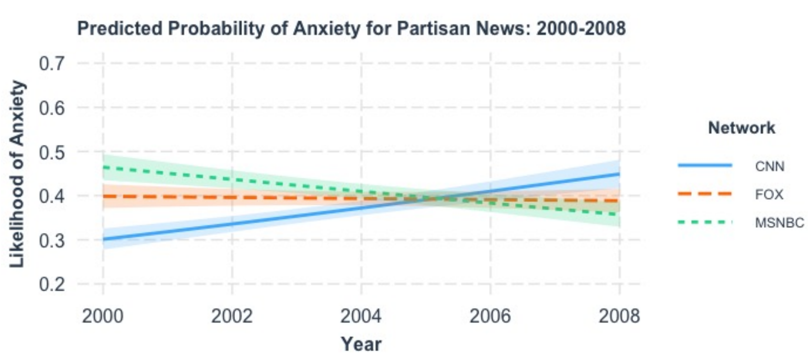


Figure 4.13: Cable News Frequency Cues for Enthusiasm Over 2000-2008

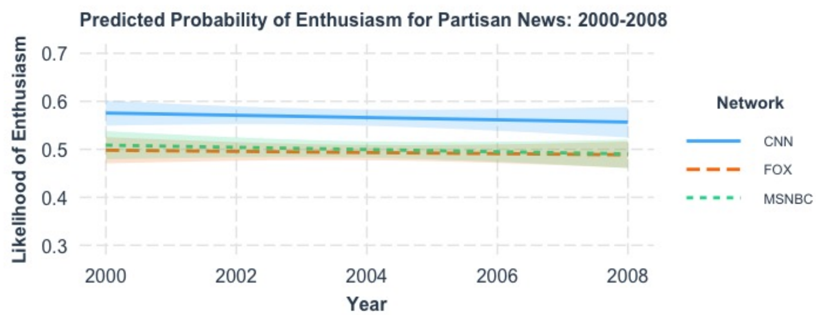
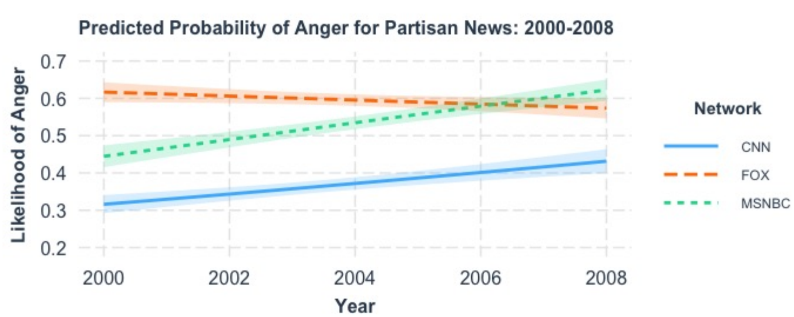


Figure 4.14: Cable News Frequency Cues for Anger Over 2000-2008



4.5.2 Discussion

Examining the differences in frequency and intensity for partisan networks reveals the changing emotional signals within the partisan news environment between 2000 and 2008. While the results do not show consistent decreasing anxiety for all three partisan networks, the anxiety cues in both frequency and intensity decrease for MSNBC, and remain constant for Fox. This is coupled with increasing anger in both frequency and intensity for MSNBC and CNN. Interestingly, by the end of 2008, anger cues for MSNBC are comparable to those on Fox: Fox began the time period with overall greater anger than its cable news counterparts.

While this is in line with my predictions, the increases in anger cues for CNN do not reach similar levels as Fox and MSNBC. CNN is considered a liberal media outlet, but its partisanship may not be as strong as MSNBC, which may account for the increased anger cues on the network that are also at lower levels than its competitors. Its founding as a 24-hour news network that took objectivity in journalism seriously, and its establishment in 1980, many years prior to the debuts of Fox and MSNBC, could also contribute to its lagging anger. Its founding journalistic philosophy could also explain why the frequency of its enthusiasm cues is greater than on MSNBC and Fox over the time period. While the networks are all reacting to competition within the cable news environment from 2000 to 2008, established founding principles—such as objective professionalized journalism on CNN and taking a partisan perspective on Fox—may contribute in unseen ways to how *much* change the emotional cues on their respective networks varies over this time frame.

4.6 Conclusion

The addition of Fox and MSNBC to the 24-hour cable news environment changed the emotional landscape of news. Prior to their arrival, CNN was the main 24-hour news network. When CNN reported stories, it focused on breaking news and used journalistic norms of objectivity to do so: multiple sides of a story were delivered to audiences, but blame was not clearly assigned. Viewers were left to draw conclusions for themselves. With Fox and MSNBC's arrival in 1996, competition emerged. However, Fox's ideological and partisan slant on the news was novel within the television news environment. With its partisan perspective came anger cues: rather than reporting multiple sides to a story, the opposition was blamed for events and attacked as part of the defense of conservative norms and in defense of the partisan group.

The associations for this increase in anger cues in partisan news are seen in the overall difference in anger cues between partisan and nonpartisan media between 2000 and 2008. On average the partisan news environment is producing higher levels and frequencies of anger cues compared to the traditional network news environment. This is because network news maintained its commitment to objective reporting, focusing on providing information to viewers without blame and without defending copartisans. The changes over time between partisan and nonpartisan news are most apparent in the angry environment that partisan news produces. The intensity and frequency of partisan hosts emoting anger from 2000 to 2008 is increasing. While the anger in nonpartisan news is both less intense and frequent as well as constant.

The changes that occurred between the partisan networks to produce this increase are not the result of Fox's insertion of more anger cues into their coverage, but of such choices by MSNBC and CNN, likely made in an effort to replicate the ratings success of Fox's partisan perspective taking. The intensity and frequency of anger on Fox is consistent. It appears to have started off angry and stayed that way from 2000 to 2008. But CNN and MSNBC started with lower levels of anger than Fox in 2000. By 2008 the intensity and frequency of anger on CNN had increased. The increasing intensity and frequency of anger on MSNBC had also risen to the levels of Fox by the end of the time period.

Additionally the changes within the partisan media environment combined with the stagnant levels of anger within nonpartisan news support the idea that elites are providing these signals to the public, rather than calibrating the news to match the present emotions of the public. If news programming was following the emotions of the public, rather than signaling to the public how they should feel, I would expect that all news programs would have similar levels of emotions in 2000 and that the frequency and intensity of emotions over the time period would move together, in similar fashions, for partisan and nonpartisan news. This is not the case. Even if just the partisan networks were responding to the emotions of the public, there should not be a difference in the levels of anger between Fox, CNN, and MSNBC in 2000, since they would be calibrating their emotional cues to public emotions. Again, this is not the case: Fox is angrier than CNN and MSNBC in 2000 and CNN and MSNBC have increasing levels of anger over the time period, drawing closer to the levels of anger of Fox.

The addition of Fox into the cable news lineup meant that anger was now a prevalent emotion in the partisan television news landscape. By the end of 2008, all three partisan cable channels were contributing to the anger in the cable news environment, with changes in anger over the time period concentrated in MSNBC and CNN. The partisan news environment had been cuing more intense and frequent anger to news audiences prior to the highly emotional election of 2016. The next chapter investigates whether additional changes occurred over election years from 2010 to 2020 or if changes in anger in the news from 2000 to 2008 merely set the stage for the 2016 election.

CHAPTER 5

Evaluating the Trump Era: 2010-2020

5.1 Introduction

The previous chapter argues that the television news environment had become angrier well before Donald Trump entered the political fray. After the entry of Fox and MSNBC into the cable news market in the late 1990s, the major change in the first eight years of the 21st century was the increase in anger in partisan media, fueled by the efforts of producers at MSNBC and CNN to compete with Fox's anger-fueled ratings juggernaut. By 2008, partisan news was broadly characterized by anger more frequent and intense than in nonpartisan news. As had been historically the case for the broadcast network news programs, the dominant emotions were anxiety and enthusiasm. Networks taking a partisan perspective to construct the news broadcast angry, rather than anxious, emotional signals, to audiences.

Despite this, pundits in both network and cable news claimed that the 2016 election was characterized by new levels of anger in the electorate. The reasons given for this emotionally charged election, and the election of Donald Trump, were the dissatisfaction of rural voters (Cramer, 2016), voters' fear of Hillary Clinton (Beinart, 2016), and anxiety about the state of the economy (Casselman, 2017). The common element among these explanations is anxiety, but the political behavior of the electorate was typically symptomatic of anger, rather than anxiety. In general, anxious citizens react by seeking additional information, but not by engaging politically through changed voting behavior (Marcus et al., 2000). Angry citizens will take action (Lerner and Keltner, 2001) and turn out to vote in the face of obstaclesValentino and Neuner, 2017. Increased voter turnout (Desilver, 2021) and high levels of partisan animosity (Geiger, 2016) were well-documented—behavior typically catalyzed by anger. If Trump's rhetoric and behavior were the singular source of that anger, it would be evident in a change in the emotional environment of U.S. news. We would expect to observe substantive changes in the intensity and frequency of anger in the news environment from 2010-2020.

This chapter tests the so-called "Trump effect"—a change in the emotional tenor of U.S. media—directly driven by Donald Trump's arrival on the national political scene. Before testing the changes to the media over this time period, I reaffirm that my argument regarding the emotionality of partisan and nonpartisan media still holds. Partisan news should have higher overall levels of anger compared to nonpartisan news, while nonpartisan news should be more anxious and enthusiastic than partisan news.

H_1: Partisan news is more intensely and frequently angry than nonpartisan news.

H_2: Nonpartisan news is more intensely and frequently anxious than partisan news.

H_3: Nonpartisan news is more intensely and frequently enthusiastic than partisan news.

I then test three sets of hypotheses to analyze whether or not the Trump campaign is associated with changes in the emotional landscape of television news. If Donald Trump truly changed the emotional tenor of the media during his election, these changes should be apparent in changes to the emotional cues being provided to audiences in partisan and nonpartisan news between 2010 and 2020. Since the observed behavior of voters matches most closely with the behavior of angry citizens, linear trends for the intensity and frequency of anger should increase for partisan news over the time period. Increasing anger in partisan news broadcasts should also coincide with decreasing anxiety, due to an anger offset. If the anchors and hosts are broadcasting anger to their audiences, they will have fewer opportunities to signal anxiety. I also anticipate stable levels of enthusiasm for both partisan and nonpartisan news over this time period.

H_4: The intensity and frequency of anger in partisan news will increase.

H_5: The intensity and frequency of anxiety in partisan news will decrease.

H_6: The intensity and frequency of enthusiasm in partisan and nonpartisan news will remain stable.

We should also expect to see the effects of a Trump candidacy within the partisan cable news networks. The strongest case for a Trump effect would be that both Democratic and Republican networks increased in anger from 2010-2020—CNN, Fox, and MSNBC should show upward trends in anger. I predict that all three will exhibit increases in anger, decreases in anxiety, and stable levels of enthusiasm over the time period. But disaggregating them may also reveal that general trends are the result of variation between partisan cable news networks.

H_7: The intensity and frequency of anger will increase for CNN, Fox, and MSNBC.

H_8: The intensity and frequency of anxiety will decrease for CNN, Fox, and MSNBC.

H_9: The intensity and frequency of enthusiasm will remain stable for CNN, Fox, and MSNBC.

The third and final observable difference should be in an observable change in emotional cues from the partisan television networks between 2014 and 2016. Donald Trump announced his candidacy for president in June of 2015. Any changes to the media driven by his campaign should be apparent upon comparing the emotional output of the news in 2014 and 2016. Since the overall change in the news environment should be rooted in the negative emotions of partisan news, there should be two specific changes in the partisan media between 2014 and 2016. First, CNN, Fox, and MSNBC should increase in anger. And second, the increase in anger should also coincide with a decrease in anxiety.

H_{10}: The intensity and frequency of anger will increase for CNN, Fox, and MSNBC from 2014 to 2016.

H_{11}: The intensity and frequency of anxiety will decrease for CNN, Fox, and MSNBC from 2014 to 2016.

If Candidate Trump and his campaign truly changed the emotional tenor of media, we should see overall increases in anger cues in partisan television news from 2010-2020 among both Democratic and Republican partisan networks. There should also be a clear discontinuity between the emotional signals in the media between 2014, prior to his entry into the Republican presidential primaries, and 2016, after his election, if his campaign is what prompted changes in the media environment. If these changes are not apparent, it is unlikely that Trump changed the media and instead harnessed the power of an angry partisan television press that had begun cuing anger in the television news environment well before his entrance onto the national stage.

5.2 Results

Twenty studies were fielded between March 2022 and January 2023 using CloudResearch's MTruk Tool Kit and Prime Panels.[1] The respondents here were a fresh sample from the respondents who participated in the validation studies in Chapter 3. In this sample respondents were randomly assigned to rate the emotionality of a news anchor in 9 segments of text, resulting in each segment being rated by respondents at least 14 times. The breakdown of how many segments were rated for each network is listed in Table 5.1.

[1]These studies were generously funded by the Russell Sage Foundation's *Small Grant in Computational Social Science*.

Table 5.1: Total Segments Rated by Respondents in the 2010-2020 Sample by Network

Network	**Segments per show**	**Segments over two weeks**	**Segments from 2010-2020**
ABC	4	40	240
NBC	4	40	240
CNN	5	50	300
Fox	5	50	300
MSNBC	6	40	360
			Total: 1440

The initial sample totalled 2822 unique respondents who completed the survey.[2] All respondents were asked "How often did you give a serious response to the questions on this survey?" Those that responded *Never* or *Some of the time* were dropped from the analysis, resulting in the exclusion of 44 participants. Respondents who participated more than once and who were inconsistent in their gender identification (switching from male to female, or vice versa) or switched party affiliation (from Democratic to Republican, or vice versa) were also dropped, with the final analysis totaling 2766 respondents.

The sample is 50.43% ($n = 1395$) Democrats and 46.64% ($n = 1290$) Republicans. While the sample was stratified on party identification, $2.93\%(n = 81)$ of the sample identified as Independents. Ideologically, $44.07\%(n = 1219)$ of the sample identify as liberals, $45.99\%(n = 1272)$ identify as conservatives, and $9.00\%(n = 249)$ of respondents identify as moderates.[3] The majority of the sample identify as female ($56.72\%, n = 1569$), have attended at least some college ($73.93\%, n = 2045$), and self-identify as white ($75.56\%, n = 2090$). The average age for respondents is 41 and a median age of 38 with self-identified ages ranging from 18-91. Additional demographic information can be found in the Appendix.

Respondents also reported their media diets and where they get information about what is going on in the world. A majority of respondents ($61.93\%, n = 1713$) watch some form of television to gain information about the world, and they also consider themselves either Very Much interested

[2]Some respondents participated in the survey more than once with those who participated in first 5 studies that were fielded were allowed to participate again in the last 5 studies.

[3]Approximately 1% or 22 respondents said they had not thought much about this.

in the news ($33.31\%, n = 917$) or Somewhat interested in the news ($50.49\%, n = 1390$). The self-reported television news diet of respondents also varies. Table 5.2 displays the percentages of respondents who stated they watched news on networks included in the sample.

Table 5.2: Which Networks Respondents Watch for the News

Network	Count	Percent
ABC	802	28.99
NBC	889	31.75
CNN	1165	42.11
Fox	1069	38.65
MSNBC	676	24.44
No Television News	335	12.11

Note: Respondents were able to select multiple networks thus percentages do not sum to 100.

Respondents rated the intensity of the newscaster's emotional expression on a scale from 0-10, where 0 indicates the newscaster is not feeling a particular emotion and 10 indicates they are intensely feeling it. They could choose from the emotional categories of angry, enthusiastic, anxious, frustrated, afraid, and hopeful, which were presented in a random order.

The emotional cues measures are formed by taking the response options and scaling them in to their respective categories for anxiety ($anxious + afraid$), enthusiasm ($enthusiastic + hopeful$) and anger ($anger + frustrated$). For the intensity of emotion variable, scales were converted to be from 0-10. Because 0 indicates the absence of an emotion, the intensity scale is truncated from .5 to 10. For the frequency of emotion variable, 0 indicates the absence of the emotion, and all emotions with a value between 0.5-0.99 were coded as 1, creating a binary variable for whether or not the newscaster was observed to be expressing each emotion.

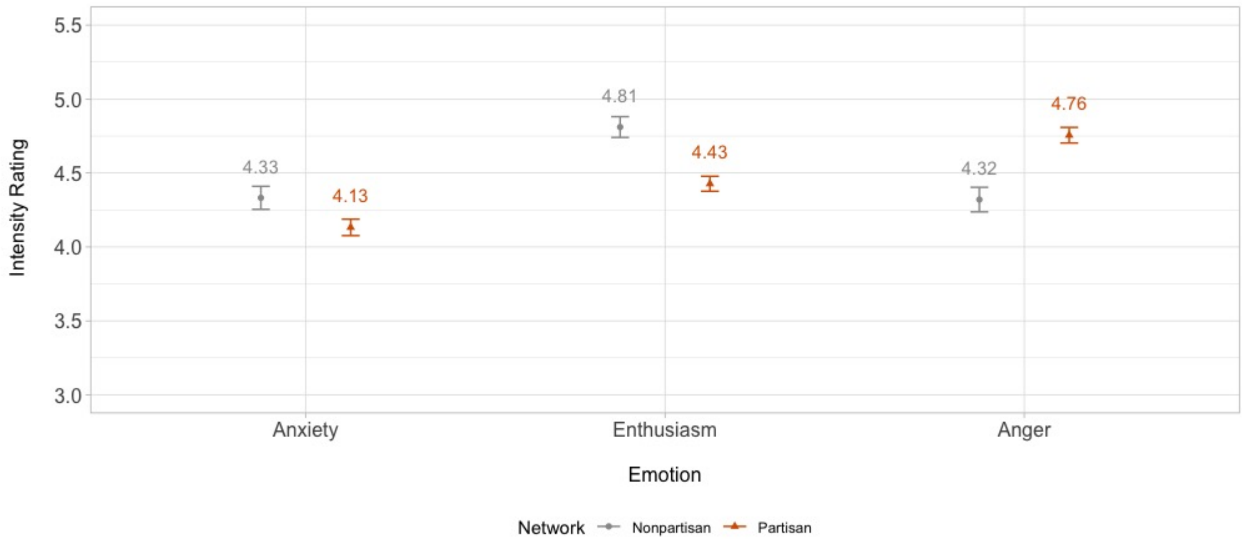
5.3 Overall Differences Between Partisan and Nonpartisan News: 2010-2020

The overall emotional differences between partisan and nonpartisan news over the years 2000-2008, which are central to my argument that what differentiates partisan and nonpartisan news is anger, should continue to hold over 2010-2020.

Figure 5.1 displays the differences in mean emotional intensity for partisan and nonpartisan news with 95% confidence intervals. The decrease between the mean of anxiety for nonpartisan (4.13) and partisan news (4.33) is statistically distinct (as confirmed by t-tests), with nonpartisan news continuing to have more intense anxiety than partisan news over the 2010-2020 time period ($p < 0.001$). The same trend applies for the intensity of enthusiasm—nonpartisan news has greater levels of intensity of enthusiasm (4.81) than partisan news (4.43).

The difference in anger intensity between partisan news and nonpartisan news remains stark. Partisan news has greater anger intensity (4.76) compared to nonpartisan news (4.32). The difference is statistically significant ($p < 0.001$) and shows that anger continues to be a driving force in partisan news.

Figure 5.1: Plot of Emotional Intensity For Nonpartisan vs. Partisan News: 2010 - 2020



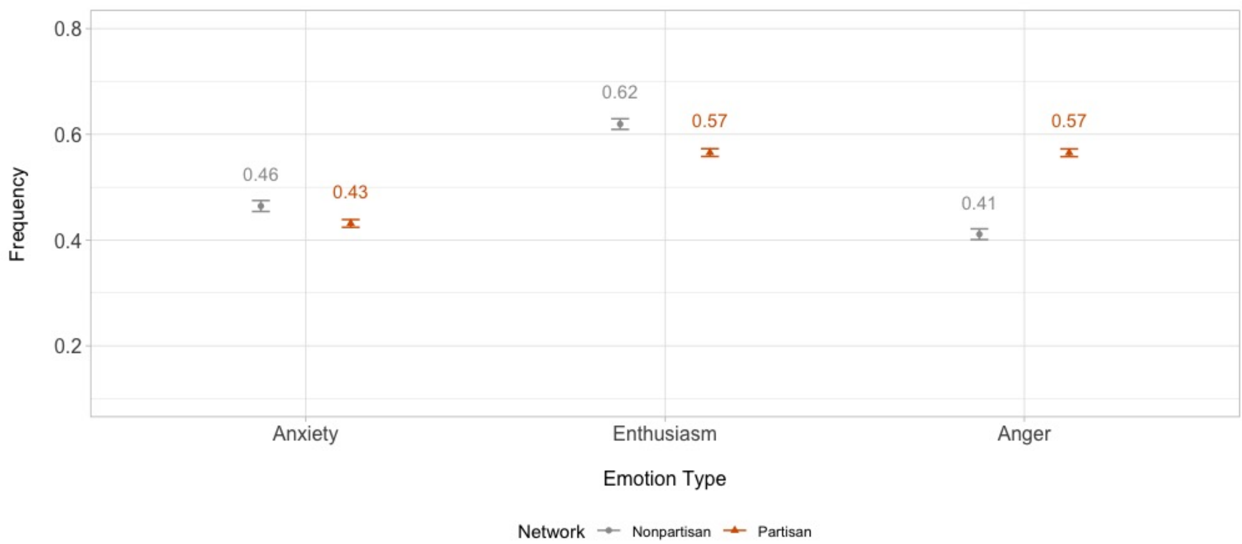
The differences in the emotional frequencies between partisan and nonpartisan news are displayed in Figure 5.2. The expected relationships between partisan and nonpartisan news continue to hold (as confirmed by Chi-square tests).[4] Nonpartisan networks have a 46% likelihood of anxious expression compared to partisan news, which has a likelihood of 43%, and this difference is statistically significant ($p < 0.001$). Not only is nonpartisan news more intensely anxious, but it continues to deploy anxiety more frequently than partisan news. Nonpartisan network news is also more likely to be enthusiastic compared to partisan cable news. Nonpartisan news has a 62% chance of enthusiastic expression compared to partisan news, which is enthusiastic 57% of the time ($p < 0.001$).

Anger also continues to be more frequent for partisan news. Partisan news has a 57% likelihood of angry expression compared to 41% for nonpartisan news, with this difference being statistically significant ($p < 0.001$). To put that into perspective, a partisan and nonpartisan network both air twenty segments in a week of news. Over that time, the nonpartisan network will only convey anger to their audience eight times, and the partisan network will convey anger eleven times. The intensity of the anger over those segments will also outpace nonpartisan news. There is also an

[4]Contingency tables and full results for each chi-square test can be found in the Appendix.

anger offset present for partisan news when pooling years from 2010-2020. There is a difference of 14 percentage points in the frequency of partisan anger compared to partisan anxiety ($p < 0.001$, as confirmed by t-tests). From Figure 5.2 the difference between nonpartisan anger and anxiety is much closer, and does not seem to display the offset that partisan news does.

Figure 5.2: Plot of Probability of Each Emotion For Nonpartisan vs. Partisan News



My overall expectations about the general media landscape in this time period hold. Partisan news environments are more intensely angry compared to their nonpartisan news counterparts. And more intense and more frequent anger is offset by less frequent anxiety in the partisan news landscape. The nonpartisan networks continue to be dominated by anxiety, but they also maintain higher levels of enthusiasm, in both frequency and intensity, than partisan news. While the overall media landscape form 2010-2020 takes the same general shape as the landscape from 2000-2008, there is still the question of whether the landscape changed between 2010 and 2020 or whether it maintained the same trends as the previous decade.

5.4 Changes in the Emotional Intensity and Frequency of Partisan and Nonpartisan News: 2010-2020

5.4.1 Emotional Intensity for Nonpartisan vs Partisan News from 2010-2020

If there are changes to the media landscape prompted by Donald Trump's candidacy, they should appear within these years. To test whether or not his candidacy can be associated with greater levels of anger in partisan news, I regress the emotional intensity of news on news type. A *year* variable, which represents each election year in the sample, is also included in the model and is interacted with news type to examine the change over time for partisan and nonpartisan networks. The following model is used for this analysis:

$$Emotion_j = \beta_0 + \beta_1 NewsType + \beta_2 Year + \beta_3 (NewsType * Year)$$

Where j is one of the three emotions: anxiety, enthusiasm, or anger. Table 5.3 displays the regression of the emotional intensity of either anxiety, enthusiasm, or anger on news type and moderated by year. For all models the constant term represents nonpartisan news. Regression results are displayed in Figures 5.3-5.5.

Table 5.3: OLS Regression for the Intensity of Anxiety, Enthusiasm, and Anger for Partisan and Nonpartisan News Over Time

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
Partisan News	0.01	-0.26^{***}	0.47^{***}
	(0.09)	(0.08)	(0.09)
Year	0.10^{***}	0.03	0.03
	(0.02)	(0.02)	(0.03)
Year*Partisan News	-0.08^{**}	-0.05	-0.02
	(0.03)	(0.03)	(0.03)
Constant	4.08^{***}	4.74^{***}	4.23^{***}
	(0.07)	(0.06)	(0.08)
N	11759	15505	13672
R^2	0.003	0.01	0.01
Adjusted R^2	0.003	0.005	0.01
Residual Std. Error	2.50 (df = 11755)	2.61 (df = 15501)	2.66 (df = 13668)
F Statistic	11.96^{***} (df = 3; 11755)	26.96^{***} (df = 3; 15501)	25.21^{***} (df = 3; 13668)
Note:			$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

The regression for anxiety is modeled in Column 1 of Table 5.5. The intercept shift for partisan news (0.01) is not statistically significant, but as the year increases, the intensity of anxiety in partisan news decreases at a rate that is statistically significant from zero (-0.08). Conversely, anxiety in nonpartisan news is increasing (0.10, $p < 0.001$). These differences can be seen in Figure 5.3. It is important to note that because of the additive nature of the logit model, the estimates for partisan anxiety over time do not appear to decrease between 2010 and 2020. The anxiety for partisan news appears to be flat.

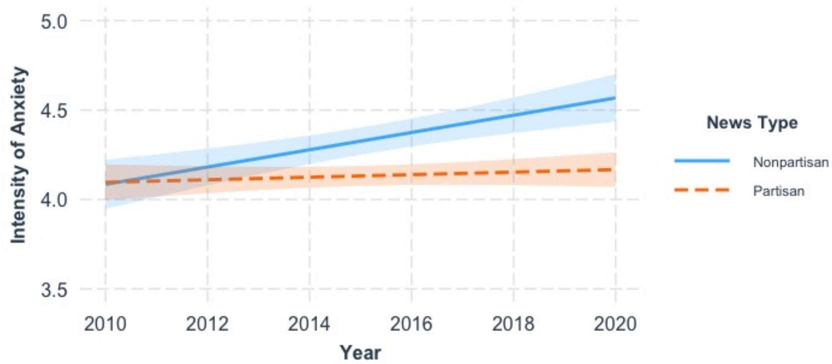


Figure 5.3: Intensity of Anxiety For Nonpartisan vs. Partisan News Over Time

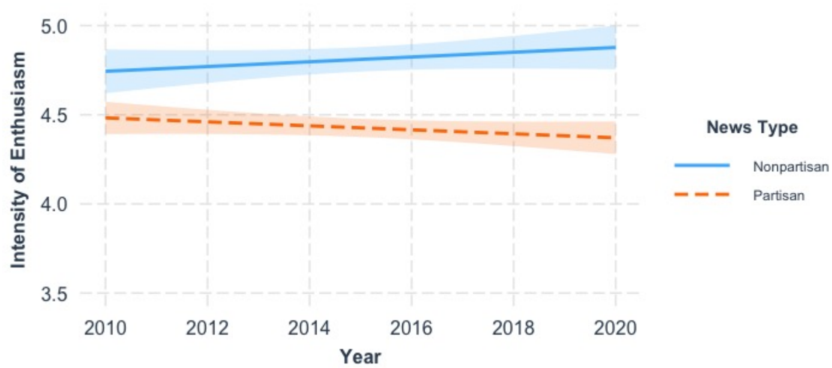


Figure 5.4: Intensity of Enthusiasm For Nonpartisan vs. Partisan News Over Time

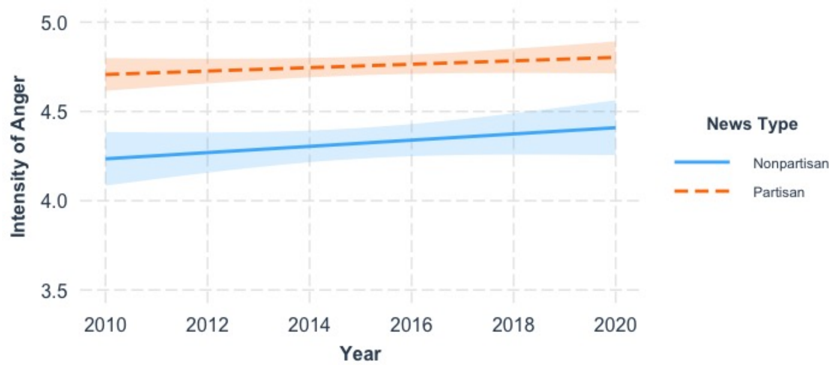


Figure 5.5: Intensity of Anger For Nonpartisan vs. Partisan News Over Time

True to my expectations, the intensity of anxiety for both partisan and nonpartisan news is consistent over this time frame. While there is an initial negative intercept shift for partisan news (-0.26, $p < 0.001$), again confirming that nonpartisan news will have higher levels of enthusiasm than partisan news neither partisan (-0.05) nor nonpartisan news (0.03) show a slope over time statistically distinct from zero, and this time trend is displayed in Figure 5.3.

Counter to my expectations and the expectations of many pundits, anger in partisan news did not increase following Trump's appearance on the national political scene. Column 3 in Table 5.3 indicates that while there is an intercept shift when moving from nonpartisan to partisan news (0.47, $p < 0.001$), the coefficient for partisanship over time is not statistically distinct from zero (-0.02), indicating a null effect. The same holds for nonpartisan news: while the intensity of anger is lower for nonpartisan news, it is also not increasing at a statistically significant rate from 2010 to 2020. This time trend for the intensity of anger is made clear in Figure 5.5.

5.4.2 Emotional Frequency for Nonpartisan vs Partisan News: 2010-2020

While respondents' perceptions of emotional intensity over 2010-2020 were surprisingly flat, with change mainly seen in increased anxiety in traditional news, it is still possible that changes to the emotionality of the media landscape were expressed in how frequently hosts conveyed anxiety, enthusiasm, or anger to their audiences. While there does not seem to be a strong case for a Trump effect regarding changes to the intensity of news between 2010 and 2020, it is possible that changes in frequency created *more* anger that was transmitted to television news viewers. Here I again regress the type of news interacted with year on emotion using an inverse logit link function, since the presence or absence of each emotion is binary.

$$Emotion_j = logit^{-1}(\beta_0 + \beta_1 NewsType + \beta_2 Year + \beta_3(NewsType * Year))$$

Where j is one of the three emotions measured— either anxiety, enthusiasm, or anger. Table 5.4 displays the results for each model, and Figures 5.6-5.8 plot the predicted probabilities for each respective emotion. Nonpartisan news is again the reference category for the regression.

I predicted that for partisan networks, the frequency of anxiety would decrease over time. This is not the case. There is an intercept shift of -0.12, resulting in a decrease in the log likelihood of partisan news transmitting anger compared to nonpartisan news and again establishing that the nonpartisan news broadcasts more anxiety than partisan news does. But the coefficient (-0.004) for the change in the log likelihood of anxiety over time for partisan news is not distinct from zero. The coefficient for the *year* variable indicates an increase in the frequency of anxiety for nonpartisan news over this time period (0.03, $p < 0.01$). Because of the additive nature of the model, Figure 5.6 displays a slight increase in anxiety over time for both nonpartisan *and* partisan news. The anxiety of partisan news, counter to my hypothesis, does not appear to be decreasing over the time frame.

Table 5.4: Logistic Regression for the Likelihood of Anxiety, Enthusiasm, and Anger for Partisan and Nonpartisan News Over Time

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
Partisan News	-0.12^{**}	-0.18^{***}	0.47^{***}
	(0.05)	(0.05)	(0.05)
Year	0.03^{**}	0.002	-0.03^{*}
	(0.01)	(0.01)	(0.01)
Year*Partisan News	−0.004	−0.02	0.06^{***}
	(0.02)	(0.02)	(0.02)
Constant	-0.23^{***}	0.48^{***}	-0.29^{***}
	(0.04)	(0.04)	(0.04)
N	26566	26563	26630
Log Likelihood	−18,215.99	−18,000.81	−18,156.03
Note:			*p<0.05; **p<0.01; ***p<0.001

As I predicted, the frequency of enthusiasm does not appear to change for either network type. Column two of Table 5.4 does indicate that the frequency of enthusiasm decreases for partisan news (-0.18, $p < 0.001$) compared to nonpartisan news. In Table 5.4, Column 2, the coefficient for the log likelihood of partisan news interacted with year is not statistically distinct from zero (-0.02) nor is the coefficient for the *year* variable (0.002), which indicates the slope for nonpartisan news. This flat trend for enthusiasm can be seen in Figure 5.6 for both partisan and nonpartisan news.

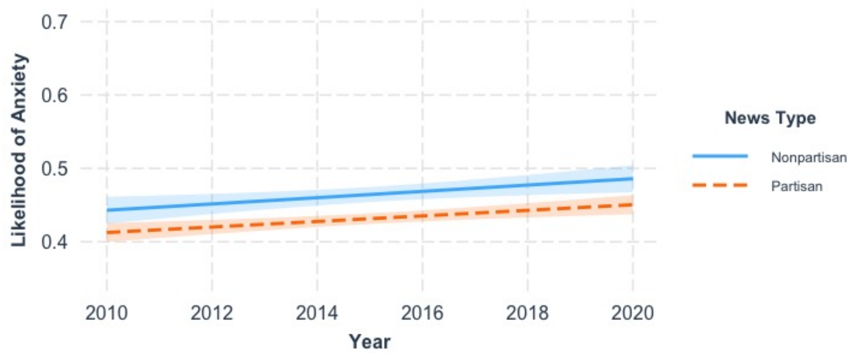


Figure 5.6: Plot of Predicted Probabilities for Anxiety For Nonpartisan vs. Partisan News Over Time

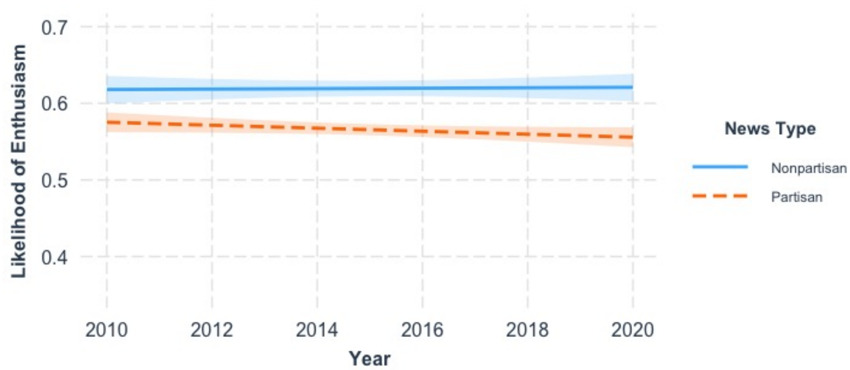


Figure 5.7: Plot of Predicted Probabilities for Enthusiasm For Nonpartisan vs. Partisan News Over Time

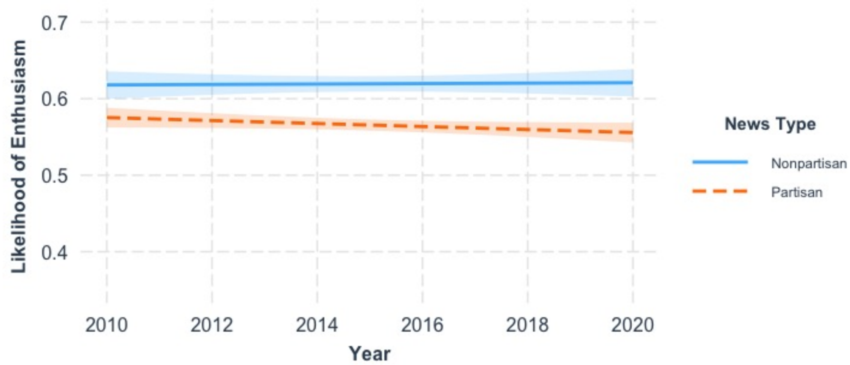


Figure 5.8: Plot of Predicted Probabilities for Anger For Nonpartisan vs. Partisan News Over Time

I predicted that the frequency of anger would increase over time for partisan news if there was a Trump effect, and anger does increase from 2010-2020. In Table 5.4, Column 3, the coefficient for the interaction of partisan news with year is positive and statistically significant $(0.06, p < 0.01)$ and there is an overall greater frequency of anger for partisan news $(0.48, p < 0.01)$ compared to nonpartisan news.

5.4.3 Discussion

The initial evidence for a Trump effect between 2010 to 2020 appears mixed. The prediction that the media was angrier after his entry into presidential politics is only partially borne out. The general intensity of anger did not increase for partisan news over time, but the likelihood of cable news broadcasting angry cues from anchors has increased. While the vitriol and insults lobbed by partisan news are not more intense, they has become more frequent. But the increase in frequency is less meaningful than it appears. The shift in the frequency of anger moves from occurring roughly 54% of the time to 58% of the time. If MSNBC airs 30 segments in a week of news, this equates to anger increasing by roughly one additional segment a week from 2010 to 2020. This seems like very little practical change given the degree to which Trump was alleged to have manipulated the media. Overall, this initial evidence puts the idea that Trump changed the emotional landscape of the media on shaky ground.

But the pooling of partisan news may hide heterogeneity between the networks. Are the networks all expressing the same levels and frequencies of anxiety, anger, and enthusiasm? Or are some networks driving these emotions? In the next section I examine if there are between-network differences for CNN. Fox, and MSNBC that may further explain the emotional environment in which partisan news viewers find themselves.

5.5 Changes in the Emotions in Partisan Cable News: 2010-2020

While there does not seem to be variation in the aggregate for partisan cable news, it is possible that the pooling of partisan networks hides variation between them from 2010 to 2020. The strongest possible case for Trump changing the media landscape is that all networks became more angry and less anxious over this time period. While that seems unlikely, given that the pooled results for partisan news do not produce the changes I might expect from a unique occurrence influencing the news, variation between the partisan networks may still provide insight into the general trends of increased participation and partisan animosity in the American public.

5.5.0.1 Emotional Intensity For Partisan Cable Networks Over 2010-2020

To examine changes in the emotional intensity within partisan news, I regress the emotional intensity of anxiety, enthusiasm, and anger on partisan network type moderated by year.

$$Emotion_j = \beta_0 + \beta_1 PartisanNetwork + \beta_2 Year + \beta_3(PartisanNetwork * Year)$$

Table 5.5 displays the changes in emotional intensity for the partisan cable networks from 2010-2020. CNN is the reference category and is represented by the constant term in the regression.

The results for changes in the intensity of partisan anxiety are mixed (Table 5.8). I predicted that a Trump effect would lower anxiety among the partisan networks, because that is the direction indicated by increased electoral participation. Anxiety increases deliberation (MacKuen et al., 2010) but stifles participation (Mutz, 2006), and over the period of 2010 to 2020 participation among the electorate increased (Desilver, 2021). Fox begins the time frame with a slightly higher level of anxiety than CNN (0.08), though the shift is not statistically significant, and MSNBC has a lower level of anxiety (-0.33, $p < 0.33$) compared to CNN in 2010. The change over time for the networks is visualized in Figure 5.9. The slope for CNN is flat (0.003, $p > 0.05$), and the changes in Fox and MSNBC are in opposition to one another: MSNBC's level of anxiety is increasing (0.10 $p < 0.05$) between 2010-2020 whereas the intensity of anxiety for Fox (-0.08, $p < 0.05$) is decreasing over time. Fox is the only network whose levels of anxiety follow my predicted pattern: the other networks either do not have changes in the intensity of anxiety (CNN) or the intensity of anxiety increases (MSNBC) during the years that Trump emerges in national politics.

The intensity of enthusiasm for the cable networks over time appear to be either stagnant or decreasing. Both MSNBC and CNN maintain their level of enthusiasm over the time period (Table 5.5, Column 3), and the essentially flat lines for their level of enthusiasm are displayed in Figure 5.10. The intensity of enthusiasm exhibited by Fox, despite higher levels of enthusiasm compared to CNN and MSNBC in 2010 (0.40, $p < 0.001$), decreases slightly from 2010-2020. None of the slopes for the change in the intensity of enthusiasm for the partisan networks are statistically significant, and the levels of enthusiasm appear to be converging for partisan news over time (Figure 5.10).

Table 5.5: Regression for the Intensity of Anxiety, Enthusiasm, and Anger for Partisan Cable News from 2010-2020

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
Fox	0.08	0.40^{***}	0.22
	(0.13)	(0.12)	(0.12)
MSNBC	-0.33^{**}	0.14	0.06
	(0.12)	(0.11)	(0.12)
Year	0.003	-0.02	-0.01
	(0.03)	(0.03)	(0.03)
Fox*Year	-0.08^{*}	-0.05	0.09^{*}
	(0.04)	(0.04)	(0.04)
MSNBC*Year	0.10^{*}	0.02	-0.001
	(0.04)	(0.04)	(0.04)
Constant	4.19^{***}	4.30^{***}	4.62^{***}
	(0.08)	(0.09)	(0.09)
N	7600	9961	9993
R^2	0.003	0.003	0.01
Adjusted R^2	0.002	0.002	0.01
Residual Std. Error	2.47 (df = 7594)	2.57 (df = 9955)	2.68 (df = 9987)
F Statistic	4.76^{***} (df = 5; 7594)	5.03^{***} (df = 5; 9955)	13.12^{***} (df = 5; 9987)
Note:			$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Figure 5.9: Plot of Intensity for Anxiety For Nonpartisan vs. Partisan News Over Time

Figure 5.10: Plot of Intensity for Enthusiasm For Nonpartisan vs. Partisan News Over Time

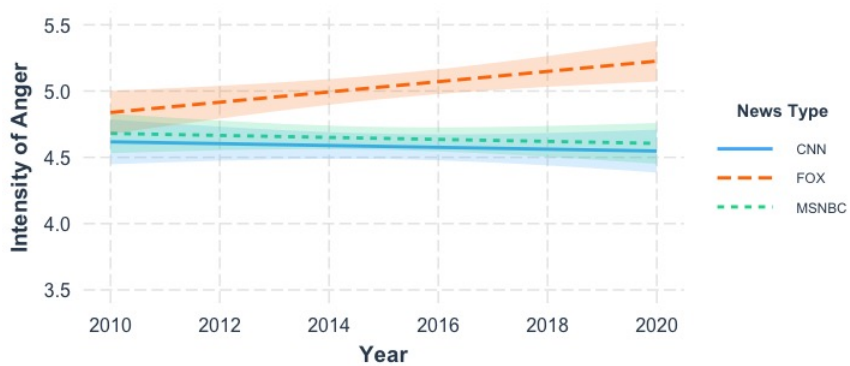


Figure 5.11: Plot of Intensity for Anger For Nonpartisan vs. Partisan News Over Time

The results for the intensity of anger over the 2010-2020 time period are much more stark. Fox has more intense anger compared to CNN and MSNBC at the start of the era, though these differences are not statistically significant. However, the slope for Fox over time is increasing (0.09, $p < 0.05$) while the change over time for both CNN and MSNBC is stagnant. Figure 5.13 displays both CNN and MSNBC maintaining not only their slope, but also similar levels of anger over time. But Fox's increase in the intensity of anger is clear and separates it from that of CNN and MSNBC. The changes in the intensity of anger in the news environment from the years 2010 to 2020 appear to occur only on Fox News.

5.5.1 Emotional Frequency For Cable Networks over 2010-2020

Perhaps the majority of the changes occurred in the *frequency* of emotions in partisan news, rather than the *intensity*, resulting in less frequent doses of anxiety and a greater number of anger cues. I regress the emotional frequency of anxiety, enthusiasm, and anger on partisan network type moderated by year to examine if changes in frequency occurred over the Trump era.

$$Emotion_j = logit^{-1}\beta_0 + \beta_1 PartisanNetwork + \beta_2 Year + \beta_3(PartisanNetwork * Year)$$

Table 5.5 displays the changes in emotional intensity for the partisan cable networks from 2010-2020. CNN is once again the reference category and is represented by the constant term in the regression. Both MSNBC (-0.39, $p < 0.001$) and Fox (-0.26, $p < 0.001$) are less frequently angry than CNN in 2010. This difference is visible in Figure 5.12.

Table 5.6: Logistic Regression for the Likelihood of Anxiety, Enthusiasm, and Anger for Partisan News Over Time

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
Fox	−0.26***	0.37***	0.15*
	(0.07)	(0.07)	(0.07)
MSNBC	−0.39***	0.14*	0.36***
	(0.07)	(0.07)	(0.07)
Year	0.01	−0.04*	0.07***
	(0.02)	(0.02)	(0.02)
Year*Fox	−0.01	0.002	0.02
	(0.02)	(0.02)	(0.02)
Year*MSNBC	0.07***	0.06**	−0.11***
	(0.02)	(0.02)	(0.02)
Constant	−0.13**	0.14**	−0.002
	(0.05)	(0.05)	(0.05)
N	17612	17613	17681
Log Likelihood	−11,996.64	−11,994.84	−12,061.31
Note:			*p<0.05; **p<0.01; ***p<0.001

The predicted changes for the networks do not bear fruit. The frequency of anxiety for both CNN (0.01) and Fox (-0.01) are both stagnant (Figure 1.12). Contrary to expectations, the frequency of anxiety for MSNBC is increasing over the time period (0.07, $p < 0.001$, Figure 5.12), moving from anxiety occurring roughly 37% of the time to approximately 47% of the time. Anxiety is not decreasing as anticipated.

While I anticipated no change in the frequency of enthusiasm, the results are again mixed. Both Fox and MSNBC began the era with higher levels of enthusiasm than CNN (Figure 5.13). Fox does not have changes to the frequency of enthusiasm (Table 5.6, Column 2) over time. MSNBC does have a slight positive slope (0.06, $p < 0.01$, Table 5.6, Column 2) but this counteracted by the negative slope for *year* (-0.04, $p < 0.5$), resulting in a slight positive change (Figure 5.13). The change to CNN over the time frame is negative (-0.04, $p < 0.05$): rather than constant enthusiasm cues, the rate at which CNN is conveying enthusiasm to audiences is decreasing.

The most critical change in frequency from 2010 to 2020, if Trump did indeed impact the media, is that the partisan networks should all have increases in the frequency of anger over time. This only occurs for two of the three networks (Table 5.6). The anger displayed by both Fox and CNN *is* increasing during the Trump era (Figure 5.14). While the coefficient for the change in frequency of anger in Fox over time is not statistically significant (0.02), the change in the frequency of anger for CNN is (0.07, $p < 0.001$). Since CNN is the baseline condition, the additive nature of the model results in an increase in the frequency of anger for Fox from 2010 to 2020. And while CNN and Fox have increasing likelihoods of anger, MSNBC is moving in the opposite direction. Its decrease in the frequency of anger (-0.11, $p < 0.001$) is evident in Figure 5.14.

Figure 5.12: Plot of Frequency of Anxiety for CNN, Fox, and MSNBC over 2010-2020

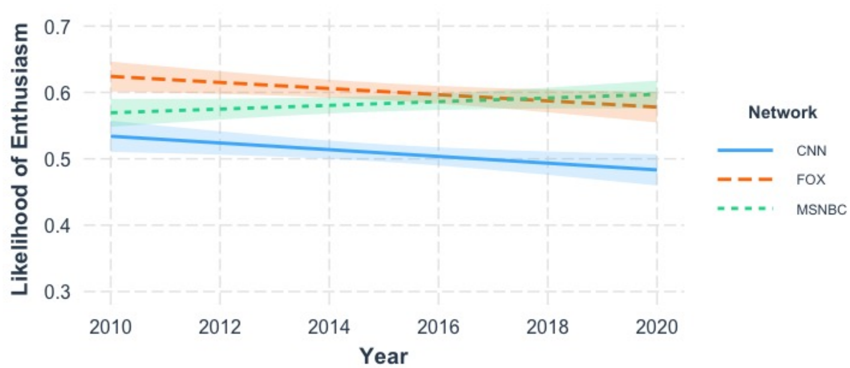


Figure 5.13: Plot of Frequency of Enthusiasm for CNN, Fox, and MSNBC over 2010-2020

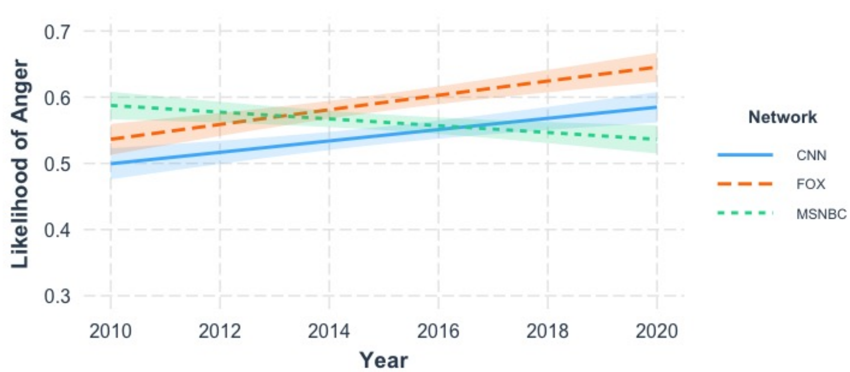


Figure 5.14: Plot of Frequency of Anger for CNN, Fox, and MSNBC over 2010-2020

5.5.2 Discussion

The changes to the intensity and frequency of emotions in partisan news do not provide strong support for a Trump effect. If Trump fundamentally changed the media over this time period, there should be shifts in both the intensity and frequency of emotions, particularly anger, across all three partisan networks. Yet anger only rises in intensity *and* frequency for Fox News. It is possible that if he did have an effect on the media, it was centered on his copartisan network. While the intensity of anxiety is decreasing for Fox, there is not an anger offset. As the frequency of anger rises, the frequency of anxiety is not decreasing, as my theory would expect. There are also increases in the frequency of anger for CNN over the time period, but the increase in intensity is absent, and CNN's intensity and frequency of anxiety are also consistent. Nor does MSNBC experience increases in the intensity of anger: instead it has decreasing instances of anger in its programming, creating stagnant levels of anger that are being broadcast less often. With its decrease in anger, MSNBC does have an upward shift in the frequency of anxiety, which conforms to my theoretical expectations of an inverse relationship between the amount of anxiety and anger cues that a network is able to broadcast during the course of a program.

The changes in emotional cues within the partisan media environment appear to be largely constant from 2010 to 2020. The era does not seem to be characterized by large shifts in the emotional signals sent from partisan news to the public. And while I argue the emotional signal that should be sent from partisan news during this period is anger, if the alternative hypothesis is that anxiety from partisan sources is contributing to the feelings of the electorate, evidence of that effect is also absent. The changes to anxiety within partisan networks over time do not indicate a positive shift in either the emotional intensity or frequency of anxiety across the networks. MSNBC is the only network that experiences increases in both the intensity and frequency of anxiety over this time frame.

5.6 Emotional Changes in the Election of 2016

The linear results for the intensity and frequency of anxiety, enthusiasm, and anger over time do not support the hypothesis that Trump fundamentally changed the partisan media over the time frame. But the final test of whether or not he impacted the media is whether change occurred between the election years of 2014 and 2016. Journalists and pundits may have been attuned to a localized change in the emotional intensity or frequency of the media. Trump entered the presidential race in 2015, so if he produced changes in the media because of his presidential campaign, these changes should be apparent in differences in the average intensity and frequency of emotional cues in the news from 2014 to 2016.

Figures 5.15 and 5.16 report the averages in the intensity and frequency of anxiety, enthusiasm, and anger for each partisan network in 2014 and 2016, respectively.

I hypothesized that if there was a Trump effect, the intensity of anger should increase and the intensity of anxiety should decrease for partisan networks between 2010 and 2016. As displayed in Figure 5.15, all networks decrease in anxiety from 2014 to 2016, but the only network with a statistically significant decrease is CNN ($p < 0.01$, as confirmed by t-test).[5] MSNBC and Fox also experience decreases in anxiety between 2014 and 2016, but the decreases are not statistically significant. The results for changes in the intensity of anger are similar. Anger is *decreasing* for all networks from 2014 to 2016, but the only statistically significant decrease is again for CNN ($p < 0.01$). There also are no statistically significant shifts in enthusiasm for any of the networks from 2014 to 2016: the direction of change for Fox and MSNBC is positive while the direction of change for CNN is once again negative. In terms of the patterns of intensity of emotions between 2014 and 2016, the intensity of anxiety *and* anger on Fox and MSNBC did not change while CNN experienced a decrease in the intensity of both emotions.

[5] Full results can be found in the appendix.

Figure 5.15: Average Intensities of Anxiety, Enthusiasm, and Anger for Partisan Networks in 2014 and 2016

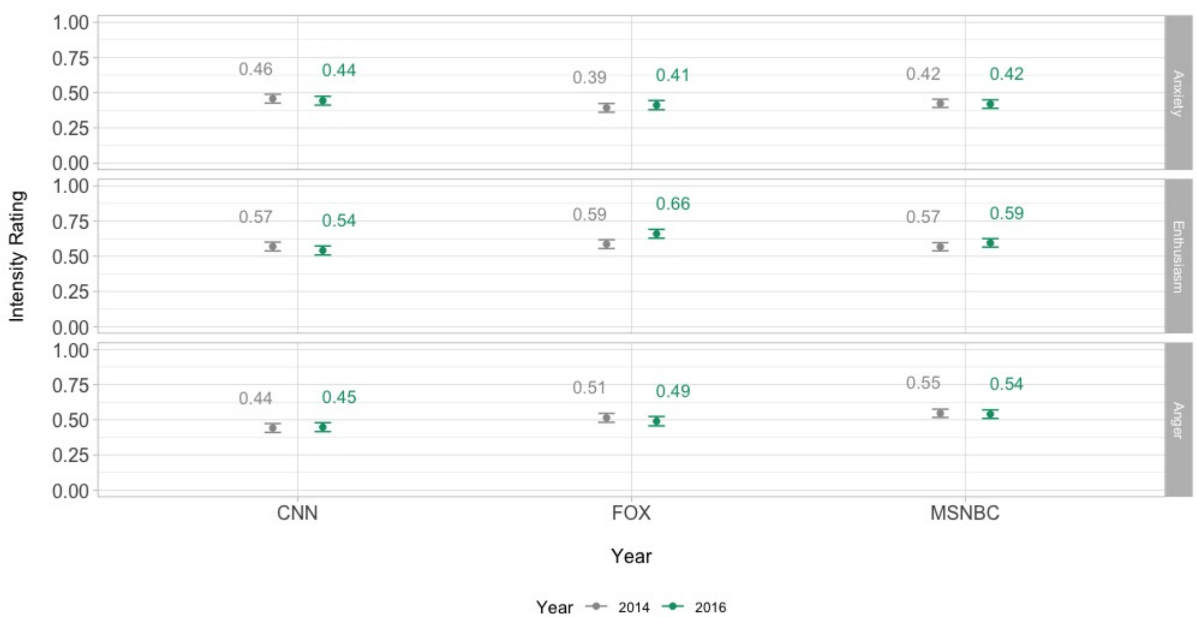


Figure 5.16: Average Frequencies of Anxiety, Enthusiasm, and Anger for Partisan Networks in 2014 and 2016

The pattern for the frequency of emotions for the partisan networks between 2014 and 2016 is similar to that of intensity (Figure 5.16). Despite my hypotheses that anxiety should decrease for all networks from 2014 to 2016, the frequency of anxiety decreases only for CNN—and the decrease is not statistically significant. In practical terms, if CNN broadcasts 25 segments per week, the number of segments that would contain anxiety would remain constant at 11.

My prediction that a Trump effect would be visible in changes in the frequency of anger for partisan networks must also be rejected. Fox and MSNBC have slight decreases in anger between 2014 and 2016: not only is the effect null, but it is in the wrong direction. The difference between the frequency of anger between 2014 and 2016 is in the correct direction for CNN, but it is also not statistically significant.

The only significant change in the frequency of emotions between 2014 and 2016 is for the enthusiasm broadcast by Fox between 2014 and 2016. The amount of enthusiasm increases by 7 points ($p < 0.01$), shifting from enthusiasm occurring in 15 of the 25 segments broadcast per week to 16 segments. Overall there are not the expected shifts in the emotional frequency of news that I would expect to see if Trump was responsible for emotional changes in the news during the course of his election.

5.6.1 Discussion

Analyzing the differences in the intensity and frequency of emotional cues from partisan networks from 2014 to 2016, there does not seem to be a Trump effect. While the intensity of anxiety decreases, as predicted, there were no decreases in the frequency of anxiety among the networks. Further, only the decrease in the intensity of anxiety for CNN was statistically significant. Additionally, the changes in anger are the opposite of my expectations: if Trump changed the media during his campaign I would expect higher levels and frequencies of anger between 2014 and 2016 in the partisan press. What is observed is that anger generally decreases in intensity and frequency, and these changes are not statistically significant.

5.7 Conclusion

During the Republican National Convention in the summer of 2016, Donald Trump made the claim that he alone could bring change to the United States and solve societal problems if elected to the presidency. After his election to the presidency, the media seemed to agree with him in one respect: that he had fundamentally changed the emotional tone in the media during the 2016 presidential campaign. Initially they speculated that citizens became more fearful both of the state of the economy and of Hillary Clinton, which caused many of them to vote for Trump. However, the behavioral outcomes of anxiety are not associated with high voter turnout and partisan animosity. Citizens who are anxious will be more considerate of contemporary considerations (Valentino et al., 2008) and may even be less likely to participate in politics, since anxiety decreases the likelihood of action (Wagner and Morisi, 2019). The fundamental emotion driving the electorate should be anger, which spurs action towards goals (Lerner and Keltner, 2001) and increases partisan polarization (Iyengar and Westwood, 2015). If Trump's arrival on the national stage changed the emotional tenor of the media, it is likely with increased partisan anger cues in the media over 2010-2020.

The anticipated general trends for partisan and nonpartisan media continue to hold from 2010 to 2020. On average partisan media is angrier and less anxious than nonpartisan news media. Nonpartisan news media also continues to have greater levels of enthusiasm than partisan news. But changes from 2010 to 2020 do not reveal evidence that Trump changed already established trends in the media. Anger and partisan media only increases in frequency and not intensity from 2010 to 2020. Conversely, while the intensity of anxiety is flat for partisan media, both traditional and partisan media have slight increases in the frequency of anxiety over this time.

Dis-aggregating the partisan networks reveals that shifts in anger for individual networks are limited. Fox is the only network that increases in both the intensity and frequency of anger from 2010 to 2020. But if Trump had a large impact on the emotional nature of the media, we would expect to see it across partisan networks, especially because of the increased partisan animosity over this time frame. While there may have been a specific effect on copartisan Fox News during this time, the change in emotions from 2014 to 2016 provides no evidence that a fundamental shift in the media occurred.

There is the potential for other modeling strategies to be used to examine the relationships over time, both within and between networks. To start this process I have plotted the data from Chapter 4 and Chapter 5 together in Appendix E, both by partisan and nonpartisan news and dis-aggregated by network. In addition, Appendix E also contains LOESS plots for the intensity and frequency of anxiety, enthusiasm, and anger over time, beginning an exploration of potential inter-dependencies between networks in response to changing television ratings. Because the data for this project is sparse, more data will have to be collected to further interrogate the potential that networks are responsive to the emotional cues being broadcast by rival networks. I discuss the potential next steps for both for further interrogating my data and for creating a more dense data set in Chapter 6.

Overall there does not seem to be evidence that large changes in the media around the time that Trump entered national politics are because of a candidate who broke with political norms. It seems more likely that the emotions shaping politics are continuations of trends that began with the entry of Fox and MSNBC into the cable news environment in the late 1990s.

CHAPTER 6

Conclusion

6.1 Summation

Using a methodological framework for human coders to categorize emotional cues in the news, I find that the news environment citizens select exposes them to different levels of anger, anxiety, and enthusiasm. Contemporary partisan news is angrier than nonpartisan news. This emotional landscape began to develop in the early 2000s with the introduction of Fox News into the cable news environment. From 2000 to 2008, the general cable news environment express more intense and frequent anger; cable networks that initially lagged in anger had gained on Fox by the end of 2008. CNN and MSNBC had increasing anger cues over this time period, both in intensity and frequency.

This increasing anger in partisan news in the early 2000s is coupled with more frequent anxiety among nonpartisan news. While the intensity of anxiety between partisan and nonpartisan networks did not differ much before 2008, over the course of election years from 2010 to 2020, traditional news outpaced partisan news in the intensity of anxiety that it was broadcasting. It also maintained its production of more frequent anxiety cues compared to partisan networks, creating a nonpartisan news environment that cues anxiety to the public.

However, the election years from 2010 to 2020 did not show the anticipated changes in the emotional landscape of partisan or nonpartisan news that I expected based on the many reports in the media about how then-Candidate Trump had changed the emotional environment of the media. While the intensity and frequency of anxiety cues in nontraditional news increased, Trump does not appear to have fundamentally changed the emotional landscape of the media, especially the partisan media. Anger cues, in both intensity and frequency, were generally consistent over nonpartisan news from 2010 to 2020. An examination of the individual partisan networks over that time frame indicates that anger cues increased for both intensity and frequency for Fox, a network friendly to Trump, but MSNBC and CNN did not generally follow suit. The intensity of anger was stable for both MSNBC and CNN over the time period, but the two networks have opposing associations with the frequency of anger: it increased for CNN and decreased for MSNBC. Further examination of the differences between the 2014 midterms and the 2016 election for partisan news indicates declines in the intensity of anger and no changes to the frequency of anger for CNN, Fox, or MSNBC. Surprisingly, the emotional cues in the news were extremely consistent from 2014 to 2016. The evidence the data brings to bear indicates that the trajectory of emotions in the news was set prior to the arrival of Trump in national politics. The emotionality of the 2016 election was not because of Trump, but has it roots in the different emotional landscapes created by partisan and nonpartisan news, which began almost two decades earlier.

My results also support the theory that elites are providing emotional signals to the public, rather than calibrating the news to match public emotions. If news programming was following the emotions of the public, rather than signaling to the public how they should feel, I would expect that all news programs would have similar levels of emotions throughout 2000 to 2020. Instead we see clear differences in the emotional cues provided by partisan and nonpartisan news, which do not seem to be moving in a similar fashion over time. While it could be the case that partisan news and not nonpartisan news is responsive to the emotions of the public, two patterns in my data seem to dispute this point. The first is that in 2000 Fox has more anger than both CNN and MSNBC: by 2008 both networks have increased their levels of anger to become closer to those broadcast by Fox. Then over the 2010 to 2020 time period the intensity *and* frequency of anger increases for Fox news but CNN and MSNBC do not. Only CNN increases in its frequency of anger over that time. If the networks were responding to the emotions of the mass public, rather than signaling how members of the public should feel about political events, these networks would be more consistently aligned with regards to emotional intensity and frequency, especially when it comes to anger.

While this dissertation provides evidence for the differences in the emotional landscapes of partisan and nonpartisan American television news, I have not causally linked them to changes in political behaviors or attitudes of citizens. Furthering this research to offer more support for the power of elite emotional cues in American media is necessary to both further test my theory and establish stronger connections between the emotional landscape of the media and the contemporary political environment in the United States.

6.2 Future Work

To test the impact of partisan news, I plan to explore both how it impacts participation variables, such as likelihood of voting and campaign activity, and polarization measures. For polarization, I plan on exploring its impact on perceptions of both elite partisans and partisan members of the American public. I have also been considering how the anger cues in the partisan news may have influenced the assault on the US Capitol on January 6, 2021. Since anger can cause citizens to take greater risks (Lerner and Keltner, 2001), I also want to test how anger—and viewing copartisan anger—may influence citizens' acceptance of political violence. The coding of the news transcripts will allow me to construct news stimuli that are angry, anxious, or enthusiastic and examine their impact on both partisan emotions and how the stimuli influence the acceptability of political violence.

Additionally, the 2020 ANES results found that Republicans still have increasing anger about the state of the nation when they report viewing partisan news, *even though* emotional responses to the state of the nation are highly correlated with feelings towards President Trump. This increase in anger may be driven by *what* Republican partisan news was angry about, not just that it was angry. When human coders evaluated the emotions felt by newscasters in election years between

2000 and 2020, I also had them highlight the text sections in the transcripts which indicated the emotions that the anchor or host was feeling. This was done any time a coder indicated that an emotion was being felt by the news anchor; when they said an emotion was not present they did not highlight text. A future direction of this project is to examine not just the emotional landscapes within partisan and nonpartisan news but to also see *what* partisan news is angry about. Since the news has the ability to tell citizens what information is important (Iyengar and Kinder, 1987), they may also be getting angry about different policies and topics. Further exploring how emotional cues intersect with agenda setting is one of the directions in which I plan to take this project.

There are also three other ways that this project shapes my research agenda. I plan on expanding my historical analysis of the news to provide a more extensive, comparative analysis of the history of news in the 19th century and the competitive cable news environment that resulted from the arrival of Fox and MSNBC in the late 1990s. This expansion will offer a more systematic review of partisan newspapers in the 19th century. The archival newspapers that I used in Chapter 2 provided anecdotal context, but further content analysis will strengthen my claim that partisan news in the American media environment is angry news. Because the newspapers of the early 19th century are not digitized in the same way that contemporary television news transcripts are, any surveys of respondents rating the emotional intensity of these texts will require reformatting. From combing over newspapers from the partisan press in Ann Arbor and Detroit in the Bentley Historical Library, the physical condition of the papers and the language used in the papers could also pose problems, and I will have to determine if I will take a more qualitative approach or try to again use human coders for examining the partisan press in the early 19th century.

My research may also examine changes in the emotional cues in news *over* the 2016 election year. The current television sample for 2016 does not have enough variation month to month to examine if, as the election drew closer, the emotional signals broadcast via television news changed. This fine grained analysis could be done by either collecting a sample from 2016 with moths being the sampling frame, rather than year; or by using machine learning to code additional transcripts based on the data already collected. While this dissertation has been focused on how to best test the theoretical claims of changes in the emotional landscape of the news over time, the texts that I have collected present an opportunity for training supervised machine learning models. Respondents who coded election years from 2000 to 2008 also coded two weeks of news from 2015, providing a test set of data to use for a supervised machine learning project that takes into account both the frequency *and* intensity of emotions. Extensively coding all news transcripts from 2000 to 2020 would help further illuminate emotional changes in the partisan and nonpartisan media landscape and may also allow for the comparison of election and non-election years over the time period. There may also be inter-dependencies in the data, particularly with regards to how networks change their programming in response to competitors gaining in the ratings. I have begun to explore these inter-dependencies over the 2000 to 2020 period in the Supplemental Data Appendix E, but the current sampling frame results in sparse data over time. Increasing the amount of data and composing a less sparse data set will allow me to better test time trends and inter-dependencies, providing an even clearer picture of the media landscape than presented in this dissertation.

Finally, my theory about the cuing of anger in partisan news is not restricted to just television news. I would expect to see these differences in the emotional environment of any media space where there are journalists that follow the professionalized norms of objectivity, compared to partisan journalists who will infuse their coverage with a partisan perspective. Online news may be another test case for my theory, both because of the partisan segmentation of the news space and the ability for me to use human coders to rate the emotions in that space using text.

This dissertation is an initial step in examining the role of emotions in the current segmented news environment. The differences in the emotional landscape demonstrated here, particularly regarding anger, many prove critical for understanding the current political climate in the United States. My future research aims to provide further insight into the role of emotions, particularly anger in the news environment and how it is influencing contemporary American politics.

APPENDIX A

ANES Appendix

A.1 2016 ANES

A.2 Demographics

This section provides demographic information for the 2016 ANES. The demographic variables here are either variables of interest in regressions (i.e. party identification) or variables that are used for controls.

A.2.1 Media

“During a typical week, how many days do you watch, read, or listen to news on TV, radio, printed newspapers, or the Internet, not including sports¿‘

Table A.1: *Number of Days per Week Respondent Consumes Media*

	N	%
Zero Days	73	1.7
One Day	187	4.4
Two Days	212	5.0
Three Days	287	6.7
Four Days	266	6.2
Five Days	641	15.0
Six Days	307	7.2
Seven Days	2293	53.7
NA	4	0.1
Total Respondents	4270	
Average: 5.54		*Median:7*

Table A.2: Mentions of Presidential Election Media Consumption for 2016 and 2020 ANES Respondents

	2016		
	Number	**Unweighted Percentage**	**Weighted Percentage**
TV News Programs	3591	84.1	83.4
TV Talk Shows or Analysis	2623	61.4	59.8
Newspapers	2078	48.7	46.9
Internet Sites	2609	61.1	59.5
Radio News or Talk	2290	53.6	52.4
None	47	1.1	1.3
Total Respondents:	4270		
	2020		
	Number	**Unweighted Percentage**	**Weighted Percentage**
TV : ALL	6906	83.4	83.8
Newspapers	3308	39.9	38.0
Internet Sites	5698	68.8	69.6
Radio News or Talk	4,199	50.7	50.9
None	178	2.1	2.0
Total Respondents:	8280		

A.2.2 Age

Table A.3: *Respondent Age*

	Min	Mean	Median	Max
Age	18.0	49.6	50.0	90.0

A.2.3 Education

Table A.4: *Respondents Who Attended At Least Some College*

	N	%
Attended College	3173	74.3
Did Not Attend College	1097	25.7

Table A.5: *Respondents' Level of Education*

	N	%
Less than 1st grade	1	0.0
1st, 2nd, 3rd or 4th grade	3	0.1
5th or 6th grade	15	0.4
7th or 8th grade	22	0.5
9th grade	32	0.7
10th grade	40	0.9
11th grade	62	1.5
12th grade no diploma	107	2.5
High school graduate - high school diploma or equivalent	815	19.1
Some college but no degree	898	21.0
Associate degree in college - Academic	288	6.7
Associate degree in college - Occupational/vocational	313	7.3
Bachelor's degree	955	22.4
Master's degree	499	11.7
Professional School Degree	88	2.1
Doctorate degree	93	2.2
NA	39	0.9

A.2.4 Current Employment

Table A.6: *If Respondent is Currently Employed*

	N	%
Currently Employed	2546	59.6
Currently Not Employed	1708	40.0
NA	16	0.4

A.2.5 Race

Table A.7: *Respondent Self-identified Race*

	N	%
White, non-Hispanic	3038	71.15
Black, non-Hispanic	397	9.3
Asian, Native Hawaiian or Pacific Islander	148	3.47
Hispanic	450	10.54
Other non-Hispanic or Mult. Racial	177	4.15
NA	33	0.77

Table A.8: *If Respondent Identifies as White*

	N	%
Not White	1199	28.1
White	3038	71.1

A.2.6 Party Identification

Table A.9: *Respondent 7 Point Party Identification*

	N	%
Strong Democrat	890	20.8
Lean Democrat	490	11.5
Democrat	559	13.1
Independent	579	13.6
Lean Republican	500	11.7
Republican	508	11.9
Strong Republican	721	16.9
NA	23	0.5
Total Respondents	4270	

A.2.7 Gender

Table A.10: *Self-Reported Gender Identification*

	N	%
Female	2242	52.5
Male	1987	46.5
NA	41	1.0
Total Respondents	4270	

A.3 Regressions for Democratic and Republican Candidates

A.3.1 Feelings Towards Presidential Candidate Hillary Clinton

Table A.11: Feelings Towards Candidate Hillary Clinton in 2016 ANES

	Anxiety	**Enthusaism**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	-0.06^{*}	0.06^{***}	-0.07^{**}
	(0.02)	(0.02)	(0.02)
Partisan News	0.10^{**}	0.06^{*}	0.20^{***}
	(0.04)	(0.03)	(0.03)
Age	-0.02	0.08^{***}	-0.05^{*}
	(0.03)	(0.02)	(0.03)
Female	0.02	0.02^{**}	0.01
	(0.01)	(0.01)	(0.01)
Attended College	-0.02	0.01	-0.01
	(0.01)	(0.01)	(0.01)
Party ID	0.45^{***}	-0.47^{***}	0.45^{***}
	(0.02)	(0.02)	(0.02)
Employed	-0.03^{*}	0.003	-0.02
	(0.01)	(0.01)	(0.01)
Ideology	0.31^{***}	-0.22^{***}	0.28^{***}
	(0.03)	(0.02)	(0.03)
White	0.09^{***}	-0.07^{***}	0.10^{***}
	(0.01)	(0.01)	(0.01)
Constant	-0.03	0.62^{***}	0.01
	(0.02)	(0.02)	(0.02)
N	2813	2813	2811
R-squared	0.43	0.52	0.46
Adj. R-squared	0.43	0.52	0.46
Residual Std. Error	0.29 (df = 2803)	0.22 (df = 2803)	0.27 (df = 2801)
F Statistic	232.03^{***} (df = 9; 2803)	335.67^{***} (df = 9; 2803)	262.78^{***} (df = 9; 2801)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

A.3.2 Feelings Towards Presidential Candidate Donald Trump

Table A.12: Feelings Towards Candidate Donald Trump in 2016 ANES

	Anxiety	Enthusiasm	Anger
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	0.05	−0.03	0.03
	(0.02)	(0.02)	(0.02)
Partisan News	-0.14^{***}	0.25^{***}	-0.07^{*}
	(0.04)	(0.03)	(0.03)
Age	0.01	0.03	−0.04
	(0.03)	(0.02)	(0.03)
Female	0.04^{**}	0.01	0.05^{***}
	(0.01)	(0.01)	(0.01)
Attended College	0.05^{**}	-0.05^{***}	0.06^{***}
	(0.01)	(0.01)	(0.01)
Party ID	-0.47^{***}	0.40^{***}	-0.47^{***}
	(0.02)	(0.02)	(0.02)
Employed	0.01	−0.01	0.001
	(0.01)	(0.01)	(0.01)
Ideology	-0.25^{***}	0.23^{***}	-0.24^{***}
	(0.03)	(0.02)	(0.03)
White	-0.05^{***}	0.06^{***}	-0.08^{***}
	(0.01)	(0.01)	(0.01)
Constant	0.81^{***}	-0.09^{***}	0.85^{***}
	(0.03)	(0.02)	(0.02)
N	2810	2813	2814
R-squared	0.40	0.47	0.44
Adj. R-squared	0.40	0.47	0.44
Residual Std. Error	0.30 (df = 2800)	0.23 (df = 2803)	0.28 (df = 2804)
F Statistic	205.49^{***} (df = 9; 2800)	279.25^{***} (df = 9; 2803)	243.27^{***} (df = 9; 2804)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

A.4 Regressions for Candidates Based on Respondent Party Identification

A.4.1 Partisan Regressions for Hillary Clinton

Table A.13: Democratic Feelings Towards Candidate Clinton in the 2016 ANES

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	-0.02	0.06	-0.02
	(0.03)	(0.03)	(0.03)
Partisan News	-0.08	0.27^{***}	-0.10^{*}
	(0.04)	(0.05)	(0.04)
Age	-0.05	0.12^{***}	-0.04
	(0.03)	(0.04)	(0.03)
Female	-0.003	0.03	-0.01
	(0.01)	(0.01)	(0.01)
Attended College	-0.02	0.02	-0.01
	(0.02)	(0.02)	(0.02)
Partisan Intensity	-0.13^{***}	0.32^{***}	-0.11^{***}
	(0.02)	(0.03)	(0.02)
Employed	-0.02	0.01	-0.02
	(0.01)	(0.02)	(0.01)
Ideology	0.16^{***}	-0.17^{***}	0.09^{**}
	(0.03)	(0.04)	(0.03)
White	0.04^{**}	-0.06^{***}	0.05^{***}
	(0.01)	(0.02)	(0.01)
Constant	0.22^{***}	0.27^{***}	0.25^{***}
	(0.03)	(0.04)	(0.03)
N	1253	1254	1253
R-squared	0.08	0.20	0.05
Adj. R-squared	0.07	0.20	0.05
Residual Std. Error	0.21 (df = 1243)	0.25 (df = 1244)	0.21 (df = 1243)
F Statistic	11.54^{***} (df = 9; 1243)	34.85^{***} (df = 9; 1244)	7.72^{***} (df = 9; 1243)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Table A.14: Republicans' Feelings Towards Candidate Clinton in the 2016 ANES

	Anxiety Model 1	Enthusiasm Model 2	Anger Model 3
Nonpartisan News	-0.06	0.03	-0.08^{*}
	(0.04)	(0.02)	(0.04)
Partisan News	0.15^{**}	-0.08^{**}	0.32^{***}
	(0.06)	(0.03)	(0.05)
Age	0.0003	0.03	-0.08
	(0.05)	(0.02)	(0.04)
Female	0.03	0.01	0.04^{*}
	(0.02)	(0.01)	(0.02)
Attended College	-0.02	-0.01	-0.01
	(0.02)	(0.01)	(0.02)
Partisan Intensity	0.11^{**}	-0.01	0.08^{*}
	(0.04)	(0.02)	(0.03)
Employed	-0.03	-0.01	-0.01
	(0.02)	(0.01)	(0.02)
Ideology	0.47^{***}	-0.27^{***}	0.46^{***}
	(0.06)	(0.03)	(0.05)
White	0.09^{***}	-0.08^{***}	0.12^{***}
	(0.03)	(0.01)	(0.02)
Constant	0.13^{*}	0.35^{***}	0.19^{***}
	(0.06)	(0.03)	(0.05)
N	1286	1286	1284
R-squared	0.12	0.13	0.15
Adj. R-squared	0.11	0.12	0.15
Residual Std. Error	0.33 (df = 1276)	0.16 (df = 1276)	0.29 (df = 1274)
F Statistic	19.06^{***} (df = 9; 1276)	21.31^{***} (df = 9; 1276)	25.62^{***} (df = 9; 1274)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

A.4.2 Partisan Regressions for Candidate Donald Trump

Table A.15: Republican Feelings Towards Candidate Trump in the 2016 ANES

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	0.06	-0.02	0.06
	(0.03)	(0.03)	(0.03)
Partisan News	-0.27^{***}	0.35^{***}	-0.19^{***}
	(0.05)	(0.05)	(0.04)
Age	-0.01	0.03	0.01
	(0.04)	(0.04)	(0.04)
Female	0.02	-0.004	0.05^{***}
	(0.02)	(0.02)	(0.01)
Attended College	0.02	-0.06^{**}	0.04
	(0.02)	(0.02)	(0.02)
Partisan Intensity	-0.12^{***}	0.19^{***}	-0.10^{***}
	(0.03)	(0.03)	(0.03)
Employed	-0.01	-0.01	0.01
	(0.02)	(0.02)	(0.02)
Ideology	-0.16^{***}	0.27^{***}	-0.14^{**}
	(0.05)	(0.05)	(0.05)
White	-0.11^{***}	0.08^{***}	-0.11^{***}
	(0.02)	(0.02)	(0.02)
Constant	0.53^{***}	0.07	0.47^{***}
	(0.05)	(0.05)	(0.04)
N	1286	1284	1286
R-squared	0.10	0.17	0.08
Adj. R-squared	0.09	0.16	0.08
Residual Std. Error	0.27 (df = 1276)	0.27 (df = 1274)	0.25 (df = 1276)
F Statistic	15.26^{***} (df = 9; 1276)	28.98^{***} (df = 9; 1274)	12.90^{***} (df = 9; 1276)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Table A.16: Democrats' Feelings Towards Candidates Trump in the 2016 ANES

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	0.03	0.01	0.02
	(0.04)	(0.02)	(0.04)
Partisan News	0.04	−0.02	0.03
	(0.06)	(0.03)	(0.06)
Age	0.01	0.004	−0.09*
	(0.04)	(0.02)	(0.04)
Female	0.04*	0.01	0.05**
	(0.02)	(0.01)	(0.02)
Attended College	0.04	−0.03**	0.07**
	(0.02)	(0.01)	(0.02)
Partisan Intensity	0.19***	−0.06***	0.22***
	(0.03)	(0.02)	(0.03)
Employed	0.02	−0.01	−0.01
	(0.02)	(0.01)	(0.02)
Ideology	−0.22***	0.12***	−0.24***
	(0.04)	(0.02)	(0.04)
White	−0.02	0.02	−0.04*
	(0.02)	(0.01)	(0.02)
Constant	0.58***	0.07***	0.63***
	(0.05)	(0.02)	(0.04)
N	1251	1255	1254
R-squared	0.07	0.06	0.11
Adj. R-squared	0.06	0.05	0.11
Residual Std. Error	0.31 (df = 1241)	0.14 (df = 1245)	0.28 (df = 1244)
F Statistic	10.16*** (df = 9; 1241)	8.67*** (df = 9; 1245)	17.36*** (df = 9; 1244)

***$p < .001$; **$p < .01$; *$p < .05$

A.5 2020 ANES

A.6 Demographics

A.6.1 Age

Table A.17: *Respondent Age*

	Min	Mean	Median	Max
Age	18.0	51.6	52.0	80.0

A.6.2 Education

Table A.18: *Respondents Who Attended At Least Some College*

	N	%
Attended College	6437	77.7
Did Not Attend College	1712	20.7
NA	131	1.6
Total Respondents	8280	

Table A.19: *Respondents' Level of Education*

	N	%
Less than High School	376	4.5
High School	1336	16.1
Some College, No Bachelor's Degree	2790	33.7
Bachelor's Degree	2055	24.8
Graduate Degree	1592	19.2
NA	131	1.6
Total Respondents	8280	

A.6.3 Current Employment

Table A.20: *If Respondent is Currently Employed*

	N	%
Currently Employed	5132	61.98
Currently Not Employed	3091	37.34
NA	16	0.4

A.6.4 Party Identification

Table A.21: *Respondent 7 Point Party Identification*

	N	%
Strong Democrat	1961	23.7
Democrat	900	10.9
Lean Democrat	975	11.8
Independent	968	11.7
Lean Republican	879	10.6
Republican	832	10.0
Strong Republican	1730	20.9
NA	35	0.4
Total Respondents	8280	

A.6.5 Ideology

Table A.22: *Respondent 7 Point Liberal-Conservative Ideology*

	N	%
Extremely Liberal	369	4.5
Liberal	1210	14.6
Slightly Liberal	918	11.1
Moderate	1818	22.0
Slightly Conservative	821	9.9
Conservative	1492	18.0
Extremely Conservative	428	5.2
NA	1224	14.8
Total Respondents	8280	

A.6.6 Gender

Table A.23: *Self-Reported Gender Identification*

	N	%
Female	4450	53.7
Male	3763	45.4
NA	67	0.8
Total Respondents	8280	

A.6.7 Race

Table A.24: *Respondent Self-identified Race*

	N	%
White	5963	72.0
Black	726	8.8
Asian, Native Hawaiian or Pacific Islander	284	3.4
Hispanic	762	9.2
Native American/Alaska Native or other race	172	2.1
Multiple Races	271	3.3
NA	102	1.2

Table A.25: *If Respondent Identifies as White*

	N	%
Not White	2215	26.8
White	5963	72.0
NA	102	1.2

A.7 Regressions For Feelings About the Nation

A.7.1 Full Model

Table A.26: Feelings about the Nation in 2020 ANES

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	0.03	-0.09^{***}	-0.0005
	(0.02)	(0.02)	(0.02)
Partisan News	0.21^{***}	0.05	0.29^{***}
	(0.04)	(0.03)	(0.04)
Age	0.02	0.001	0.01
	(0.01)	(0.01)	(0.01)
Female	0.05^{***}	-0.01	0.01
	(0.01)	(0.01)	(0.01)
Attended College	0.02^{**}	-0.01	0.03^{**}
	(0.01)	(0.01)	(0.01)
Party ID	-0.23^{***}	0.26^{***}	-0.20^{***}
	(0.01)	(0.01)	(0.01)
Employed	-0.02^{*}	-0.01	-0.02^{*}
	(0.01)	(0.01)	(0.01)
Ideology	-0.14^{***}	0.16^{***}	-0.13^{***}
	(0.02)	(0.02)	(0.02)
White	0.02^{**}	-0.003	0.01
	(0.01)	(0.01)	(0.01)
Constant	0.76^{***}	0.10^{***}	0.80^{***}
	(0.02)	(0.01)	(0.02)
N	5277	5274	5276
R-squared	0.24	0.33	0.18
Adj. R-squared	0.24	0.33	0.18
Residual Std. Error	0.23 (df = 5267)	0.20 (df = 5264)	0.23 (df = 5266)
F Statistic	183.27^{***} (df = 9; 5267)	288.58^{***} (df = 9; 5264)	130.98^{***} (df = 9; 5266)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

A.7.2 Feelings about the Nation for Partisans Television Viewers

A.7.2.1 Democrats

Table A.27: Feelings about the Nation in 2020 ANES for Democrats

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	0.07^{*}	-0.03	0.05
	(0.03)	(0.02)	(0.03)
Partisan News	0.29^{***}	-0.14^{***}	0.32^{***}
	(0.04)	(0.03)	(0.04)
Age	0.01	-0.01	-0.02
	(0.02)	(0.01)	(0.02)
Female	0.05^{***}	-0.01	0.02^{*}
	(0.01)	(0.01)	(0.01)
Attended College	0.03^{*}	-0.01	0.04^{**}
	(0.01)	(0.01)	(0.01)
Partisan Intensity	0.11^{***}	-0.04^{**}	0.09^{***}
	(0.02)	(0.01)	(0.02)
Employed	-0.001	-0.002	-0.005
	(0.01)	(0.01)	(0.01)
Ideology	-0.20^{***}	0.11^{***}	-0.25^{***}
	(0.02)	(0.02)	(0.02)
White	0.01	-0.01	0.01
	(0.01)	(0.01)	(0.01)
Constant	0.67^{***}	0.19^{***}	0.75^{***}
	(0.02)	(0.02)	(0.02)
N	2500	2501	2501
R-squared	0.11	0.04	0.12
Adj. R-squared	0.11	0.04	0.11
Residual Std. Error	0.21 (df = 2490)	0.16 (df = 2491)	0.20 (df = 2491)
F Statistic	33.94^{***} (df = 9; 2490)	12.67^{***} (df = 9; 2491)	35.99^{***} (df = 9; 2491)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

A.7.2.2 Republicans

Table A.28: Feelings about the Nation in 2020 ANES for Republicans

	Anxiety	**Enthusiasm**	**Anger**
	Model 1	**Model 2**	**Model 3**
Nonpartisan News	0.05	-0.12^{***}	0.02
	(0.04)	(0.03)	(0.04)
Partisan News	0.04	0.24^{***}	0.14^{*}
	(0.06)	(0.05)	(0.06)
Age	0.03	-0.005	0.05^{*}
	(0.02)	(0.02)	(0.02)
Female	0.03^{**}	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
Attended College	0.03^{*}	-0.01	0.01
	(0.01)	(0.01)	(0.01)
Partisan Intensity	-0.04^{*}	0.14^{***}	-0.02
	(0.02)	(0.02)	(0.02)
Employed	-0.03^{*}	-0.02	-0.02
	(0.01)	(0.01)	(0.01)
Ideology	-0.02	0.14^{***}	0.09^{**}
	(0.03)	(0.03)	(0.03)
White	0.03^{*}	0.01	0.01
	(0.02)	(0.01)	(0.02)
Constant	0.50^{***}	0.23^{***}	0.50^{***}
	(0.03)	(0.03)	(0.03)
N	2311	2307	2309
R-squared	0.02	0.08	0.02
Adj. R-squared	0.02	0.07	0.01
Residual Std. Error	0.25 (df = 2301)	0.23 (df = 2297)	0.26 (df = 2299)
F Statistic	5.07^{***} (df = 9; 2301)	20.88^{***} (df = 9; 2297)	4.41^{***} (df = 9; 2299)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

APPENDIX B

Measuring Perceptions of Emotions Appendix

B.1 Study 1: Categorization and Intensity Study

B.1.1 Stimuli Examples

Carl stood up in front of the city council/classroom and said he is feeling aggressive. When Carl uses the word ”aggressive,” what sort of emotion do you think he is trying to convey?

The respondent is given the options to categorize the word as *anger*, *fear*, or *other* with the selection of other also offering a text entry box.

Carl is at a city council meeting/classroom and what they are discussing is making him feel angry.

What words below do you think Carl would use to describe how he feels?

The respondent is given a randomized set of 8 words from the possible 40 words used from LIWC.

B.1.2 List of LIWC Words

The words offered to be categorized or to be placed into categories are below. The words were slightly modified in context to make sure that they made sense in the stimuli offered to respondents.

Table B.1: LIWC Words Used and Emotional Categorization

Anger	**Anxiety**
aggressive	afraid
annoyed	awkward
argue	confused
bitter	dread
bother	embarrass
cruel	fear
destroy	humiliate
enemy	nervous
frustrated	overwhelmed
furious	restless
hate	risk
jealous	shame
mad	suspicious
obnoxious	tense
pushy	terrify
resentful	turmoil
rude	uncomfortable
stupid	unsure
vicious	upset
violent	worried

B.1.3 Correct Identification of LIWC Words

Table B.2: Percent Correct and T-Test Results for Text Selection Condition

Text Selection	N	Correct	sd	se	ci	t	df	p
Category	5917	0.68	0.47	0.01	0.01	32.53	12232	2.20E-16
Word Choice	6323	0.40	0.49	0.01	0.01			

Table B.3: Percent Correct and T-Test Results for Context Condition

Context	N	Correct	sd	se	ci	t	df	p
Non-Political	6143	0.54	0.50	0.01	0.01	2.6	12237	0.009315
Political	6097	0.52	0.50	0.01	0.01			

Table B.4: Within Text Selection Type Comparison for Political and Non-Political Context

Text Selection	Context	N	Correct	sd	se	ci	df	t	p
Category	Non-Political	3037	0.70	0.46	0.01	0.02	5870	3.52	0.0004
Category	Political	2880	0.65	0.48	0.01	0.02			
Word Choice	Non-Political	3106	0.39	0.49	0.01	0.02	6314	-0.54	0.59
Word Choice	Political	3217	0.40	0.49	0.01	0.02			

B.1.4 Average Intensity Ratings for Anxiety and Anger Words

For both tables A.2 and A.3 the number of respondents who scored each word is 307

Table B.5: Average Intensity Ratings of of Anxiety Words

Word	Rating	sd	se	ci
terrify	0.85	0.21	0.01	0.02
fear	0.84	0.23	0.01	0.03
afraid	0.81	0.22	0.01	0.02
dread	0.74	0.25	0.01	0.03
turmoil	0.61	0.27	0.02	0.03
worried	0.61	0.3	0.02	0.03
tense	0.6	0.28	0.02	0.03
nervous	0.56	0.28	0.02	0.03
overwhelmed	0.56	0.27	0.02	0.03
upset	0.48	0.28	0.02	0.03
uncomfortable	0.46	0.29	0.02	0.03
risky	0.45	0.26	0.02	0.03
suspicious	0.45	0.27	0.02	0.03
humiliate	0.44	0.31	0.02	0.04
unsure	0.43	0.3	0.02	0.03
shame	0.42	0.29	0.02	0.03
restless	0.4	0.27	0.02	0.03
embarrassed	0.38	0.28	0.02	0.03
confused	0.35	0.28	0.02	0.03
awkward	0.31	0.25	0.01	0.03

Table B.6: Average Intensity Ratings of Anger Words

Word	Rating	sd	se	ci
furious	0.89	0.18	0.01	0.02
hate	0.83	0.23	0.01	0.03
violent	0.8	0.27	0.02	0.03
vicious	0.78	0.25	0.01	0.03
destroy	0.74	0.29	0.02	0.03
aggress	0.73	0.22	0.01	0.03
mad	0.73	0.26	0.01	0.03
enemy	0.7	0.26	0.02	0.03
cruel	0.67	0.29	0.02	0.03
resent	0.63	0.25	0.01	0.03
frust	0.6	0.26	0.01	0.03
bitter	0.59	0.26	0.02	0.03
argue	0.57	0.26	0.01	0.03
annoy	0.53	0.3	0.02	0.03
rude	0.5	0.27	0.02	0.03
bother	0.42	0.28	0.02	0.03
obnoxious	0.41	0.28	0.02	0.03
jealous	0.4	0.29	0.02	0.03
pushy	0.39	0.26	0.01	0.03
stupid	0.36	0.27	0.02	0.03

B.2 Study2: Partisan Differences in Emotion Ratings

B.2.1 Emotional Intensity by Network and Partisan Identification

Note: Pooled indicates the intensity rating when Party Identification is not taken into account.

Table B.7: Emotional Intensity for ABC

Network	Emotion	PartyID	N	Intensity Score	sd	se	ci
ABC	Anger	Democrat	52	0.10	0.20	0.03	0.06
ABC	Anger	Republican	62	0.12	0.24	0.03	0.06
ABC	Anger	Pooled	120	0.11	0.22	0.02	0.04
ABC	Anxiety	Democrat	52	0.28	0.32	0.04	0.09
ABC	Anxiety	Republican	62	0.37	0.33	0.04	0.08
ABC	Anxiety	Pooled	120	0.33	0.33	0.03	0.06
ABC	Enthusiasm	Democrat	52	0.31	0.38	0.05	0.11
ABC	Enthusiasm	Republican	62	0.24	0.32	0.04	0.08
ABC	Enthusiasm	Pooled	120	0.26	0.35	0.03	0.06

Table B.8: Emotional Intensity for FOX

Network	Emotion	PartyID	N	Intensity Score	sd	se	ci
FOX	Anger	Democrat	71	0.34	0.33	0.04	0.08
FOX	Anger	Republican	74	0.24	0.31	0.04	0.07
FOX	Anger	Pooled	153	0.29	0.32	0.03	0.05
FOX	Anxiety	Democrat	71	0.25	0.36	0.04	0.08
FOX	Anxiety	Republican	74	0.21	0.26	0.03	0.06
FOX	Anxiety	Pooled	153	0.23	0.31	0.03	0.05
FOX	Enthusiasm	Democrat	71	0.20	0.29	0.03	0.07
FOX	Enthusiasm	Republican	74	0.20	0.28	0.03	0.07
FOX	Enthusiasm	Pooled	153	0.20	0.28	0.02	0.05

Table B.9: Emotional Intensity for MSNBC

Network	Emotion	PartyID	N	Intensity Score	sd	se	ci
MSNBC	Anger	Democrat	73	0.24	0.32	0.04	0.08
MSNBC	Anger	Republican	84	0.21	0.28	0.03	0.06
MSNBC	Anger	Pooled	167	0.23	0.31	0.02	0.05
MSNBC	Anxiety	Democrat	73	0.26	0.31	0.04	0.07
MSNBC	Anxiety	Republican	84	0.24	0.28	0.03	0.06
MSNBC	Anxiety	Pooled	167	0.26	0.30	0.02	0.05
MSNBC	Enthusiasm	Democrat	73	0.18	0.31	0.04	0.07
MSNBC	Enthusiasm	Republican	84	0.16	0.27	0.03	0.06
MSNBC	Enthusiasm	Pooled	167	0.16	0.28	0.02	0.04

B.2.2 T-Test Results for Partisan Identities

Table B.10: T-Test Results for Partisan Social Identities' Impact on Emotion Intensity Ratings

Network	Emotion	PartyID	N	Intensity	se	t	df	p
ABC	Anger	Democrat	52	0.10	0.03	-0.62774	112	0.5315
ABC	Anger	Republican	62	0.12	0.03			
ABC	Anxiety	Democrat	52	0.28	0.04	-1.5127	110.13	0.1332
ABC	Anxiety	Republican	62	0.37	0.04			
ABC	Enthusiasm	Democrat	52	0.31	0.05	1.0718	99.435	0.2864
ABC	Enthusiasm	Republican	62	0.24	0.04			
FOX	Anger	Democrat	71	0.34	0.04	1.8377	141.15	0.06821
FOX	Anger	Republican	74	0.24	0.04			
FOX	Anxiety	Democrat	71	0.25	0.04	0.78191	128.61	0.4357
FOX	Anxiety	Republican	74	0.21	0.03			
FOX	Enthusiasm	Democrat	71	0.20	0.03	-0.1043	142.42	0.9171
FOX	Enthusiasm	Republican	74	0.20	0.03			
MSNBC	Anger	Democrat	73	0.24	0.04	0.61773	143.31	0.5377
MSNBC	Anger	Republican	84	0.21	0.03			
MSNBC	Anxiety	Democrat	73	0.26	0.04	0.35391	146.87	0.7239
MSNBC	Anxiety	Republican	84	0.24	0.03			
MSNBC	Enthusiasm	Democrat	73	0.18	0.04	0.51455	143.8	0.6077
MSNBC	Enthusiasm	Republican	84	0.16	0.03			

B.3 Study 3: Audio vs. Text Mode

Table B.11: Comparison of Intensity Scores for Anxiety in Audio vs. Text Stimuli

Network	Mode	N	Mean	se	Emotion	p-value	Bonferroni	BH
ABC	Audio	51	6.33	0.80	Anxiety	0.96	1	0.96
ABC	Text	128	7.42	0.53	Anxiety	0.96		
CNN	Audio	54	5.94	0.84	Anxiety	0.36	1	0.45
CNN	Text	150	6.91	0.45	Anxiety	0.36		
FOX	Audio	49	4.61	0.75	Anxiety	0.23	1	0.38
FOX	Text	213	7.66	0.36	Anxiety	0.23		
MSNBC	Audio	52	8.75	0.87	Anxiety	0.13	0.65	0.32
MSNBC	Text	221	8.38	0.34	Anxiety	0.13		
NBC	Audio	50	5.54	0.79	Anxiety	0.06	0.28	0.28
NBC	Text	221	8.06	0.35	Anxiety	0.06		
ABC	Audio	53	2.87	0.45	Afraid	0.27	1	0.34
ABC	Text	129	3.48	0.32	Afraid	0.27		
CNN	Audio	58	2.53	0.41	Afraid	0.1	0.5	0.17
CNN	Text	154	3.32	0.24	Afraid	0.1		
FOX	Audio	52	1.79	0.37	Afraid	5.05E-06	0.00002	0.00002
FOX	Text	213	3.84	0.19	Afraid	5.05E-06		
MSNBC	Audio	55	3.87	0.52	Afraid	0.97	1	0.97
MSNBC	Text	221	3.89	0.19	Afraid	0.97		
NBC	Audio	52	2.60	0.43	Afraid	0.01273	0.06	0.03
NBC	Text	221	3.79	0.19	Afraid	0.01273		

Table B.12: Comparison of Intensity Scores for Enthusiasm in Audio vs. Text Stimuli

Network	Mode	N	Mean	se	Emotion	p-value	Bonferroni	BH
ABC	Audio	51	6.33	0.80	Anxiety	0.96	1	0.96
ABC	Text	128	7.42	0.53	Anxiety	0.96		
CNN	Audio	54	5.94	0.84	Anxiety	0.36	1	0.45
CNN	Text	150	6.91	0.45	Anxiety	0.36		
FOX	Audio	49	4.61	0.75	Anxiety	0.23	1	0.38
FOX	Text	213	7.66	0.36	Anxiety	0.23		
MSNBC	Audio	52	8.75	0.87	Anxiety	0.13	0.65	0.32
MSNBC	Text	221	8.38	0.34	Anxiety	0.13		
NBC	Audio	50	5.54	0.79	Anxiety	0.06	0.28	0.28
NBC	Text	221	8.06	0.35	Anxiety	0.06		
ABC	Audio	53	2.87	0.45	Afraid	0.27	1	0.34
ABC	Text	129	3.48	0.32	Afraid	0.27		
CNN	Audio	58	2.53	0.41	Afraid	0.1	0.5	0.17
CNN	Text	154	3.32	0.24	Afraid	0.1		
FOX	Audio	52	1.79	0.37	Afraid	5.05E-06	0.00002	0.00002
FOX	Text	213	3.84	0.19	Afraid	5.05E-06		
MSNBC	Audio	55	3.87	0.52	Afraid	0.97	1	0.97
MSNBC	Text	221	3.89	0.19	Afraid	0.97		
NBC	Audio	52	2.60	0.43	Afraid	0.01273	0.06	0.03
NBC	Text	221	3.79	0.19	Afraid	0.01273		

Table B.13: Comparison of Intensity Scores for Anger in Audio vs. Text Stimuli

Network	Mode	N	Mean	se	Emotion	p-value	Bonferroni	BH
ABC	Audio	69	3.29	0.41	Anger	0.81	1	0.81
ABC	Text	184	3.17	0.26	Anger	0.81		
CNN	Audio	73	4.00	0.40	Anger	0.8	1	0.81
CNN	Text	170	4.12	0.27	Anger	0.8		
FOX	Audio	69	3.81	0.44	Anger	0.78	1	0.81
FOX	Text	174	3.95	0.27	Anger	0.78		
MSN	Audio	77	4.06	0.43	Anger	0.48	1	0.81
MSN	Text	179	3.71	0.27	Anger	0.48		
NBC	Audio	64	2.91	0.42	Anger	0.28	1	0.81
NBC	Text	175	3.43	0.26	Anger	0.28		
ABC	Audio	71	3.03	0.39	Frustration	0.19	0.95	0.72
ABC	Text	188	3.64	0.26	Frustration	0.19		
CNN	Audio	73	4.51	0.43	Frustration	0.43	1	0.72
CNN	Text	180	4.12	0.25	Frustration	0.43		
FOX	Audio	68	3.31	0.45	Frustration	0.35	1	0.72
FOX	Text	213	4.38	0.22	Frustration	0.35		
MSN	Audio	75	4.21	0.43	Frustration	0.73	1	0.73
MSN	Text	221	4.38	0.22	Frustration	0.73		
NBC	Audio	65	3.54	0.45	Frustration	0.65	1	0.73
NBC	Text	221	3.76	0.21	Frustration	0.65		

APPENDIX C

The Reemergence of Emotion Appendix

C.1 Demographics

Demographic information is based on the exclusion of those participants that said they were ‘Never‘ serious or only serious ‘Some of the time‘ which resulted in participants 16 excluded via their unique IP Address. additional respondents were excluded based on party identification switching (from Republican to Democrat, or Democrat to Republican) and gender identification inconsistencies, resulting in a sample of 2278 unique respondents. To compile demographic information, the respondents’ most recent responses to the survey were used for those that participated more than once.

Table C.1: How Seriously Respondents Took the Survey for Final Sample of 2278 Respondents

“How often did you give a serious response to the questions on this survey?”		
	Count	Percent
Always	2162	95%
Most of the time	99	4.3%
Half the time	17	0.75%

Table C.2: Respondent 7-Point Party Identification

	Number	Percent
Strong Democrat	651	28.58
Democrat	539	23.66
Lean Democrat	27	1.18
Independent	21	0.92
Lean Republican	48	2.11
Republican	556	24.41
Strong Republican	435	19.09

n=2278

Table C.3: Respondent Party Identification Inclusive of Leaners

	Number	Percent
Democrats	1217	53.42
Independents	21	0.92
Republicans	1040	45.65

n=2278

Table C.4: Respondent 7-Point Liberal-Conservative Ideology

	Number	Percent
Extremely Liberal	318	13.96
Liberal	534	23.44
Slightly Liberal	237	10.40
Moderate	179	7.86
Slightly Conservative	282	12.38
Conservative	509	22.34
Extremely Conservative	202	8.87
Haven't Thought Much About It	16	0.70

n=2278, 1 respondent NA

Table C.5: Respondent Gender

	Number	Percent
Female	1181	51.84
Male	1071	47.01
Other	21	0.92

5 respondents did not answer this question

Table C.6: White or Non-White Respondents

	Number	Percent
White	1638	71.90
Non-White	634	27.83

7 respondents did not answer this question

Table C.7: Respondent Ages

Minimum	Median	Mean	Max	*NA*
18.00	37.00	40.03	80.00	37

Table C.8: Respondent Level of Educational Attainment

	Number	Percent
No School	0	0
Elementary school	2	0.01
Middle school	5	0.22
High school	518	22.74
Associate's or CC	309	13.56
Bachelor's	1005	44.12
Master's	346	15.19
Professional degree	50	2.19
Doctorate	43	1.88

Table C.9: Educational Attainment: No College or At Least Some College

	Number	Percent
Some College	1753	76.95
No College	525	23.05

C.2 Averages and Frequency of Emotion Among Cable News 2000-2008

C.2.1 Intensity

Table C.10: Average Level of Emotional Intensity for Partisan and Nonpartisan News: 2000-2008

Network	Emotion	N	Mean	se	T-test	df	p-value
Nonpartisan	Anger	1975	3.97038	0.05539754	-6.02	3808.8	1.90E-09
Partisan	Anger	5294	4.370325	0.03665686			
Nonpartisan	Anxiety	2014	3.889772	0.05493185	1.83	3897.7	0.07
Partisan	Anxiety	4084	3.767997	0.03738809			
Nonpartisan	Enthusiasm	2323	4.312742	0.05325871	4.98	4191.7	6.71E-07
Partisan	Enthusiasm	5451	4.000734	0.03306524			

C.2.2 Frequency

Table C.11: Frequency of Anxiety for Partisan and Nonpartisan News: 2000-2008

		Absent	Present	Row Marginal
Traditional	Anxiety	2365	2014	4379
	Expected	2584.434	1794.566	
Partisan	Anxiety	6417	4084	10501
	Expected	6197.566	4303.434	
Column Marginal		8782	6098	
Chi-squared	64.128			
df	1			
p-value	1.17E-15			

Table C.12: Frequency of Enthusiasm for Partisan and Nonpartisan News: 2000-2008

		Absent	Present	Row Marginal
Traditional	Enthusiasm	2055	2323	4378
	Expected	2090.115	2287.885	
Partisan	Enthusiasm	5047	5451	10498
	Expected	5011.885	5486.115	
Column Marginal		7102	7774	
Chi-squared	1.5545			
df	1			
p-value	0.2125			

Table C.13: Frequency of Anger for Partisan and Nonpartisan News: 2000-2008

		Absent	Present	Row Marginal
Traditional	Anger	2394	1975	4369
	Expected	2240.288	2128.712	
Partisan	Anger	5256	5294	10550
	Expected	5409.712	5140.288	
Column Marginal		7650	7269	
Chi-squared	30.411			
df	1			
p-value	3.50E-08			

Table C.14: Anger Offset: Difference Between the Frequency of Anger and Anxiety for Partisan News

	Anger Offset						
Traditional	Anger	1975	3.97038	0.05539754	1.03	3985.7	0.3
Traditional	Anxiety	2014	3.889772	0.05493185			
Partisan	Anxiety	4084	3.767997	0.03738809	-11.504	9169.5	2.20E-16
Partisan	Anger	5294	4.370325	0.03665686			

Figure C.1: Average Intensity for Cable News Networks: 2000-2008

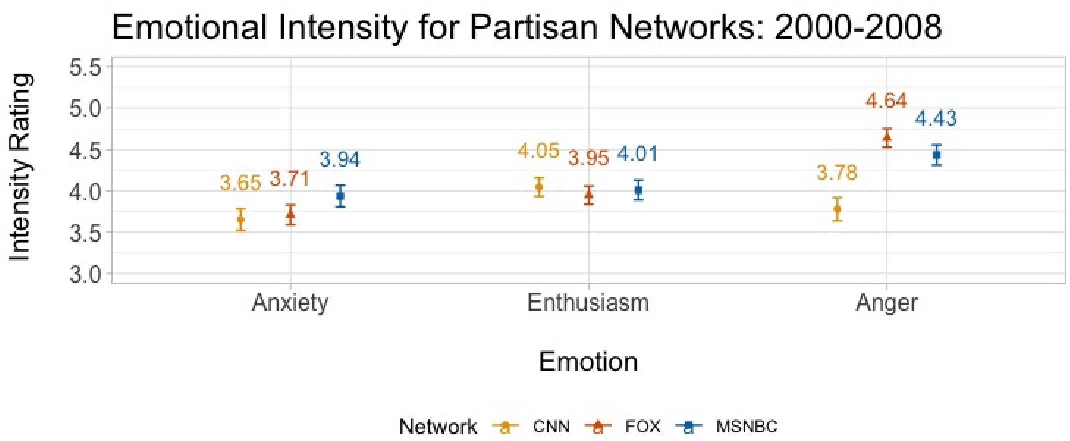
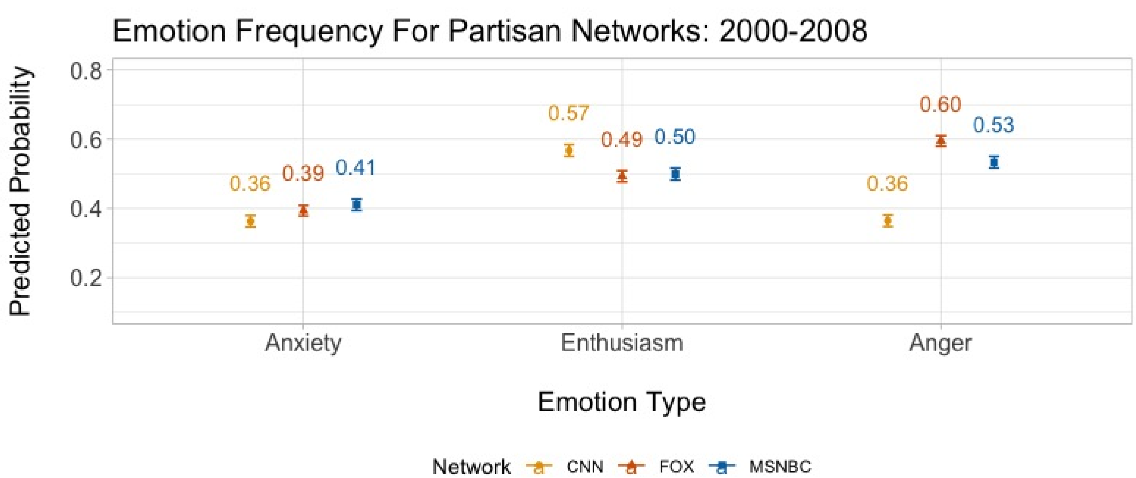


Figure C.2: Average Frequency for Cable News Networks: 2000-2008



APPENDIX D

Evaluating the Trump Era Appendix

D.1 Demographics

Demographic information is based on the exclusion of those participants that said they ‘Never‘ serious or only serious ‘Some of the time‘ totalling 43 unique participants excluded via IP Address. 9 additional respondents were excluded based on party identification switching (from Republican to Democrat, or Democrat to Republican) and gender identification inconsistencies, resulting in a sample 2766 unique respondents. To compile demographic information, the respondents’ most recent responses to the survey were used for those that participated more than once.

Table D.1: How Seriously Respondents Took the Survey for Final Sample of 2766 Respondents

“How often did you give a serious response to the questions on this survey?”		
	Count	Percent
Always	2560	92.5%
Most of the time	156	5.6%
Half the time	50	1.8%

Table D.2: Respondent 7-Point Party Identification

	Number	Percent
Strong Democrat	646	23.35
Democrat	400	14.46
Lean Democrat	85	3.07
Independent	81	2.93
Lean Republican	115	4.16
Republican	469	16.96
Strong Republican	484	17.50

n=2766

Table D.3: Respondent Party Identification Inclusive of Leaners

	Number	Percent
Democrats	1395	50.43
Independents	81	2.93
Republicans	1290	46.64

n=2766

Table D.4: Respondent 7-Point Liberal-Conservative Ideology

	Number	Percent
Extremely Liberal	381	13.77
Liberal	563	20.35
Slightly Liberal	275	9.94
Moderate	249	9.00
Slightly Conservative	332	12.00
Conservative	605	12.87
Extremely Conservative	335	12.11
Haven't Thought Much About It	22	0.79

n=2766, 4 respondents NA

Table D.5: Respondent Gender

	Number	Percent
Female	1569	56.72
Male	175	42.48
Other	16	0.58

6 respondents did not answer this question

Table D.6: White or Non-White Respondents

	Number	Percent
White	2090	75.56
Non-White	669	24.18

7 respondents did not answer this question

Table D.7: Respondent Ages

Minimum	Median	Mean	Max	*NA*
18.00	38.00	41.00	91.00	29

Table D.8: Respondent Level of Educational Attainment

	Number	Percent
No School	4	0.14
Elementary school	1	0.04
Middle school	7	0.25
High school	709	25.63
Associate’s or CC	472	17.06
Bachelor’s	1113	40.24
Master’s	383	13.85
Professional degree	45	1.63
Doctorate	32	1.16

Table D.9: Educational Attainment: No College or At Least Some College

	Number	Percent
Some College	2045	73.93
No College	721	26.07

D.2 Regressions for the Intensity and Frequency of Partisan and Nonpartisan News

Table D.10: Regression for the Intensity of Anxiety, Enthusiasm, and Anger for Partisan vs. Nonpartisan News

	Dependent variable: Intensity		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
Partisan News	-0.20^{***}	-0.38^{***}	0.44^{***}
	(0.05)	(0.04)	(0.05)
Constant	4.33^{***}	4.81^{***}	4.32^{***}
	(0.04)	(0.04)	(0.04)
N	11759	15505	13672
R^2	0.001	0.005	0.01
Adj. R^2	0.001	0.005	0.01
Res. Std. Error	2.50 (df = 11757)	2.61 (df = 15503)	2.66 (df = 13670)
F Statistic	17.11^{***} (df = 1; 11757)	77.10^{***} (df = 1; 15503)	72.19^{***} (df = 1; 13670)

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Table D.11: Logistic Regression for the Likelihood of Anxiety, Enthusiasm, and Anger for Partisan vs. Nonpartisan News

	Dependent variable:		
	Anxiety	Enthusiasm	Anger
	(1)	(2)	(3)
Partisan News	-0.13^{***}	-0.22^{***}	0.62^{***}
	(0.03)	(0.03)	(0.03)
Constant	-0.14^{***}	0.49^{***}	-0.36^{***}
	(0.02)	(0.02)	(0.02)
N	26566	26563	26630
Log Likelihood	−18,225.86	−18,002.43	−18,165.65
Note:			*p<0.05; **p<0.01; ***p<0.001

D.3 T-test and Chi-squared results for 2010-2020

D.3.1 Intensity of Emotions for Partisan and Nonpartisan News

Network	Emotion	N	Mean	se	T-test	df	p-value
Nonpartisan Partisan	Anger Anger	3679 9993	4.32 4.76	0.04 0.03	-8.68	6832.10	2.20E-16
Nonpartisan Partisan	Anxiety Anxiety	4159 7600	4.33 4.13	0.04 0.03	4.09	8298.80	4.28E-05
Nonpartisan Partisan	Enthusiasm Enthusiasm	5544 9961	4.81 4.43	0.04 0.03	8.69	11117.00	2.20E-16

D.3.2 Frequency of Emotions for Partisan and Nonpartisan News

Table D.12: Chi-squared Test for the Difference in Partisan and Nonpartisan Anxiety

		Absent	Present
Nonpartisan	Anxiety	4795	4159
	Expected	4990.66	3963.34
Partisan	Anxiety	10012	7600
	Expected	9816.34	7795.66
X-squared	26.007		
df	1		
p-value	3.40E-07		

Table D.13: Chi-squared Test for the Difference in Partisan and Nonpartisan Enthusiasm

		Absent	Present
Nonpartisan	Enthusiasm	3406	5544
	Expected	3725.82	5224.17
Partisan	Enthusiasm	7652	9961
	Expected	7332.17	10280.82
X-squared	70.712		
df	1		
p-value	2.2E-16		

Table D.14: Chi-squared Test for the Difference in Partisan and Nonpartisan Anger

		Absent	Present
Nonpartisan	Anger	5270	3679
	Expected	4354.53	4594.47
Partisan	Anger	7688	9993
	Expected	8603.47	9077.53
X-squared	564		
df	1		
p-value	2.2e-16		

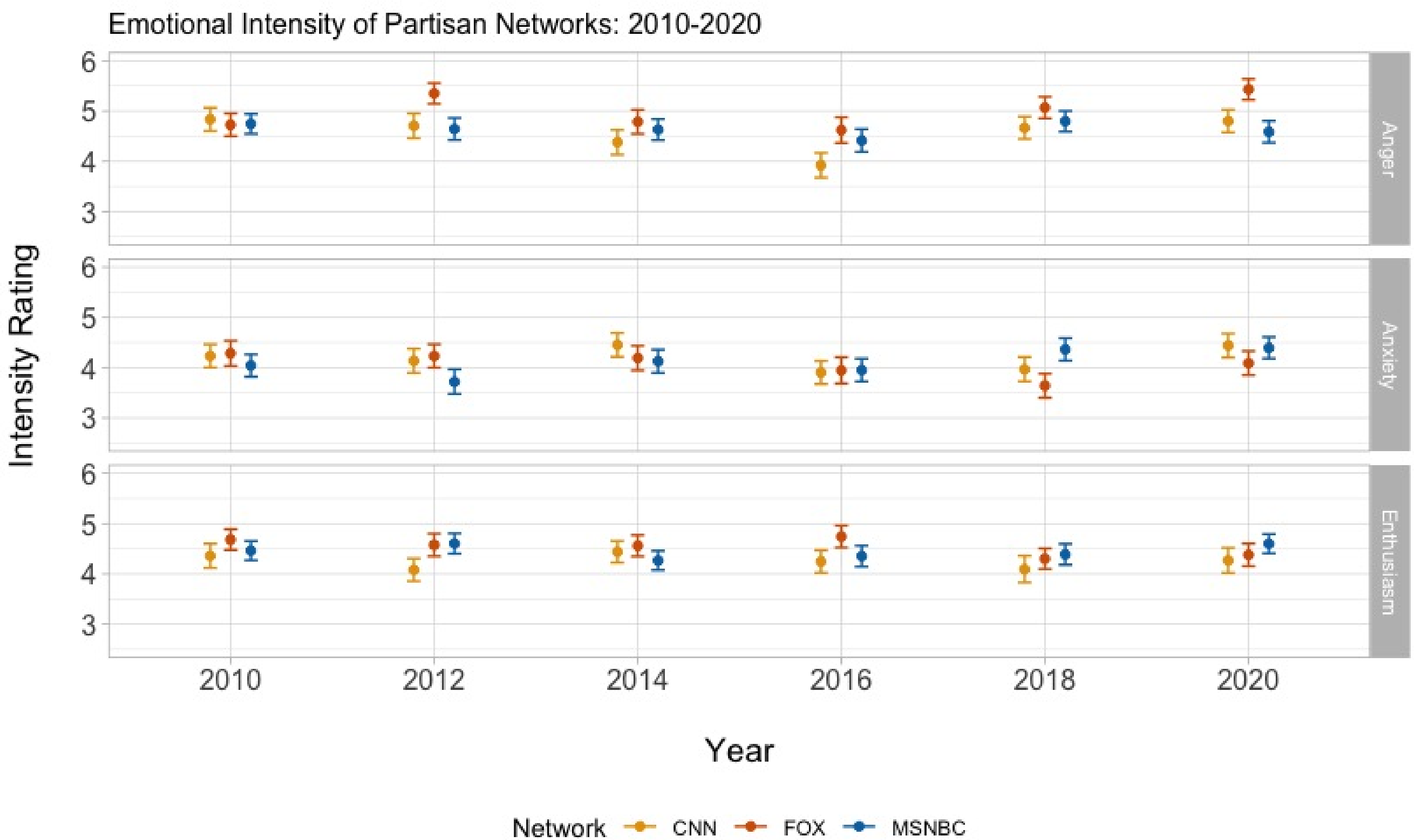
D.3.3 Testing for Partisan Anger Offset

Table D.15: T-test for Anger Offset Between Partisan Anger and Anxiety

Emotion	N	Mean	se	T-test	df	p-value
Anger	17681	0.56	0.003	25.336	35291	2.2E-16
Anxiety	17612	0.43	0.004			

D.4 Partisan News: 2010-2020 with year as a factor

Figure D.1: Plot of Emotional Intensity for Partisan News for Each Year: 2010-2020



D.4.1 Testing Changes in Intensity and Frequency from 2014 to 2016

Table D.16: Means for Emotional Intensity for Partisan Networks in 2014 and 2016 with t-test Results

Network	Emotion	year	N	Mean	se	t-test	df	pvalue
CNN	Anger	2014	425	4.38	0.13	2.589	852.92	0.009791
CNN	Anger	2016	430	3.92	0.13			
FOX	Anger	2014	495	4.79	0.12	0.92529	904.54	0.3551
FOX	Anger	2016	430	4.62	0.13			
MSNBC	Anger	2014	608	4.63	0.11	1.3727	1148.7	0.1701
MSNBC	Anger	2016	561	4.42	0.12			
CNN	Anxiety	2014	441	4.45	0.12	3.2676	866.54	0.001127
CNN	Anxiety	2016	428	3.90	0.12			
FOX	Anxiety	2014	377	4.19	0.12	1.3454	731.16	0.1789
FOX	Anxiety	2016	361	3.94	0.13			
MSNBC	Anxiety	2014	466	4.13	0.12	1.0615	896.68	0.2887
MSNBC	Anxiety	2016	433	3.95	0.12			
CNN	Enthusiasm	2014	548	4.44	0.11	1.2174	1060.2	0.2237
CNN	Enthusiasm	2016	520	4.25	0.11			
FOX	Enthusiasm	2014	561	4.56	0.11	-1.1717	1140.6	0.2415
FOX	Enthusiasm	2016	582	4.74	0.11			
MSNBC	Enthusiasm	2014	632	4.27	0.10	-0.60742	1234.3	0.5437
MSNBC	Enthusiasm	2016	617	4.35	0.11			

Table D.17: Means for Emotional Frequency for 2014 and 2016 with t-test Results

Network	Emotion	year	N	Mean	se	t-test	df	p-value
CNN	Anger	2014	962	0.44	0.02	-0.2702	1920	0.787
CNN	Anger	2016	960	0.45	0.02			
FOX	Anger	2014	963	0.51	0.02	1.0157	1821.9	0.3099
FOX	Anger	2016	877	0.49	0.02			
MSNBC	Anger	2014	1113	0.55	0.01	0.27014	2138.3	0.7871
MSNBC	Anger	2016	1038	0.54	0.02			
CNN	Anxiety	2014	964	0.46	0.02	0.63571	1928	0.525
CNN	Anxiety	2016	966	0.44	0.02			
FOX	Anxiety	2014	961	0.39	0.02	-0.84382	1818	0.3989
FOX	Anxiety	2016	877	0.41	0.02			
MSNBC	Anxiety	2014	1099	0.42	0.01	0.22674	2122.2	0.8206
MSNBC	Anxiety	2016	1033	0.42	0.02			
CNN	Enthusiasm	2014	963	0.57	0.02	1.2334	1921.9	0.2176
CNN	Enthusiasm	2016	961	0.54	0.02			
FOX	Enthusiasm	2014	957	0.59	0.02	-3.2664	1833.6	0.001109
FOX	Enthusiasm	2016	882	0.66	0.02			
MSNBC	Enthusiasm	2014	1114	0.57	0.01	-1.2994	2140.6	0.1939
MSNBC	Enthusiasm	2016	1037	0.59	0.02			

APPENDIX E

Supplemental Data Appendix

E.1 Introduction

This appendix provides additional information for the full sample, election years 2000 to 2020. There are three sections in this appendix which display the data in different ways. The first section plots the means for emotional intensity and frequency using year as a factor. This occurs both for the data pooled to reflect partisan and nonpartisan networks and for the data broken out into individual networks.

The second and third sections display emotional intensity and frequency using loess curves set to differing spans. The second section plots the data by partisan and nonpartisan network, with subsections that display the data by individual days and pooled by year. The third section plots the data by individual network, with subsections that display the data by individual days and pooled by year. Some spans resulted in singular or near singular issues in `r`. These have been noted in each individual section.

E.2 Plots for Emotional Intensity and Frequency with Year as a Factor

E.2.1 Plots by Whether the Network is Partisan or Nonpartisan

Figure E.1: Plot of Emotional Intensity by Partisan and Nonpartisan News Over Election Years with Year as a Factor: 2000-2020

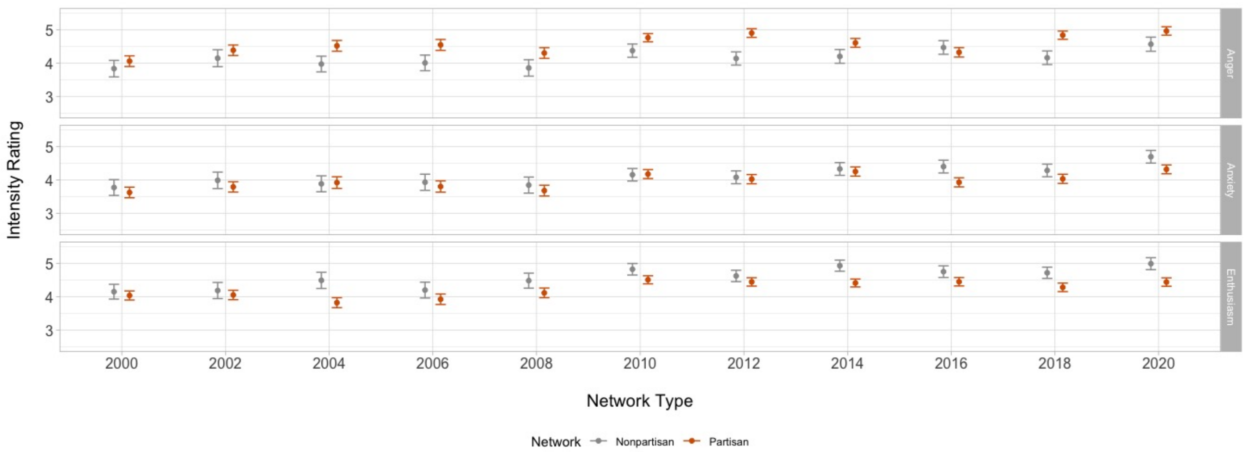
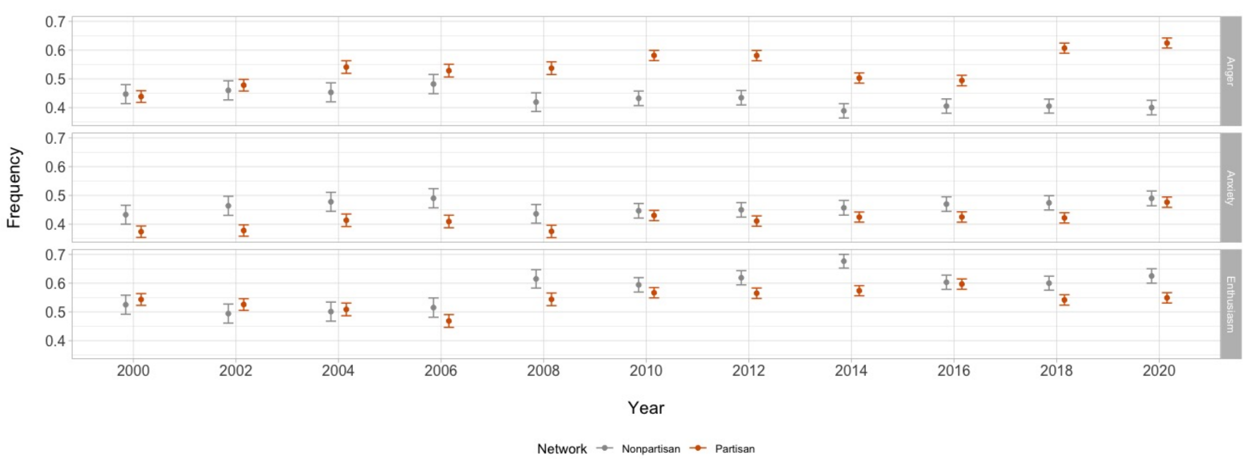


Figure E.2: Plot of Emotional Frequency by Partisan and Nonpartisan News Over Election Years with Year as a Factor: 2000-2020



E.2.2 Plots by Network

Figure E.3: Plot of Emotional Intensity by Network Over Election Years with Year as a Factor: 2000-2020

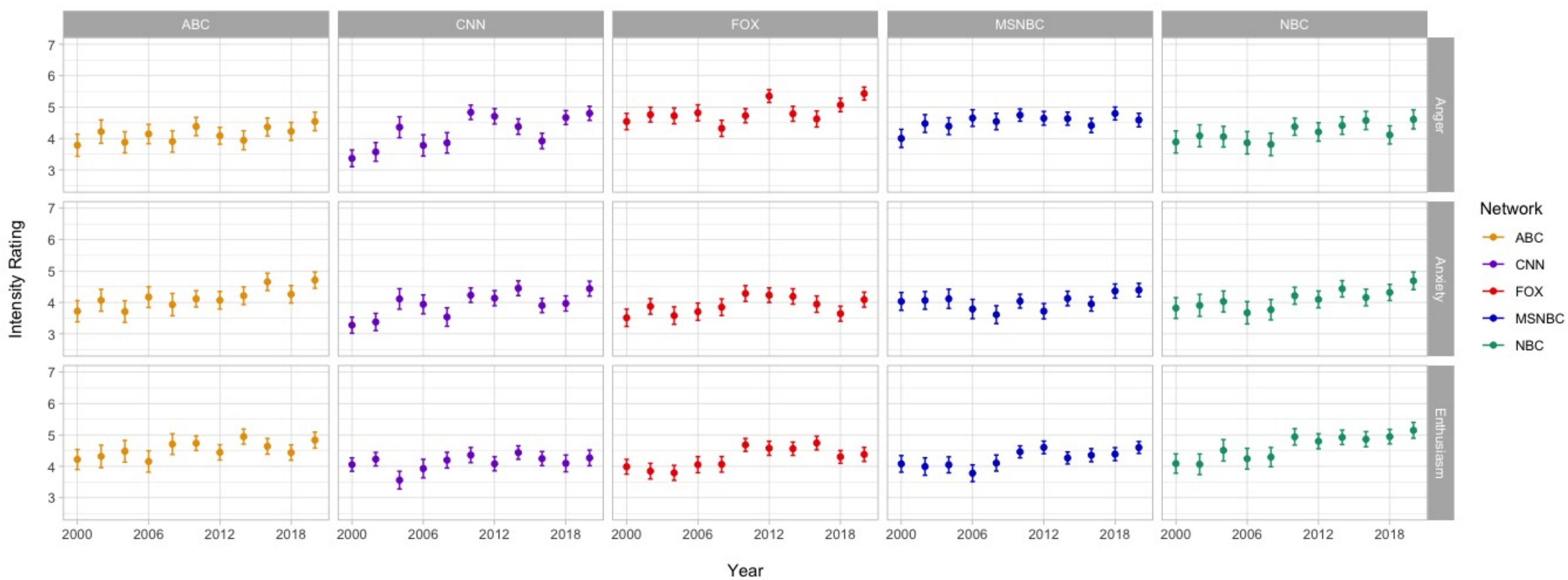
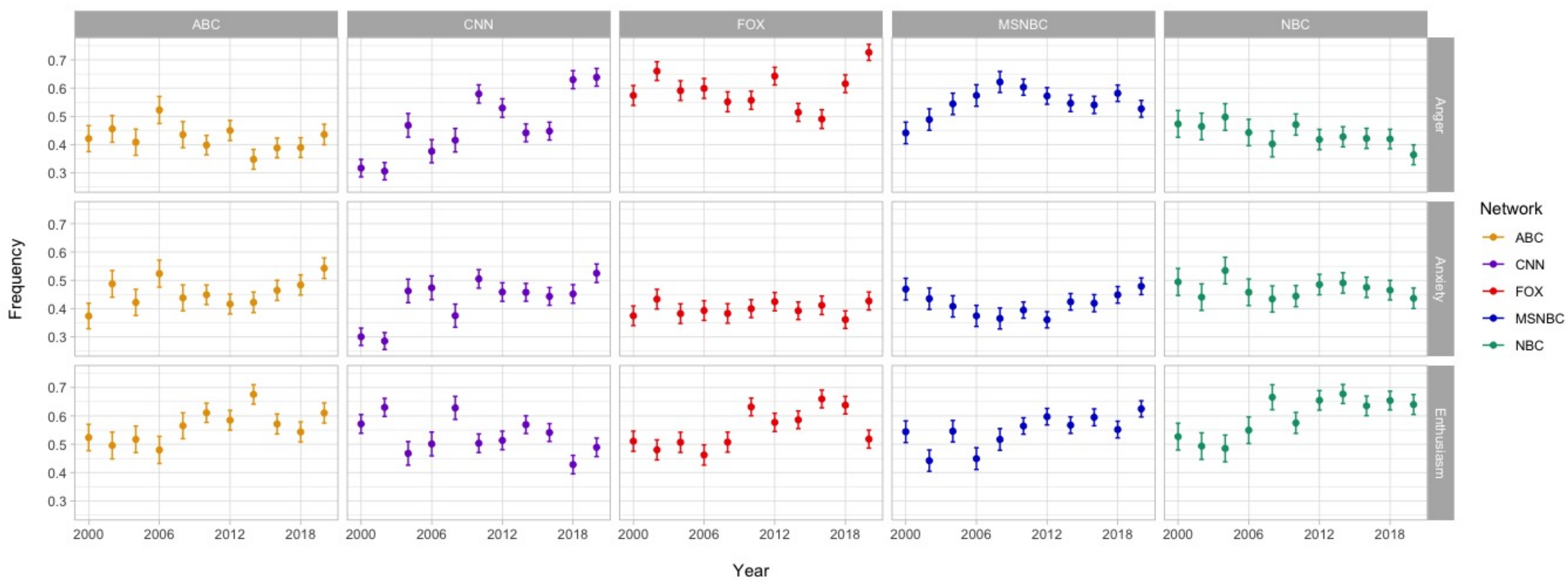


Figure E.4: Plot of Emotional Frequency by Network Over Election Years with Year as a Factor: 2000-2020



E.3 Loess Plots for Emotional Intensity and Frequency by Partisan and Nonpartisan Network Type

E.3.1 Loess Plots Where Time is Days

E.3.1.1 Intensity

Figure E.5: Loess Plot of Emotional Intensity of Anger by Partisan and Nonpartisan News Over Days Where Span = .75

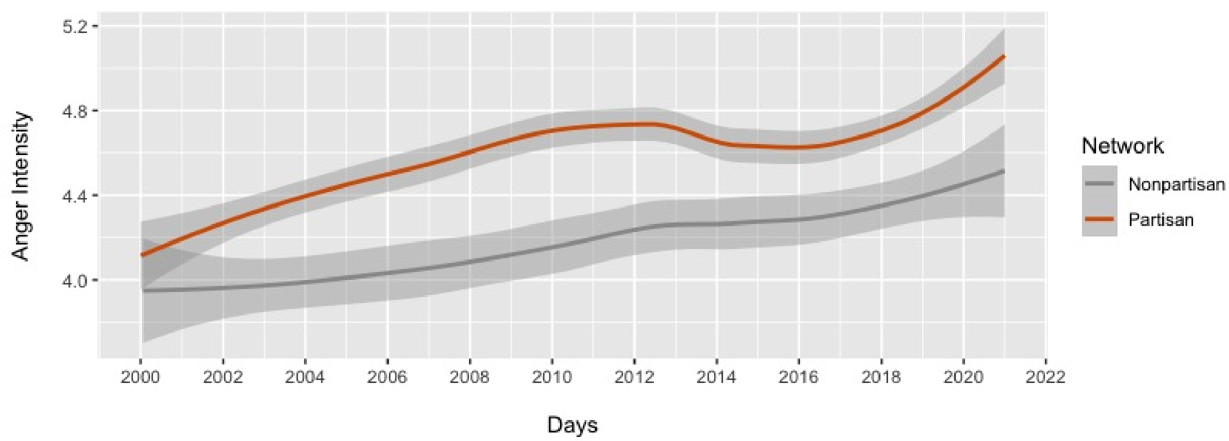


Figure E.6: Loess Plot of Emotional Intensity of Anger by Partisan and Nonpartisan News Over Days Where Span = .5

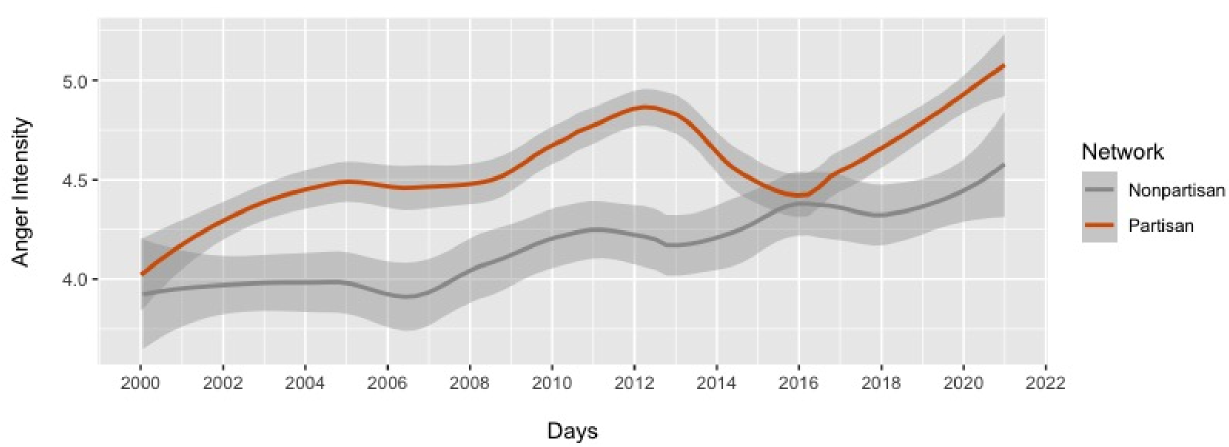


Figure E.7: Loess Plot of Emotional Intensity of Anger by Partisan and Nonpartisan News Over Days Where Span = .25

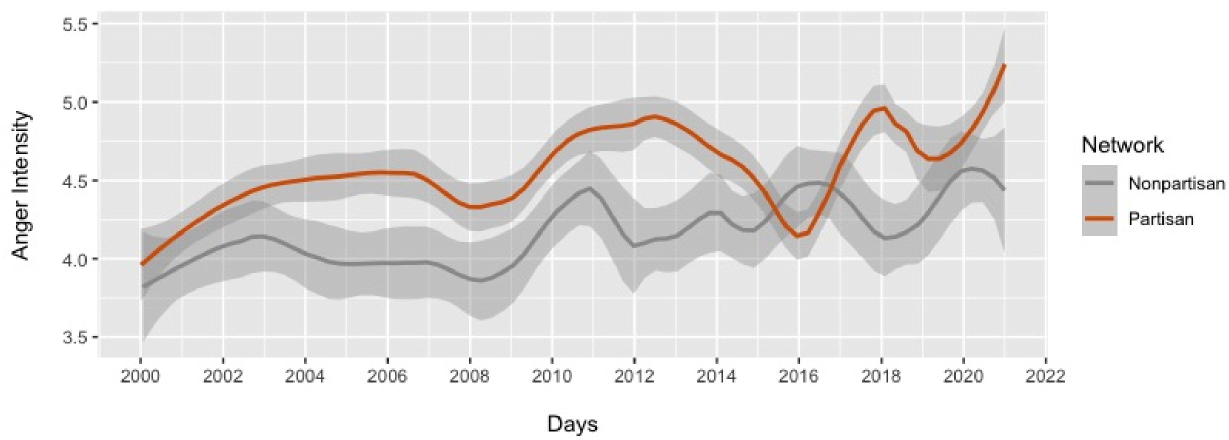


Figure E.8: Loess Plot of Emotional Intensity of Anxiety by Partisan and Nonpartisan News Over Days Where Span = .75

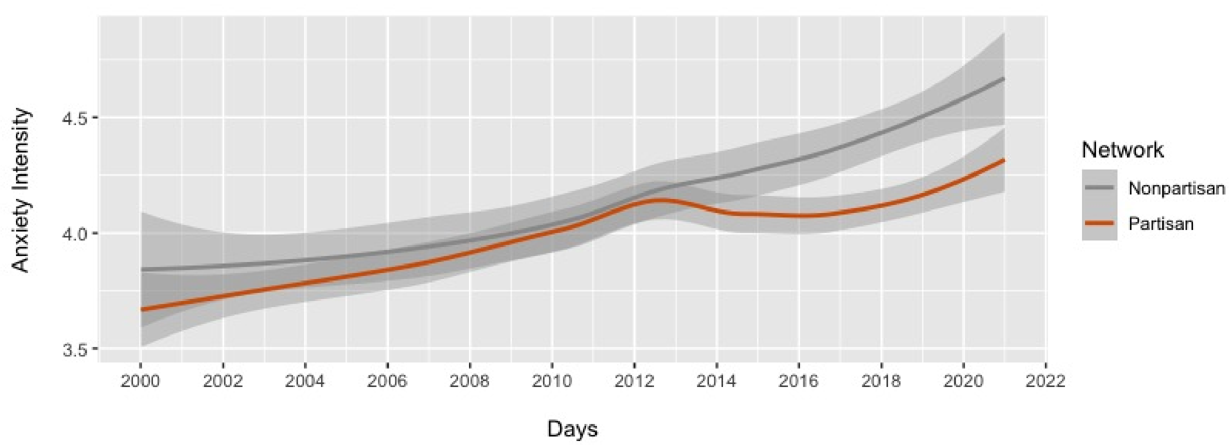


Figure E.9: Loess Plot of Emotional Intensity of Anxiety by Partisan and Nonpartisan News Over Days Where Span = .5

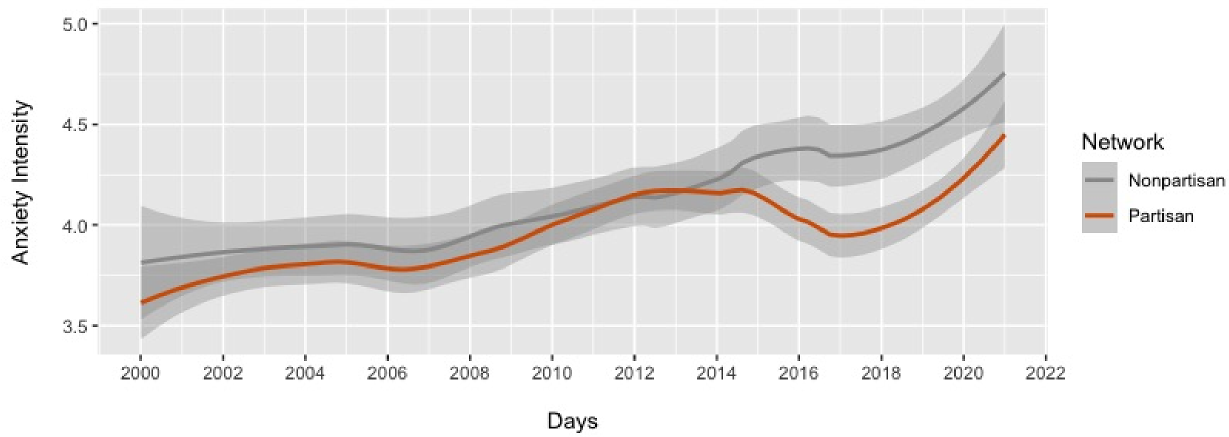


Figure E.10: Loess Plot of Emotional Intensity of Anxiety by Partisan and Nonpartisan News Over Days Where Span = .25

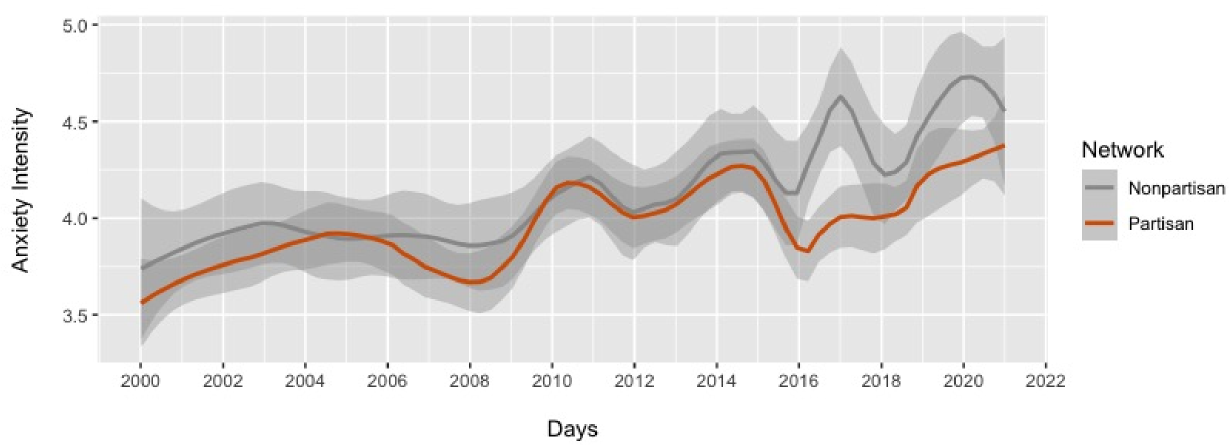


Figure E.11: Loess Plot of Emotional Intensity of Enthusiasm by Partisan and Nonpartisan News Over Days Where Span = .75

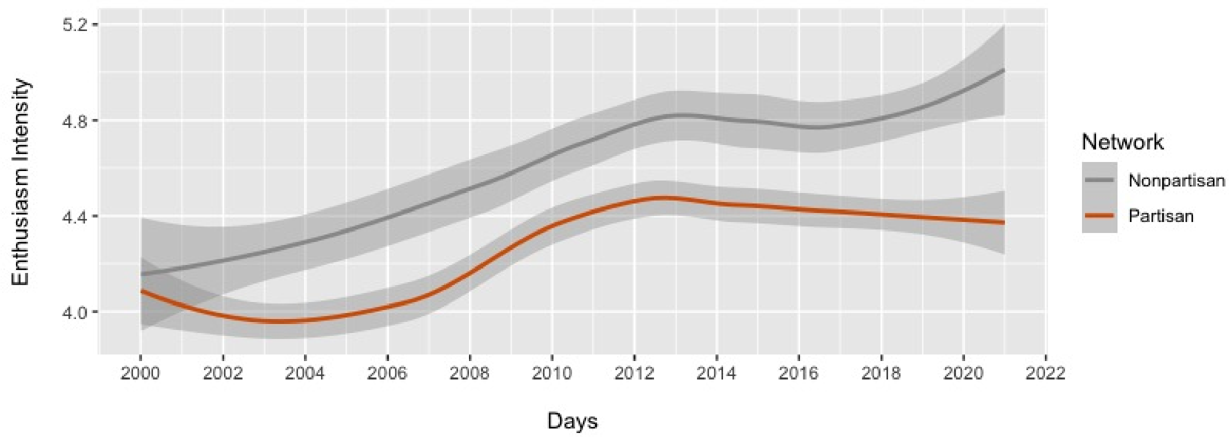


Figure E.12: Loess Plot of Emotional Intensity of Enthusiasm by Partisan and Nonpartisan News Over Days Where Span = .5

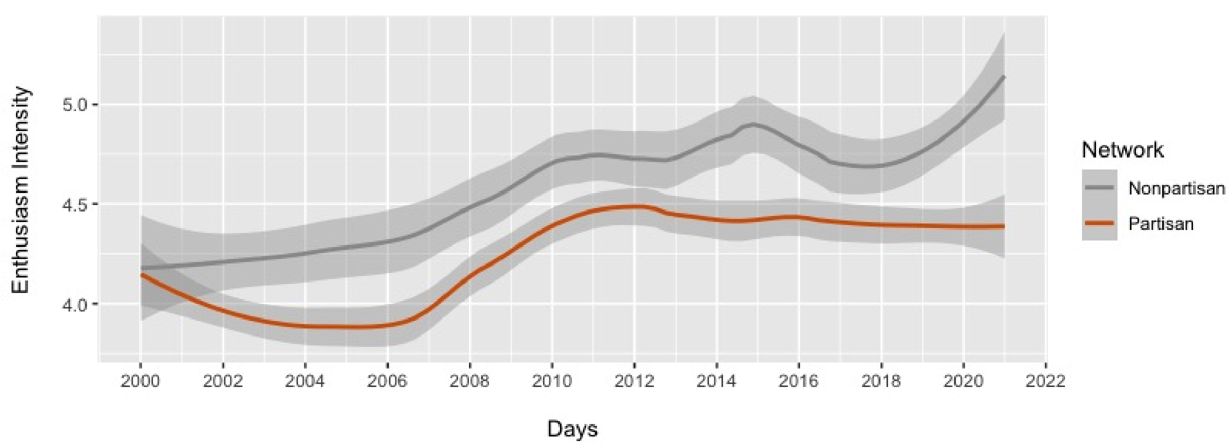
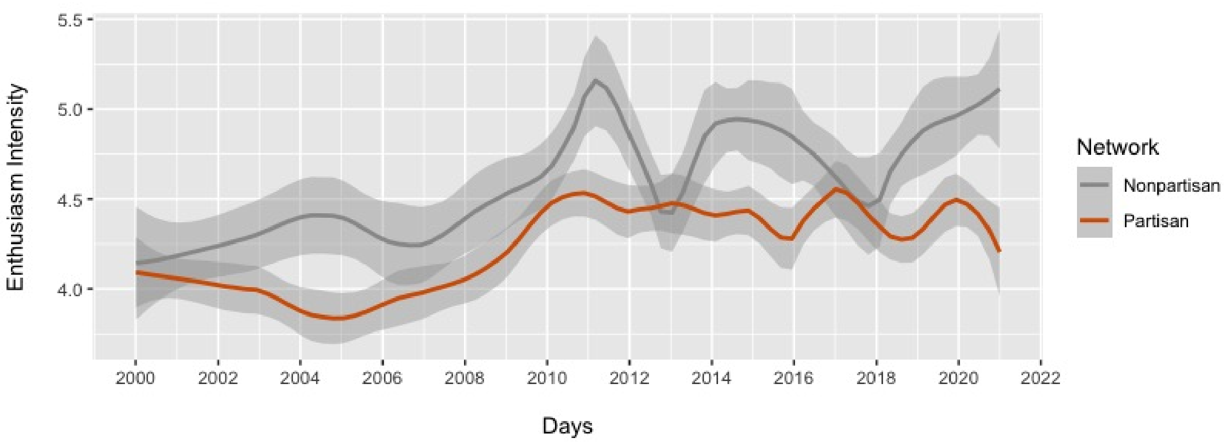


Figure E.13: Loess Plot of Emotional Intensity of Enthusiasm by Partisan and Nonpartisan News Over Days Where Span = .25



E.3.1.2 Frequency

Figure E.14: Loess Plot of Frequency of Anger by Partisan and Nonpartisan News Over Years Where Span = .75

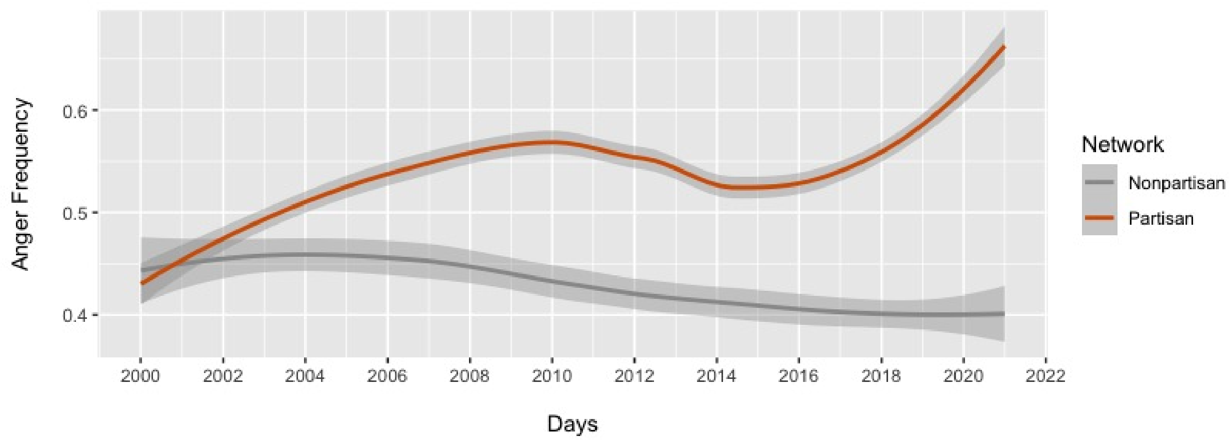


Figure E.15: Loess Plot of Frequency of Anger by Partisan and Nonpartisan News Over Years Where Span = .5

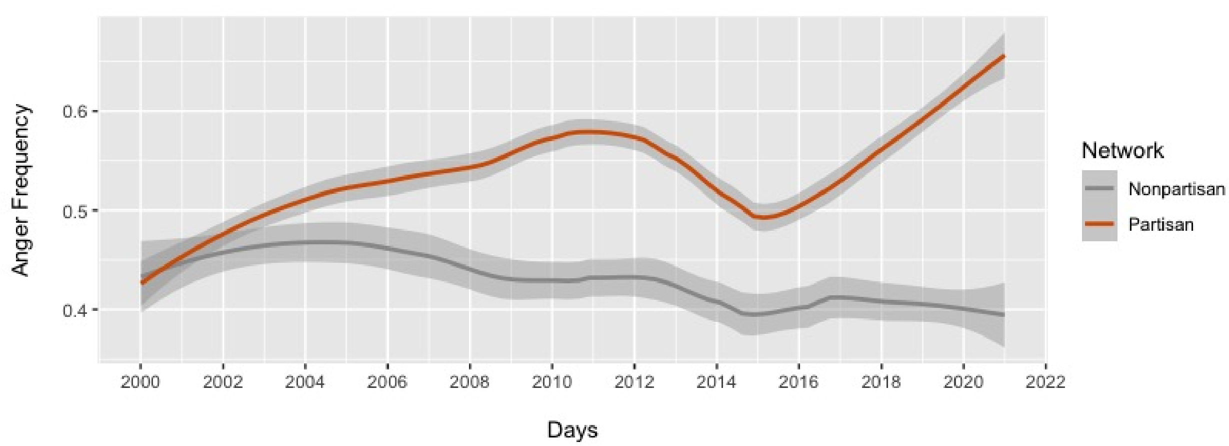


Figure E.16: Loess Plot of Frequency of Anger by Partisan and Nonpartisan News Over Years Where Span = .25

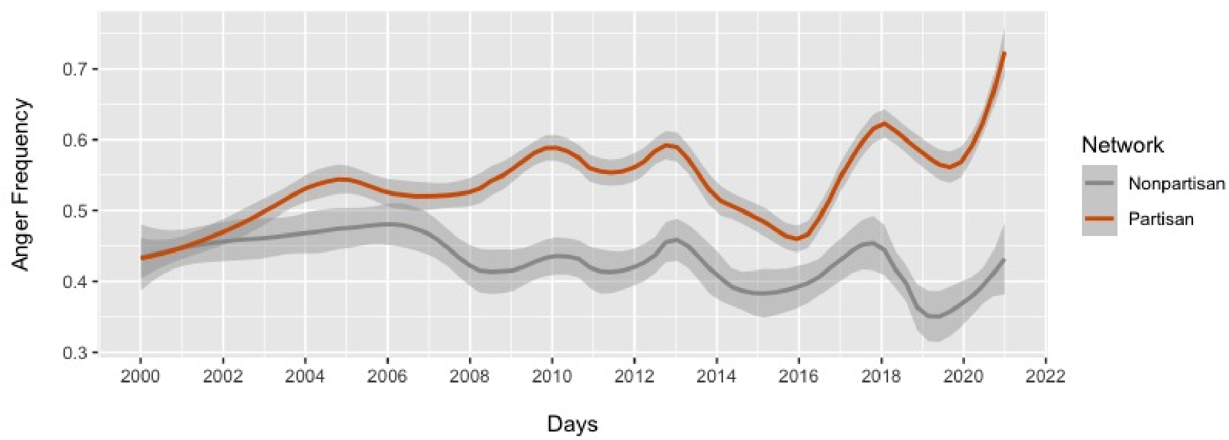


Figure E.17: Loess Plot of Frequency of Anxiety by Partisan and Nonpartisan News Over Years Where Span = .75

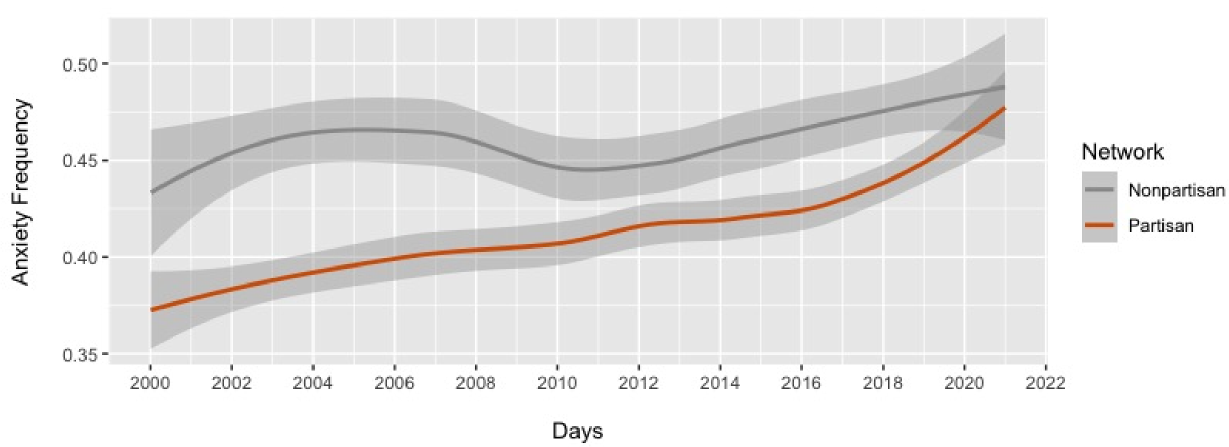


Figure E.18: Loess Plot of Frequency of Anxiety by Partisan and Nonpartisan News Over Years Where Span = .5

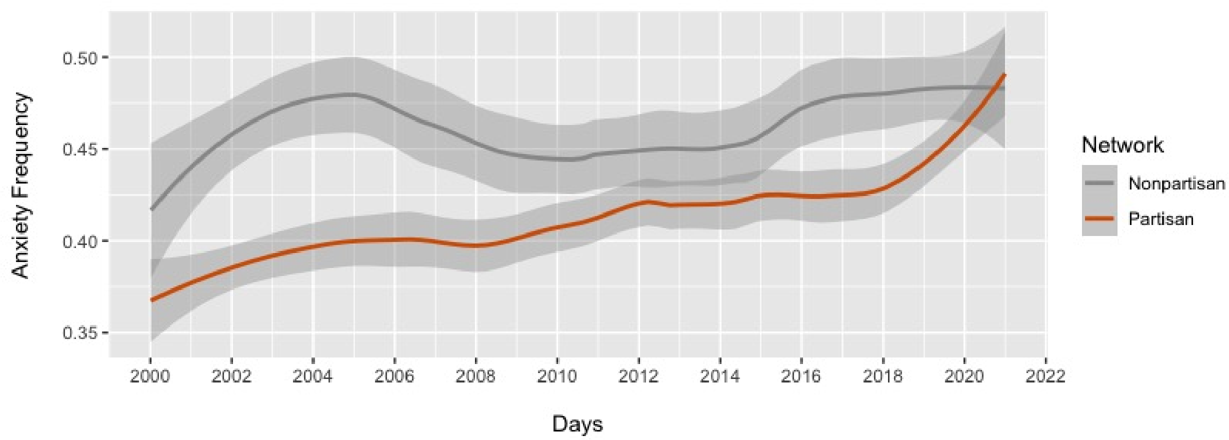


Figure E.19: Loess Plot of Frequency of Anxiety by Partisan and Nonpartisan News Over Years Where Span = .25

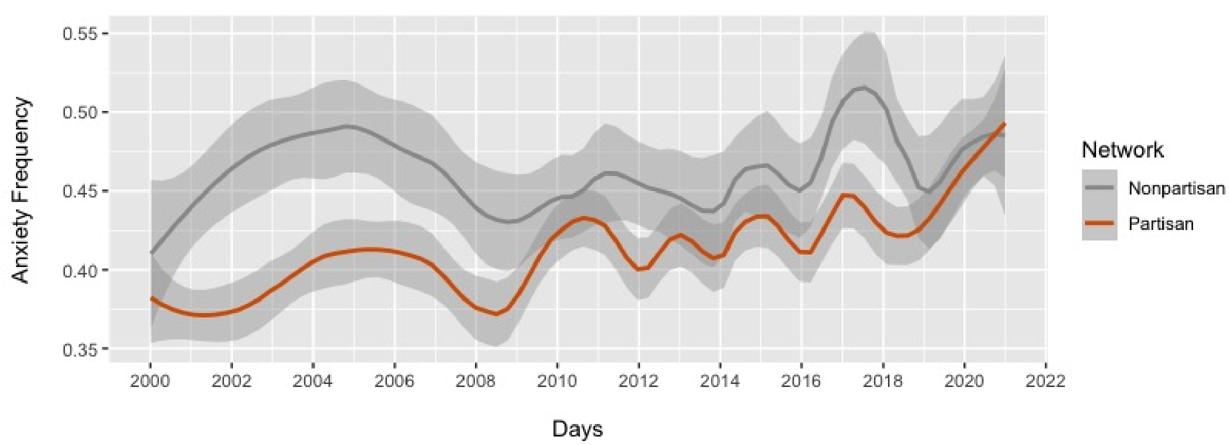


Figure E.20: Loess Plot of Frequency of Enthusiasm by Partisan and Nonpartisan News Over Years Where Span = .75

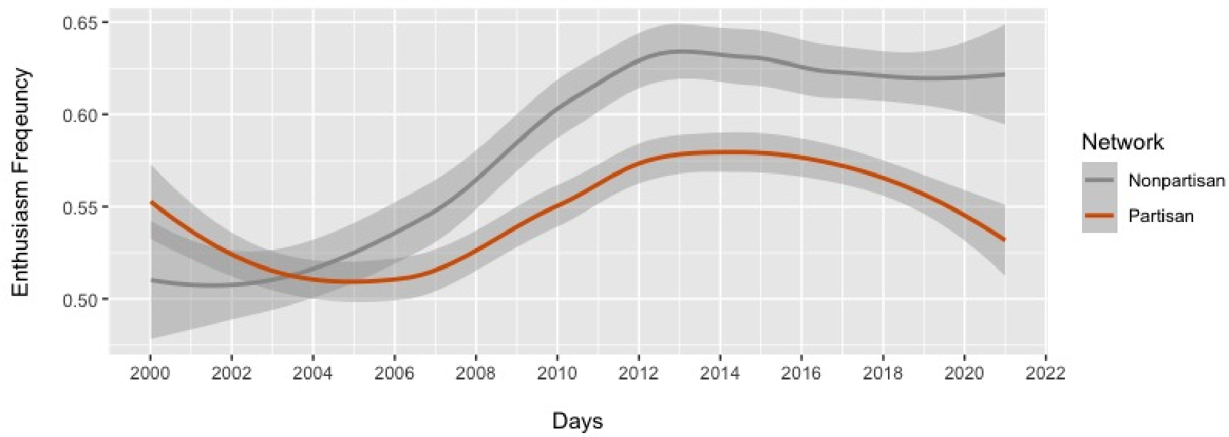


Figure E.21: Loess Plot of Frequency of Enthusiasm by Partisan and Nonpartisan News Over Years Where Span = .5

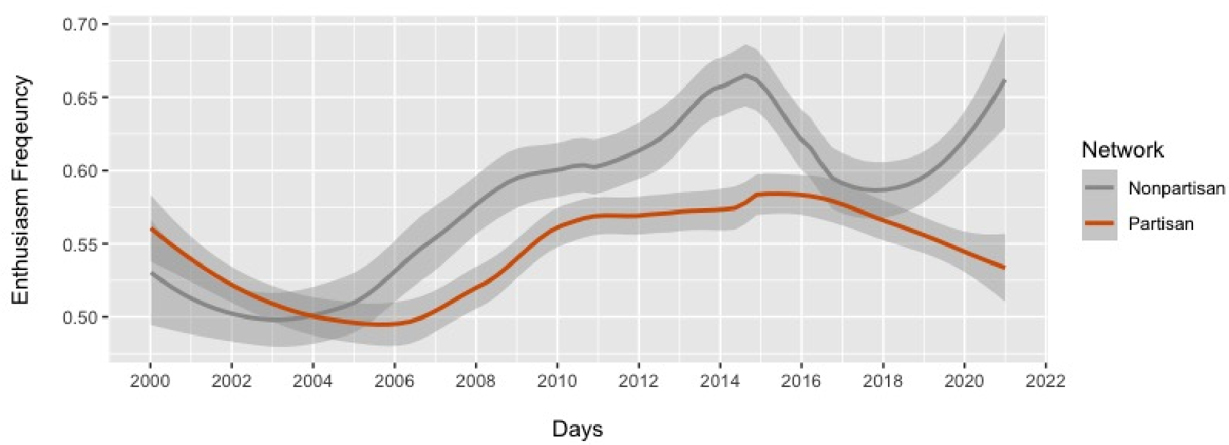
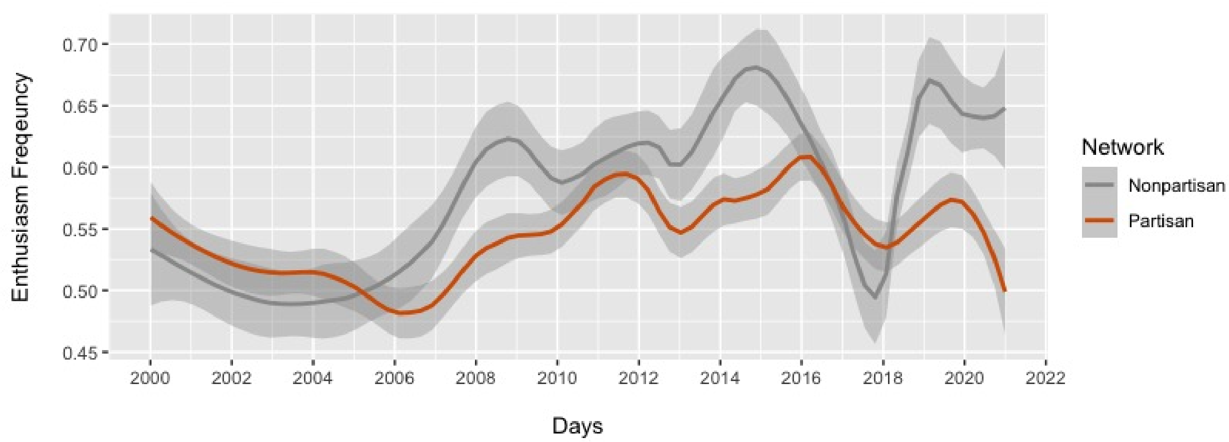


Figure E.22: Loess Plot of Frequency of Enthusaism by Partisan and Nonpartisan News Over Years Where Span = .25



E.3.2 Loess Plots Where Time is Pooled by Year

E.3.2.1 Intensity

Figure E.23: Loess Plot of Emotional Intensity of Anger by Partisan and Nonpartisan News Over Election Years Where Span = .75

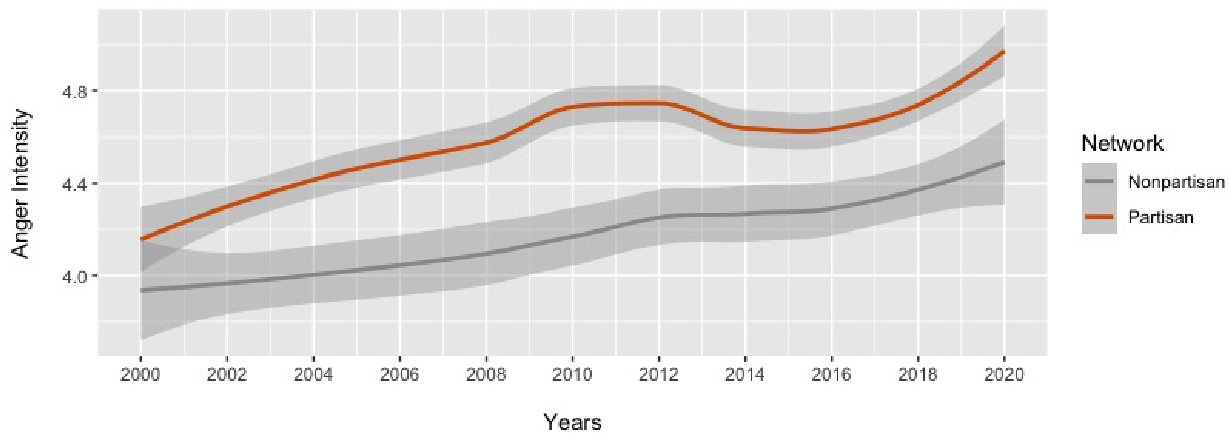
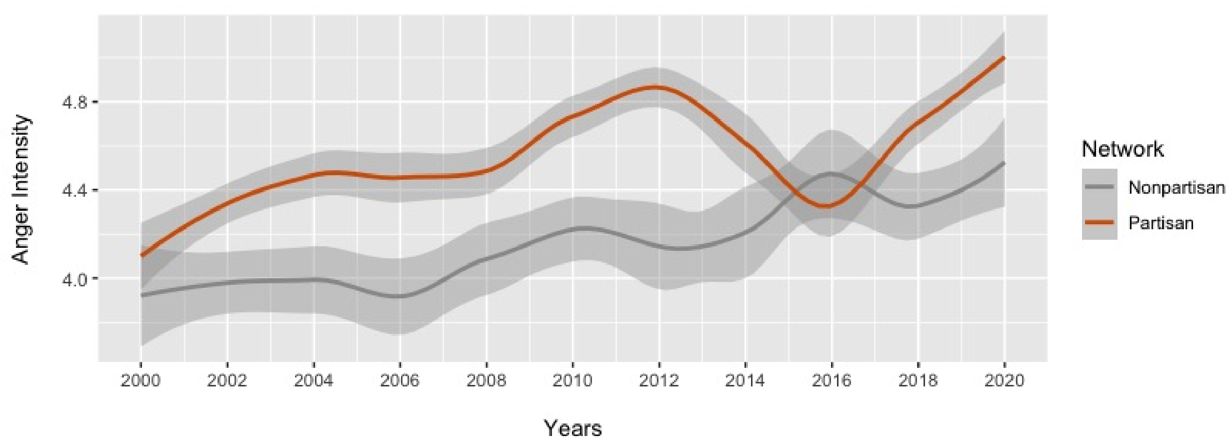


Figure E.24: Loess Plot of Emotional Intensity of Anger by Partisan and Nonpartisan News Over Election Years Where Span = .5



Note: The plot for the emotional intensity of anger by partisan and nonpartisan news over election years where the span = 0.25 results in near singularities and so the plot is omitted

Figure E.25: Loess Plot of Emotional Intensity of Anxiety by Partisan and Nonpartisan News Over Election Years Where Span = .75

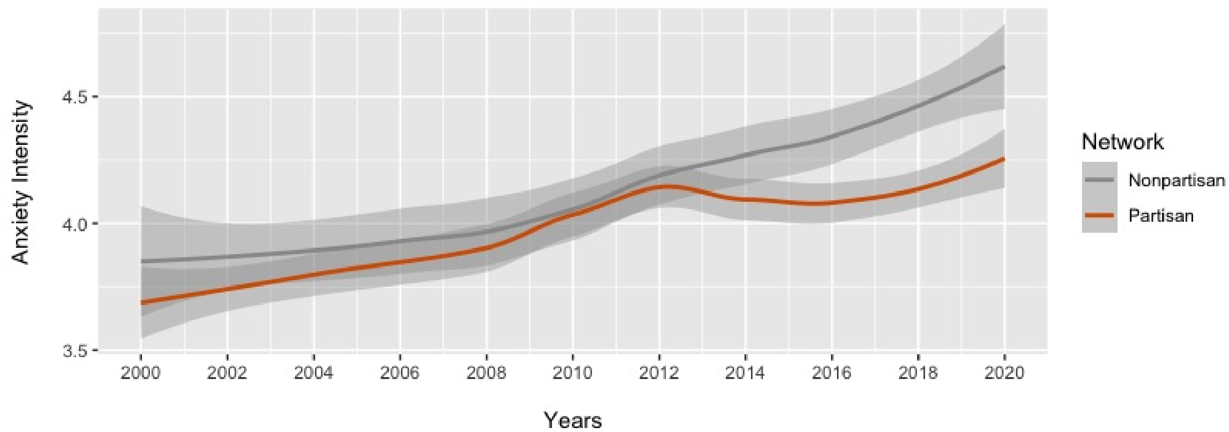


Figure E.26: Loess Plot of Emotional Intensity of Anxiety by Partisan and Nonpartisan News Over Election Years Where Span = .5

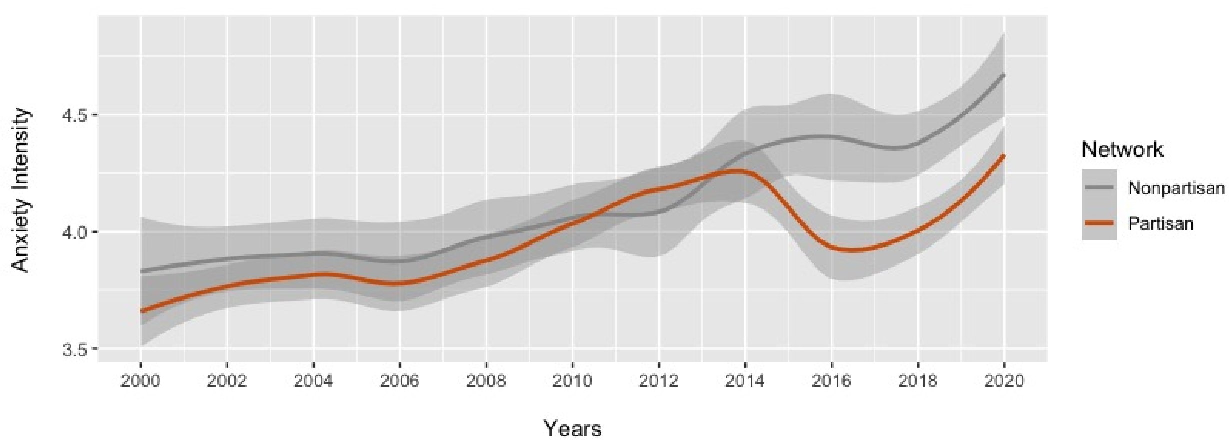


Figure E.27: Loess Plot of Emotional Intensity of Anxiety by Partisan and Nonpartisan News Over Election Years Where Span = .25

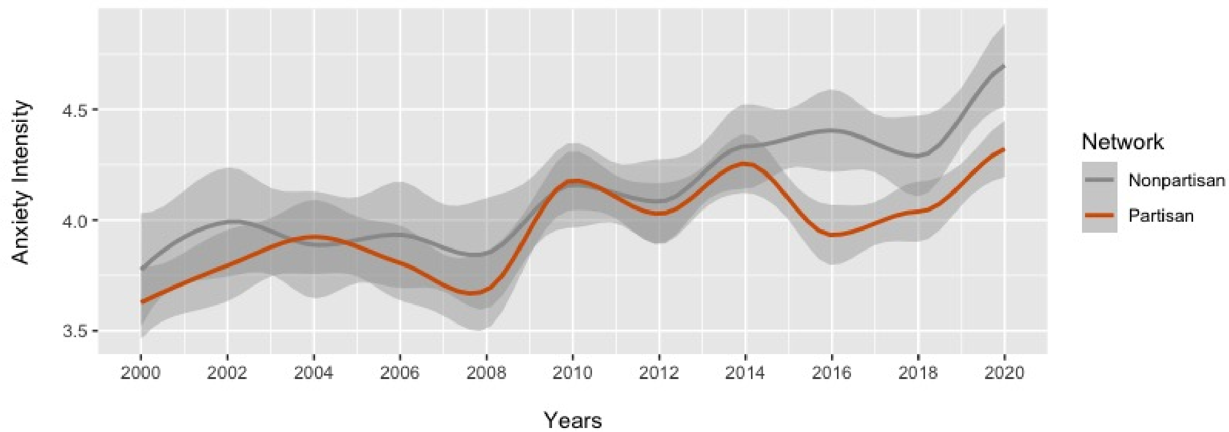


Figure E.28: Loess Plot of Emotional Intensity of Enthusiasm by Partisan and Nonpartisan News Over Election Years Where Span = .75

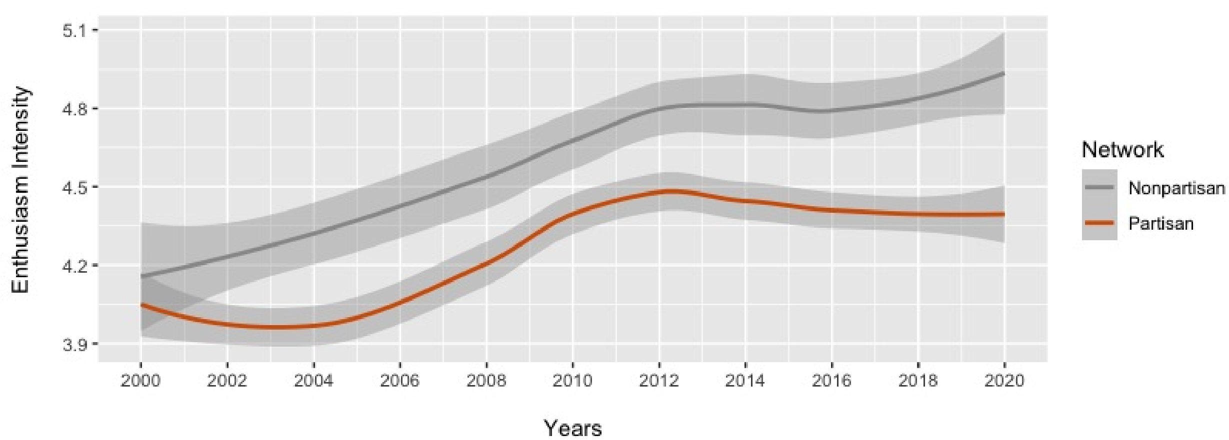


Figure E.29: Loess Plot of Emotional Intensity of Enthusiasm by Partisan and Nonpartisan News Over Election Years Where Span = .5

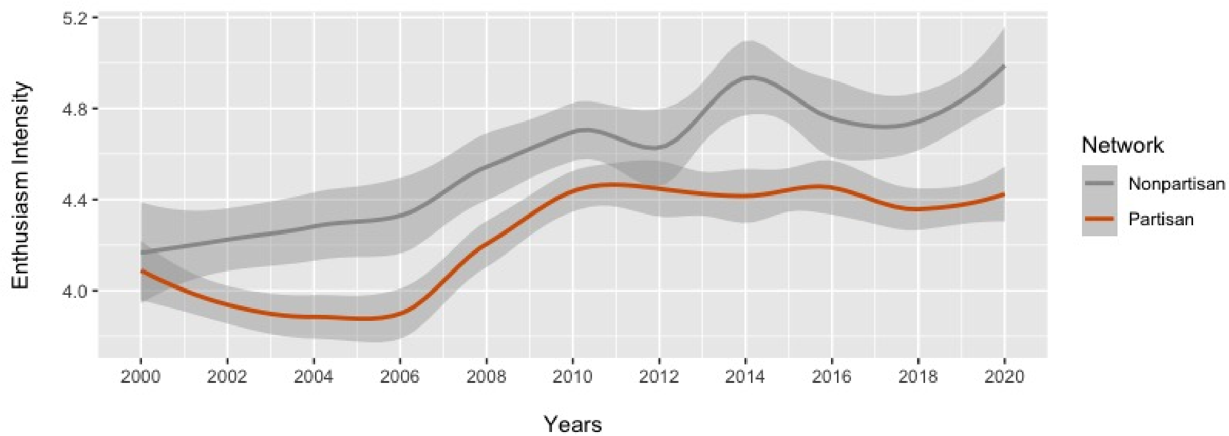
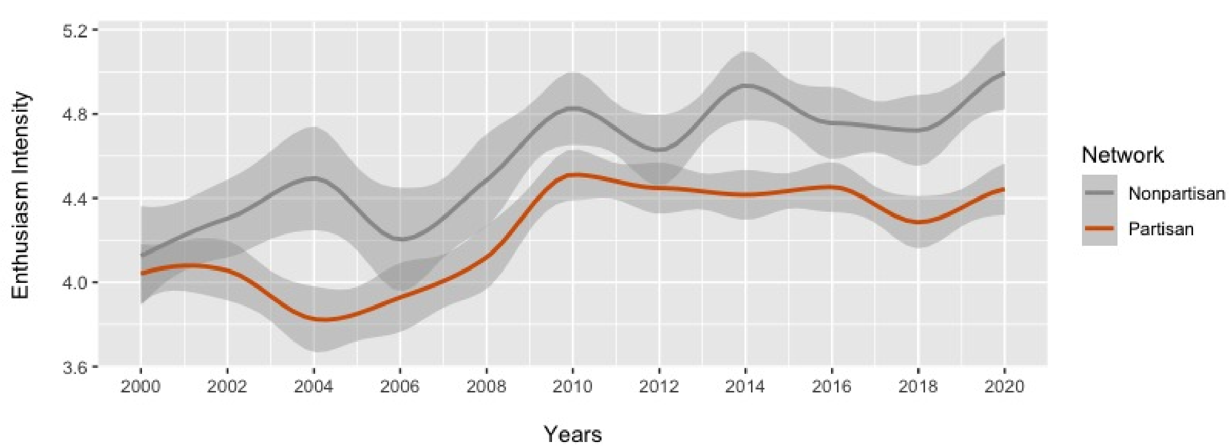


Figure E.30: Loess Plot of Emotional Intensity of Enthusiasm by Partisan and Nonpartisan News Over Election Years Where Span = .25



E.3.2.2 Frequency

Figure E.31: Loess Plot of Frequency of Anger by Partisan and Nonpartisan News Over Years Where Span = .75

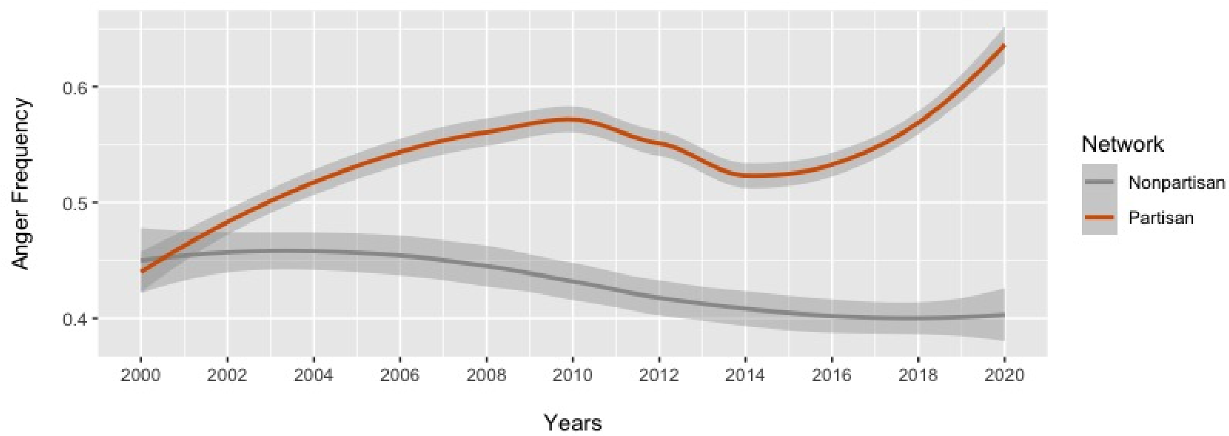
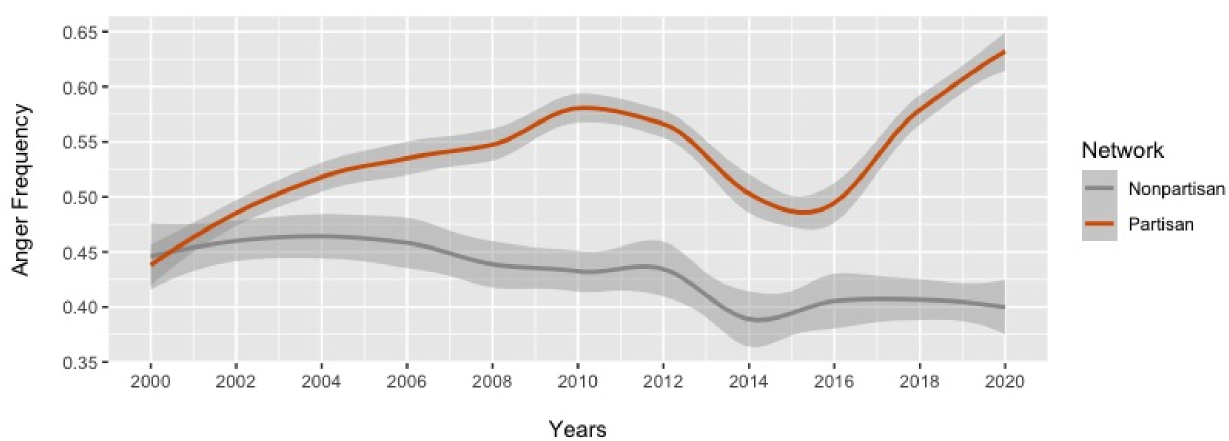


Figure E.32: Loess Plot of Frequency of Anger by Partisan and Nonpartisan News Over Years Where Span = .5



Note: The plot for the frequency of anger by partisan and nonpartisan news over election years where the span = 0.25 results in near singularities and so the plot is omitted

Figure E.33: Loess Plot of Frequency of Anxiety by Partisan and Nonpartisan News Over Years Where Span = .75

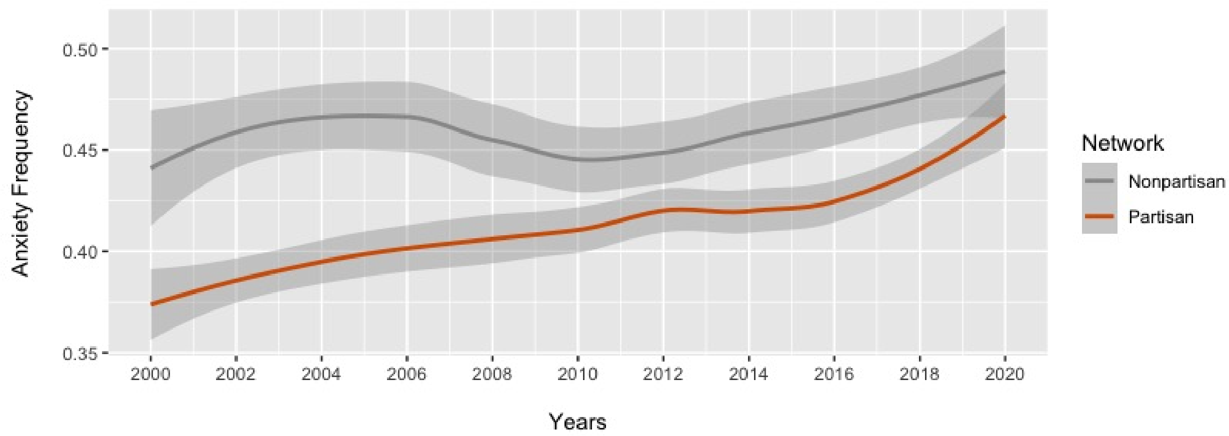
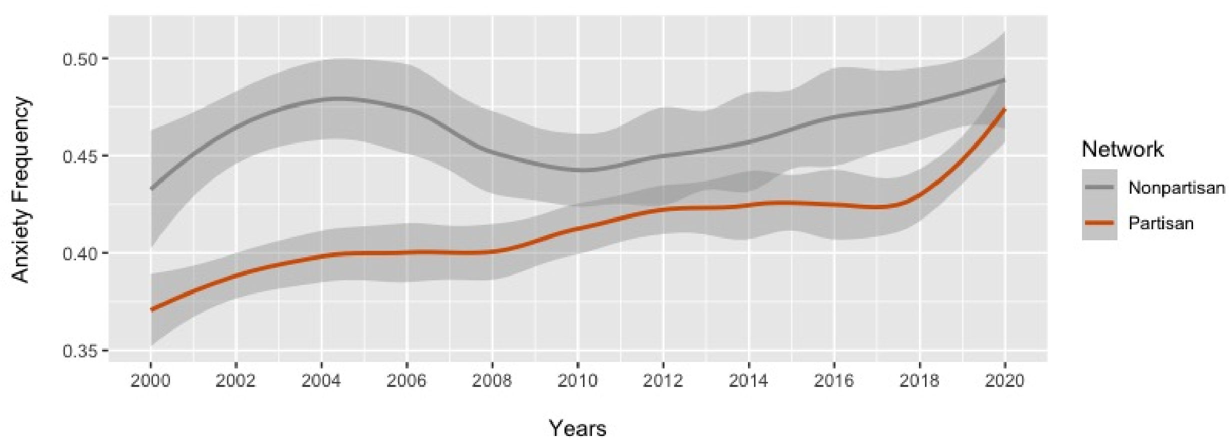


Figure E.34: Loess Plot of Frequency of Anxiety by Partisan and Nonpartisan News Over Years Where Span = .5



Note: The plot for the frequency of anxiety by partisan and nonpartisan news over election years where the span = 0.25 results in near singularities and so the plot is omitted

Figure E.35: Loess Plot of Frequency of Enthusiasm by Partisan and Nonpartisan News Over Years Where Span = .75

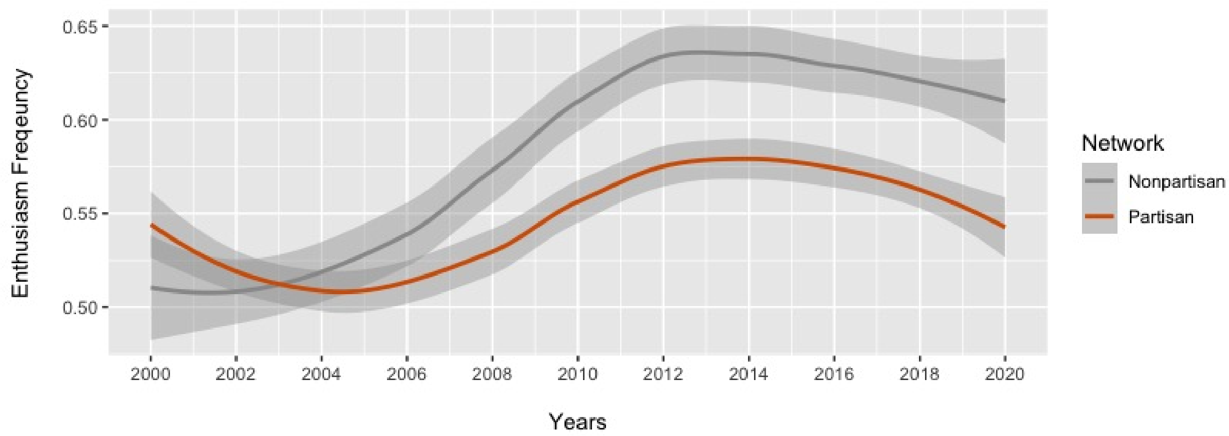
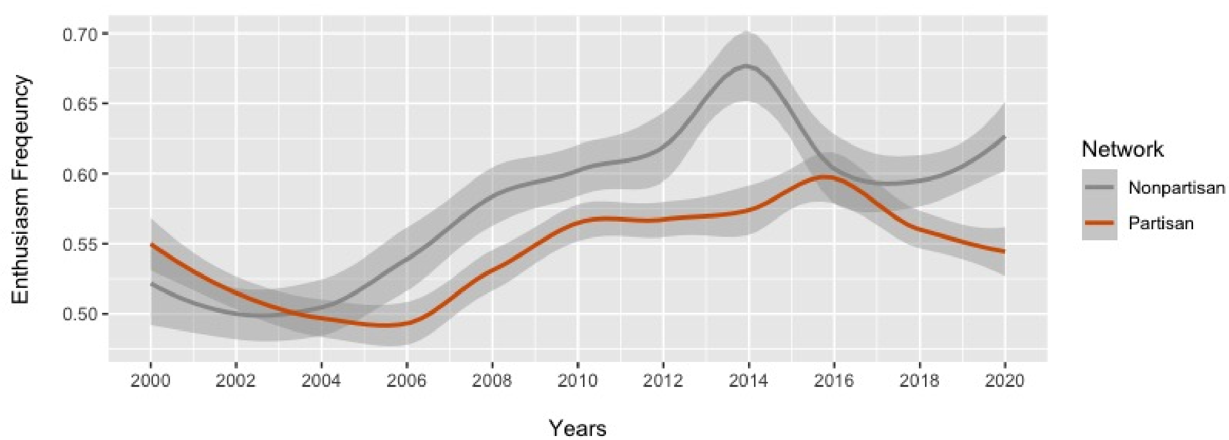


Figure E.36: Loess Plot of Frequency of Enthusiasm by Partisan and Nonpartisan News Over Years Where Span = .5



Note: The plot for the frequency of enthusiasm by partisan and nonpartisan news over election years where the span = 0.25 results in near singularities and so the plot is omitted

E.4 Loess Plots for Emotional Intensity and Frequency by Network

E.4.1 Loess Plots Where Time is Days

E.4.1.1 Intensity

Figure E.37: Loess Plot of Emotional Intensity of Anger by Network Over Days Where Span = .75

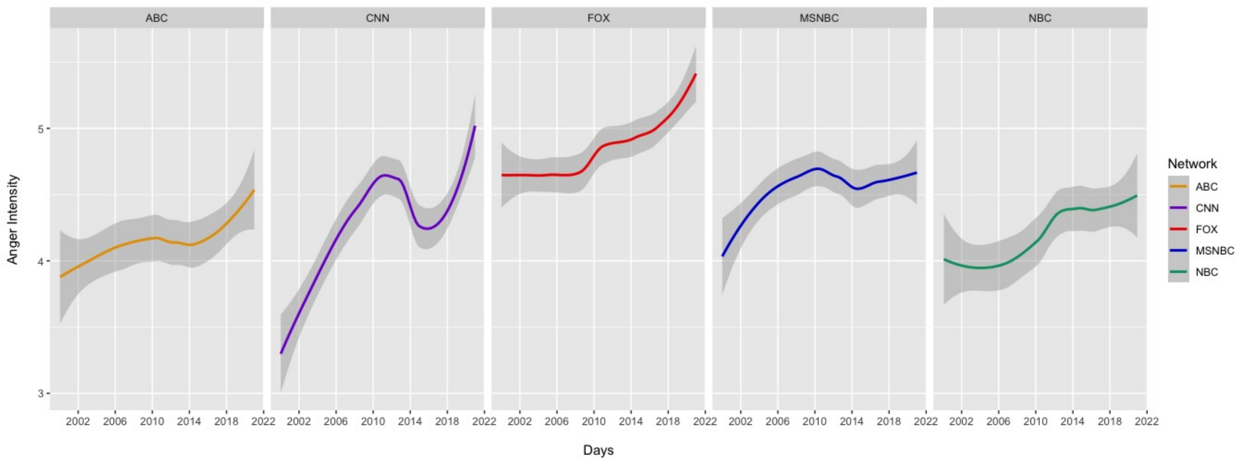


Figure E.38: Loess Plot of Emotional Intensity of Anger by Network Over Days Where Span = .5

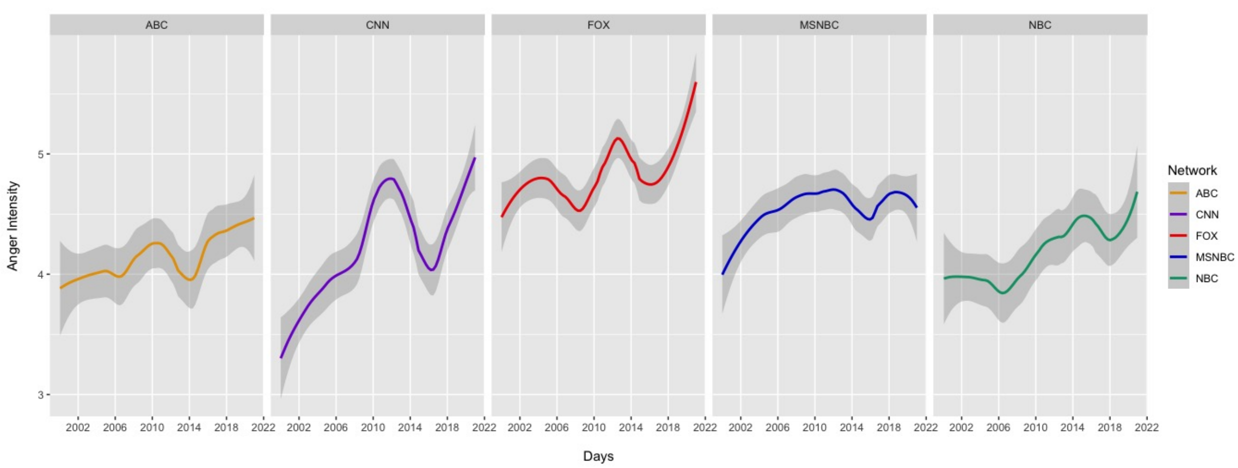


Figure E.39: Loess Plot of Emotional Intensity of Anger by Network Over Days Where Span = .25

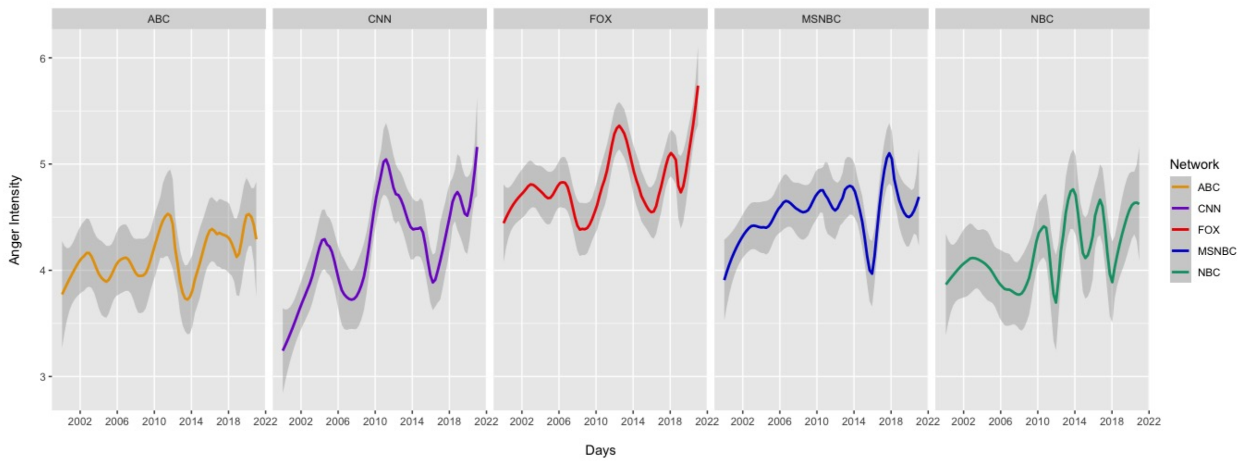


Figure E.40: Loess Plot of Emotional Intensity of Anxiety by Network Over Days Where Span = .75

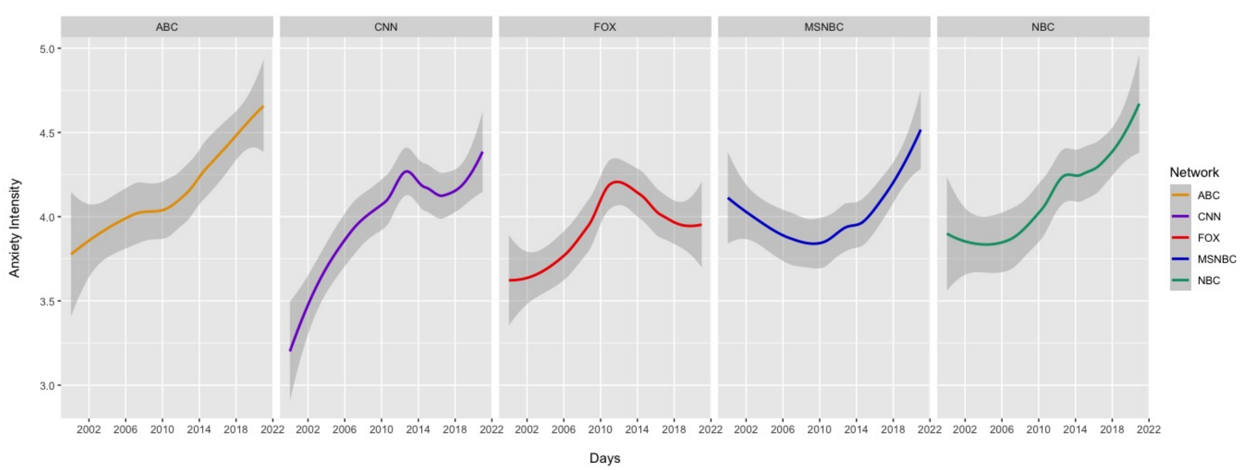


Figure E.41: Loess Plot of Emotional Intensity of Anxiety by Network Over Days Where Span = .5

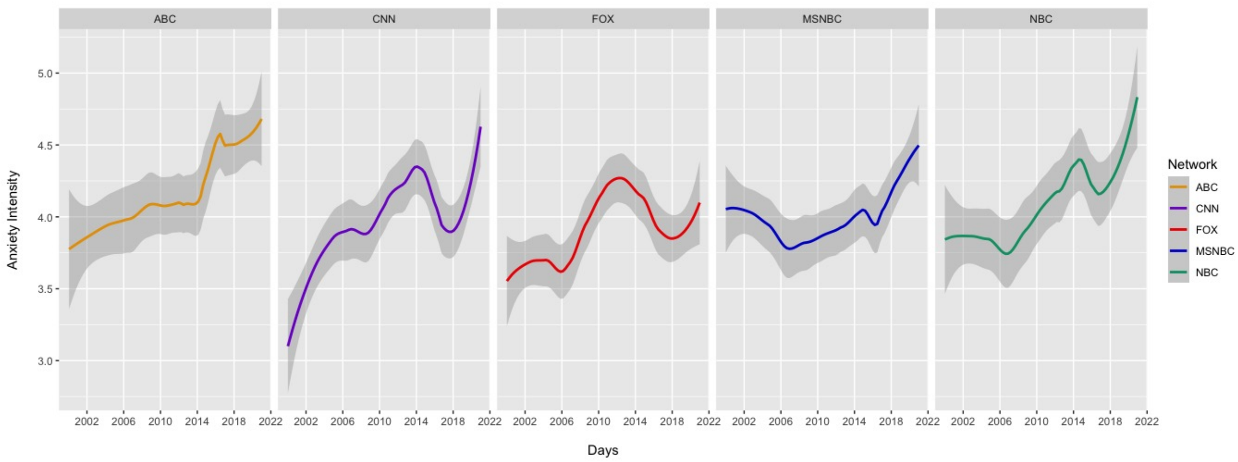


Figure E.42: Loess Plot of Emotional Intensity of Anxiety by Network Over Days Where Span = .25

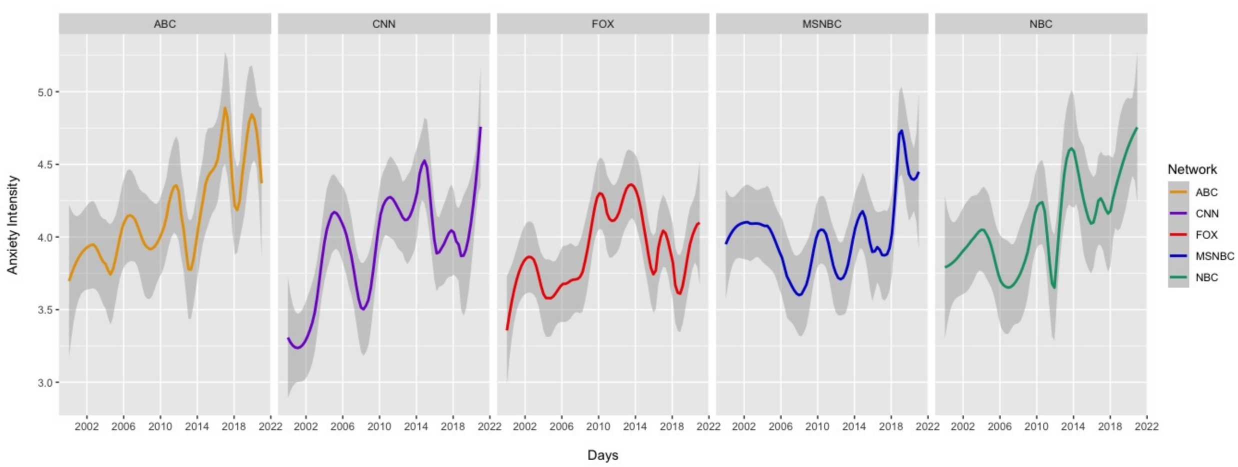


Figure E.43: Loess Plot of Emotional Intensity of Enthusiasm by Network Over Days Where Span = .75

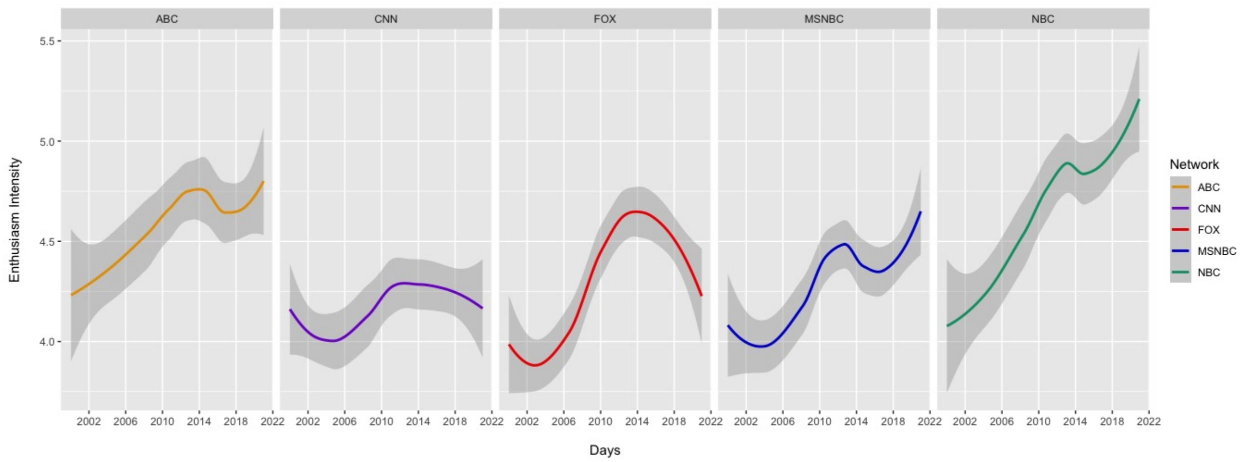


Figure E.44: Loess Plot of Emotional Intensity of Enthusiasm by Network Over Days Where Span = .5

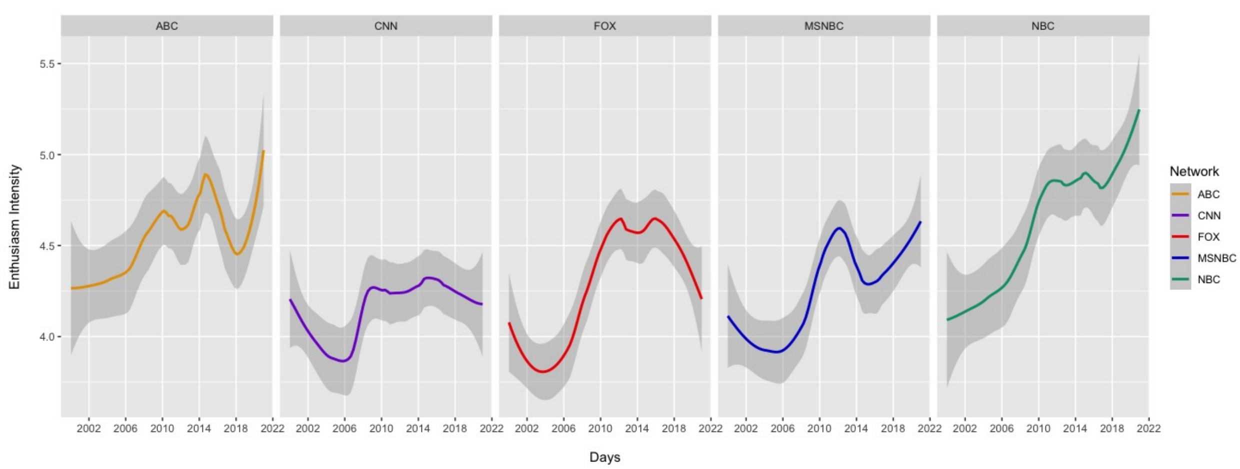
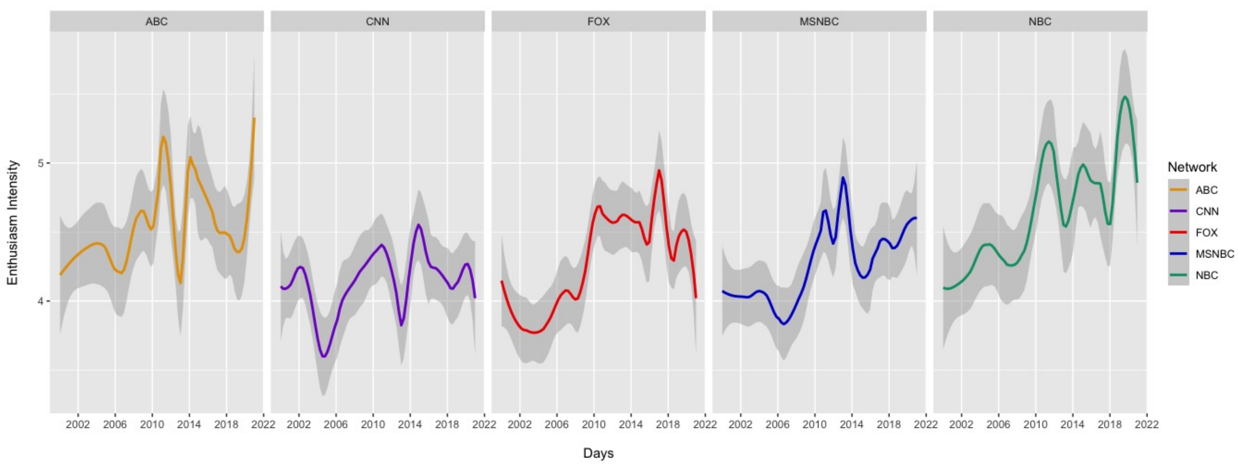


Figure E.45: Loess Plot of Emotional Intensity of Enthusiasm by Network Over Days Where Span = .25



E.4.1.2 Frequency

Figure E.46: Loess Plot of Frequency of Anger by Network Over Days Where Span = .75

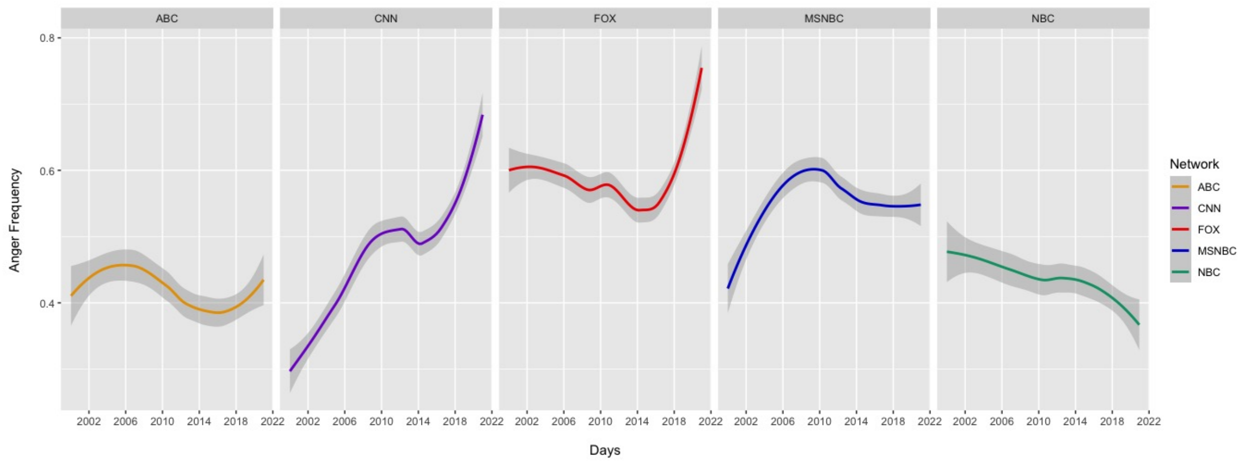


Figure E.47: Loess Plot of Frequency of Anger by Network Over Days Where Span = .5

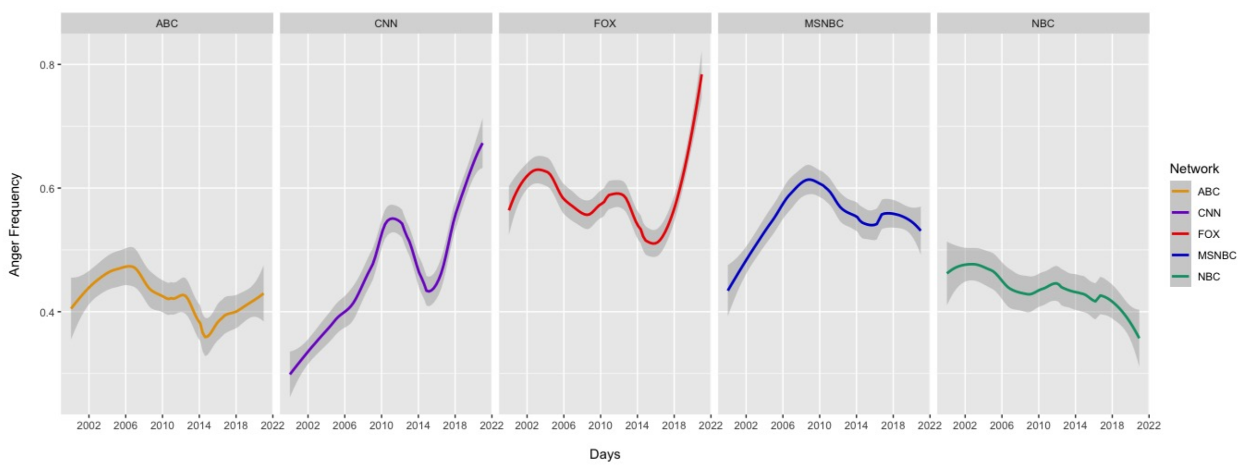


Figure E.48: Loess Plot of Frequency of Anger by Network Over Days Where Span = .25

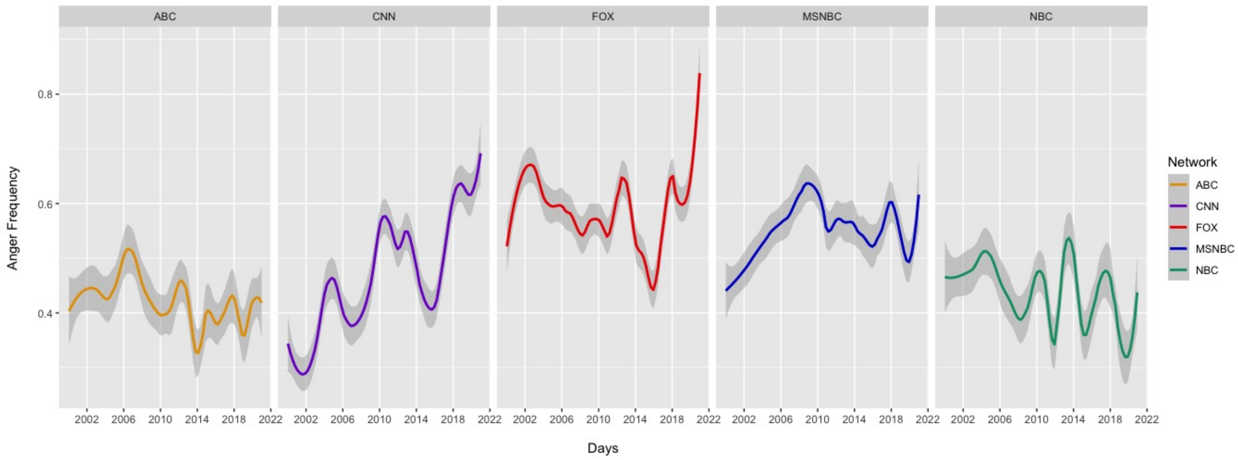


Figure E.49: Loess Plot of Frequency of Anxiety by Network Over Days Where Span = .75

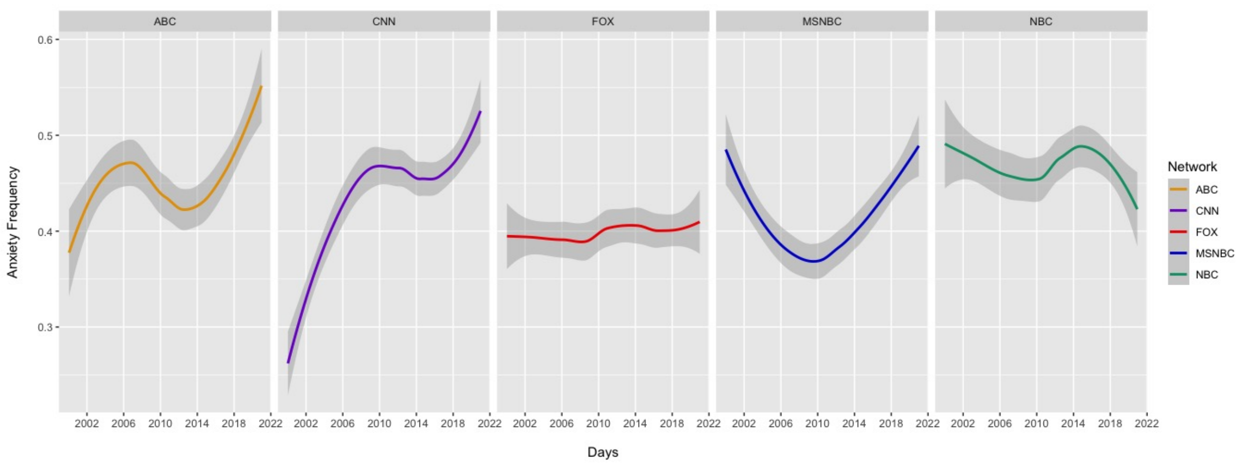


Figure E.50: Loess Plot of Frequency of Anxiety by Network Over Days Where Span = .5

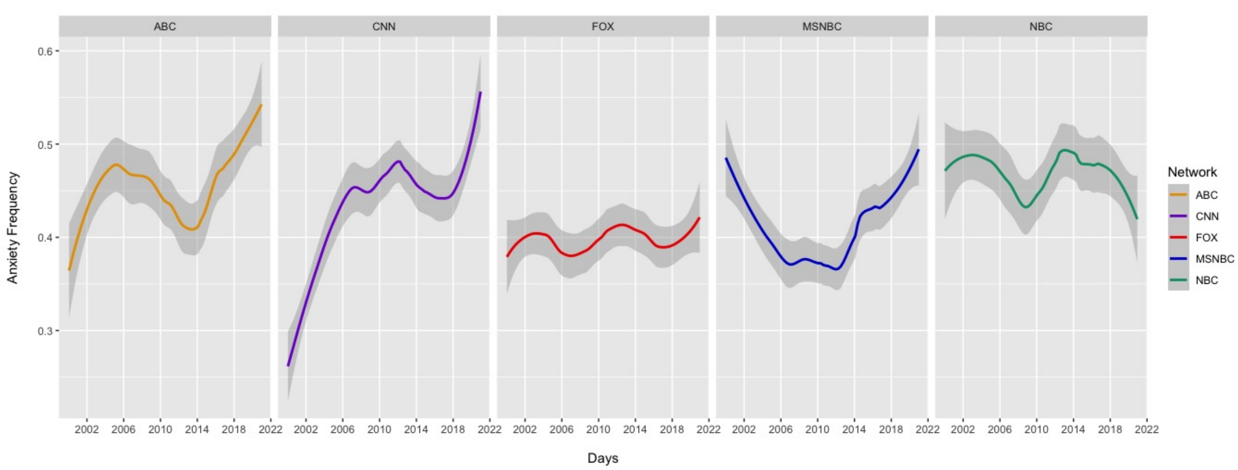


Figure E.51: Loess Plot of Frequency of Anxiety by Network Over Days Where Span = .25

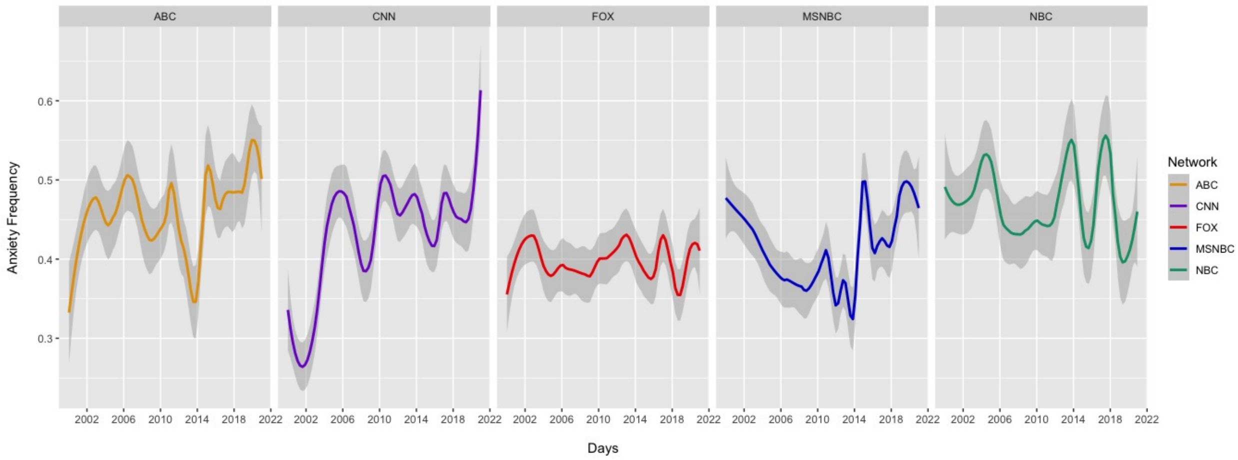


Figure E.52: Loess Plot of Frequency of Enthusiasm by Network Over Days Where Span = .75

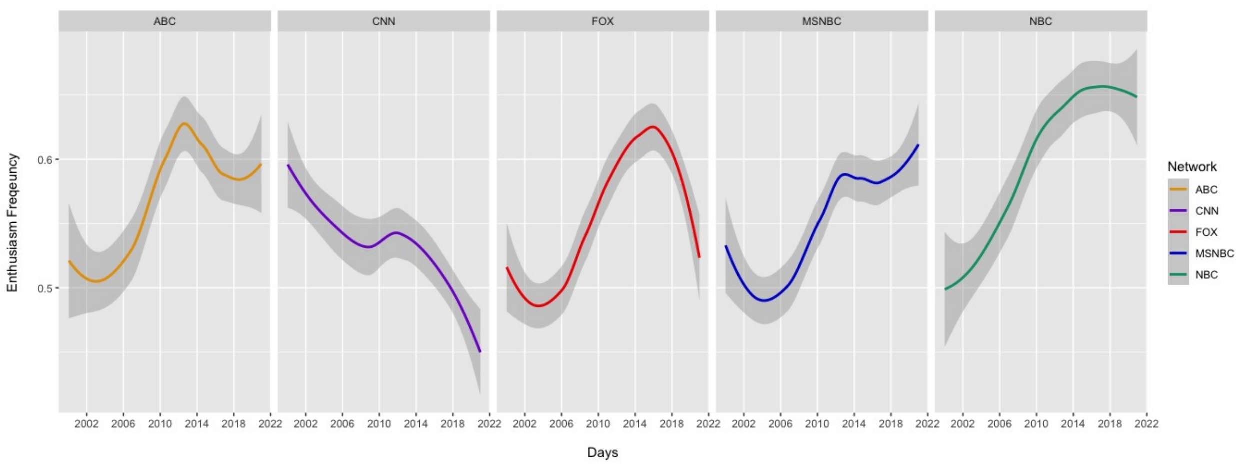


Figure E.53: Loess Plot of Frequency of Enthusiasm by Network Over Days Where Span = .5

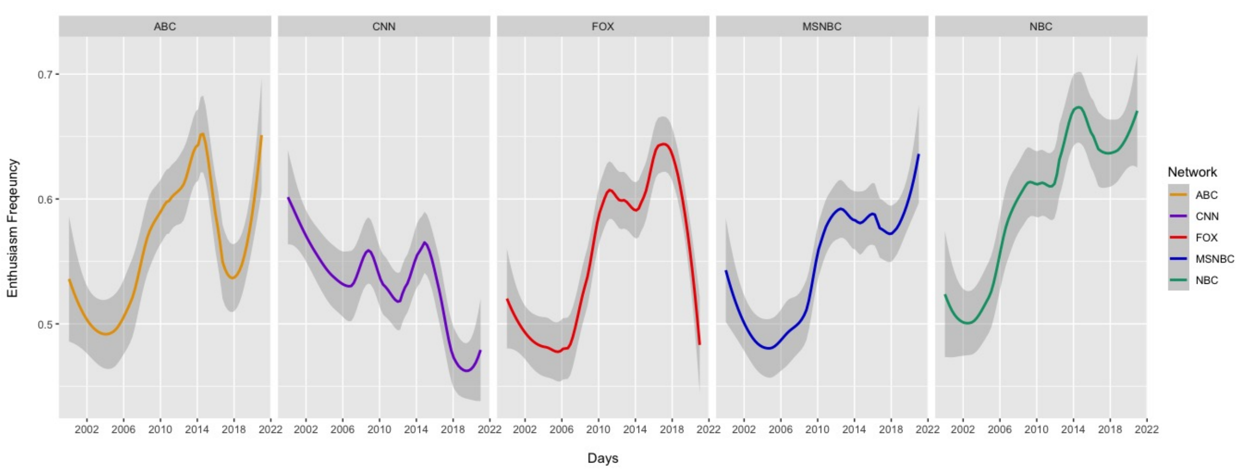
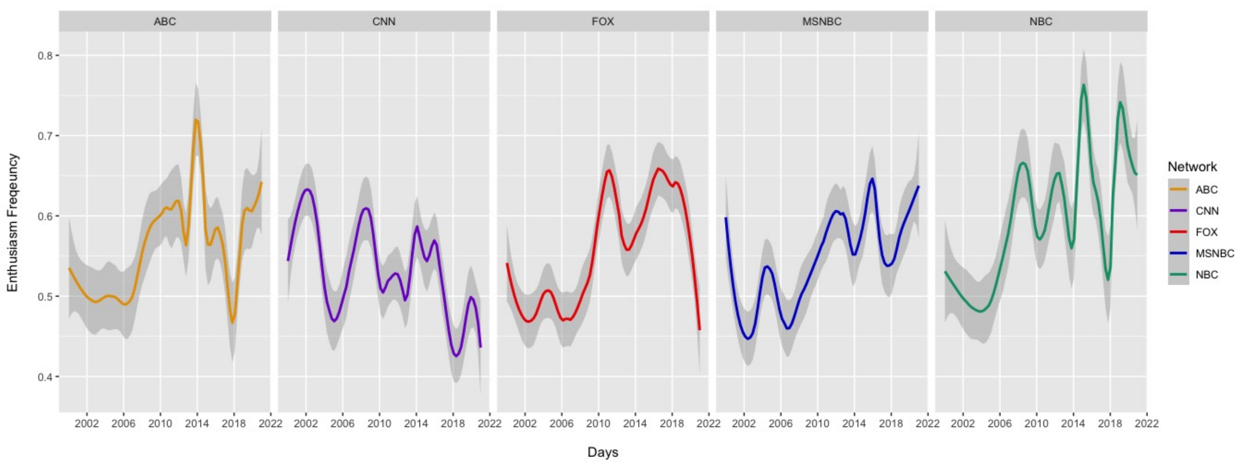


Figure E.54: Loess Plot of Frequency of Enthusiasm by Network Over Days Where Span = .25



E.4.2 Loess Plots Where Time is Pooled by Year

E.4.2.1 Intensity

Figure E.55: Loess Plot of Emotional Intensity of Anger by Network Over Years Where Span = .75

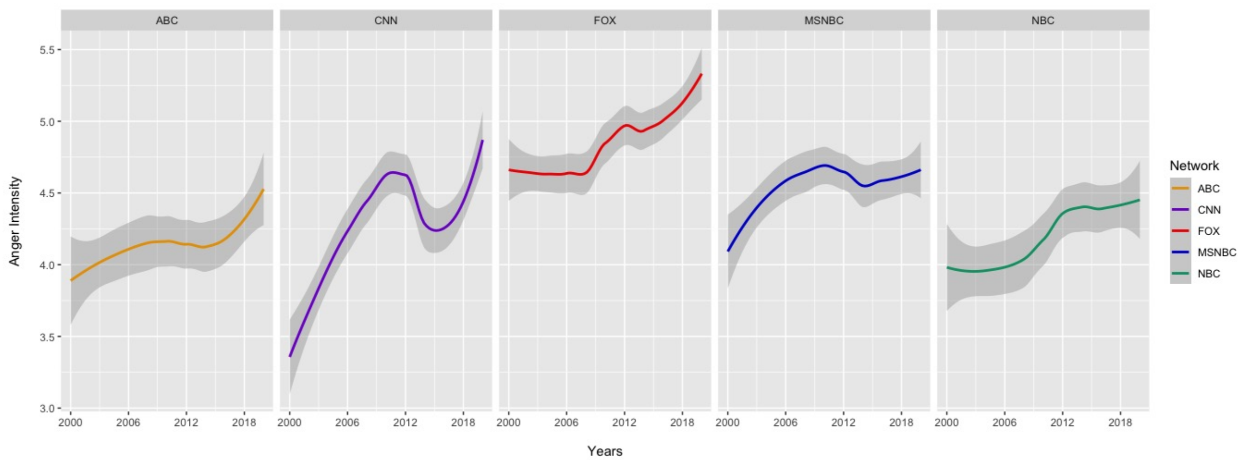


Figure E.56: Loess Plot of Emotional Intensity of Anger by Network Over Years Where Span = .5

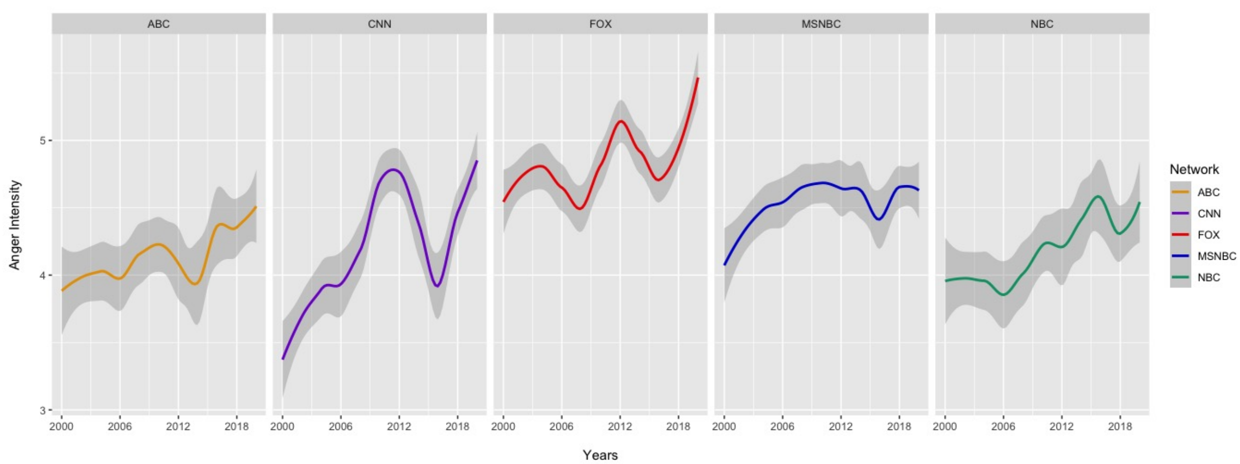


Figure E.57: Loess Plot of Emotional Intensity of Anger by Network Over Years Where Span = .25

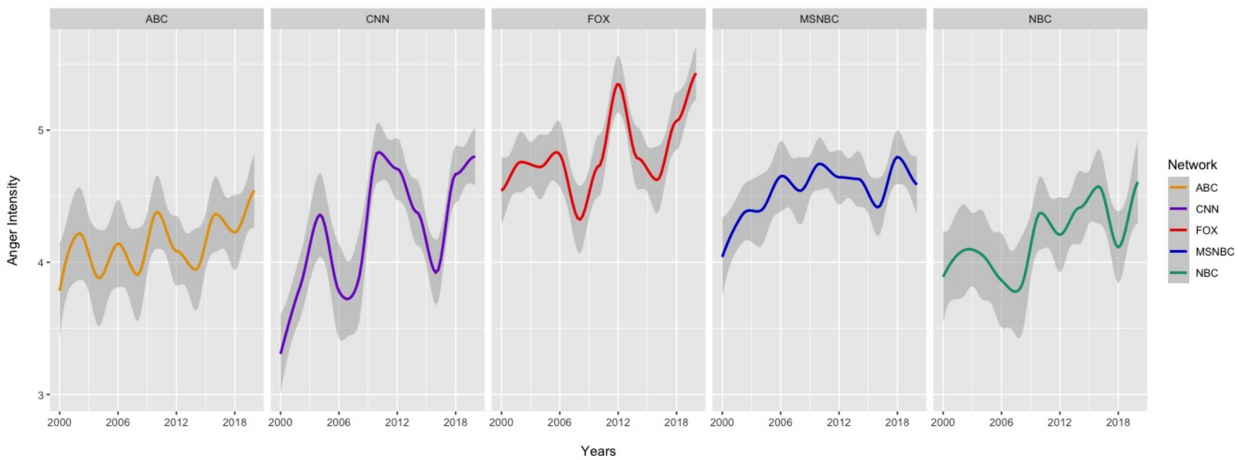


Figure E.58: Loess Plot of Emotional Intensity of Anxiety by Network Over Years Where Span = .75

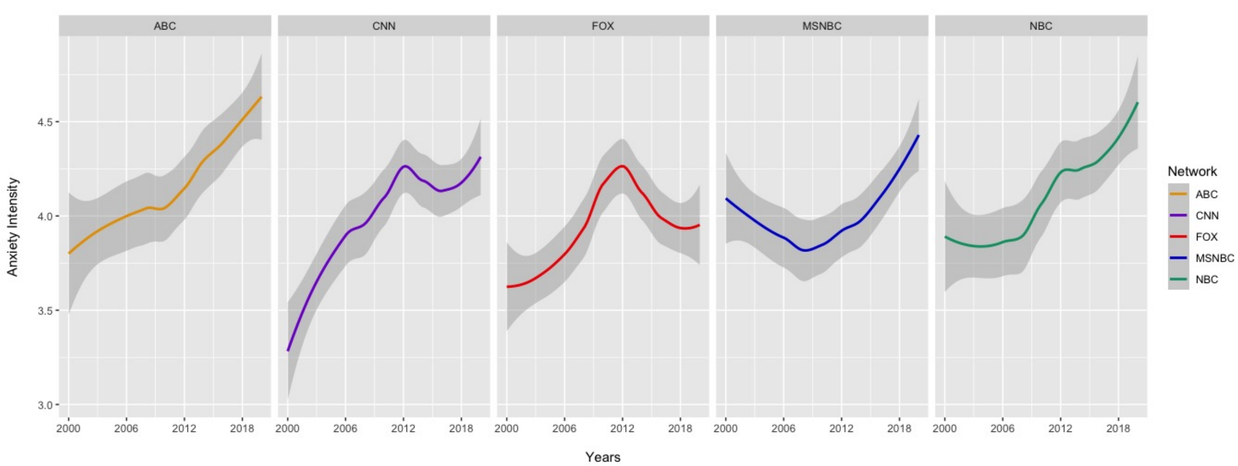


Figure E.59: Loess Plot of Emotional Intensity of Anxiety by Network Over Years Where Span = .5

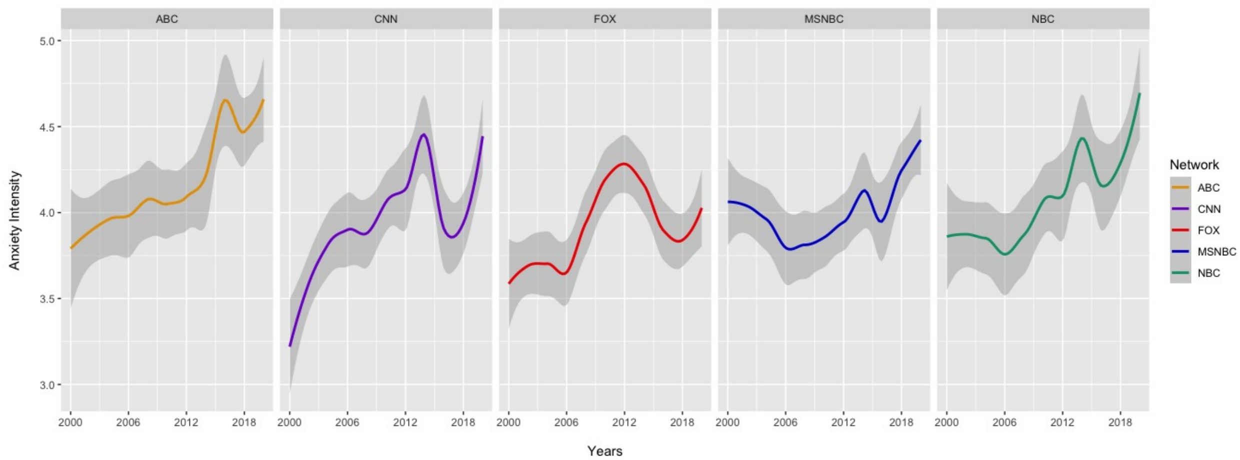


Figure E.60: Loess Plot of Emotional Intensity of Anxiety by Network Over Years Where Span = .25

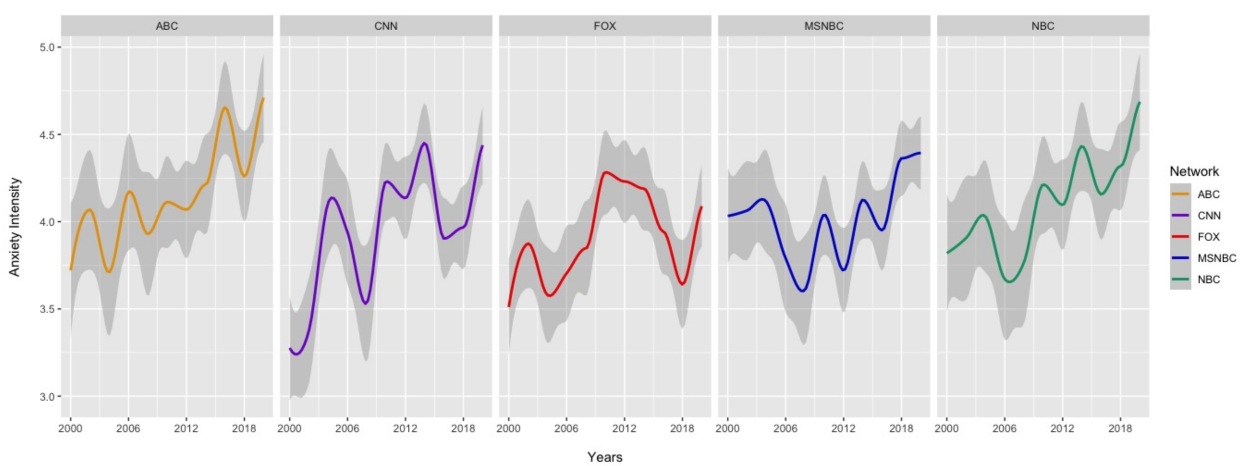


Figure E.61: Loess Plot of Emotional Intensity of Enthusiasm by Network Over Years Where Span = .75

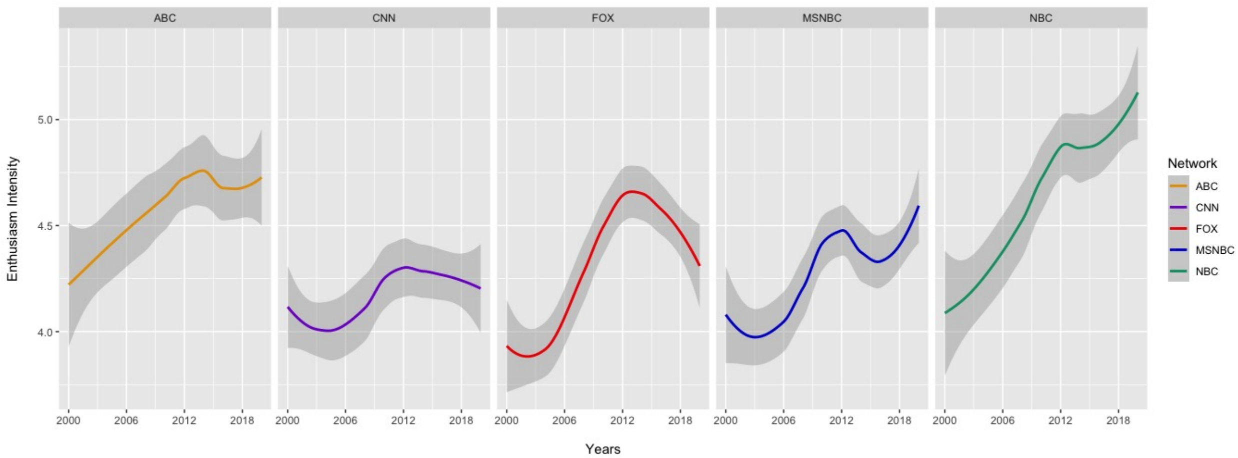


Figure E.62: Loess Plot of Emotional Intensity of Enthusiasm by Network Over Years Where Span = .5

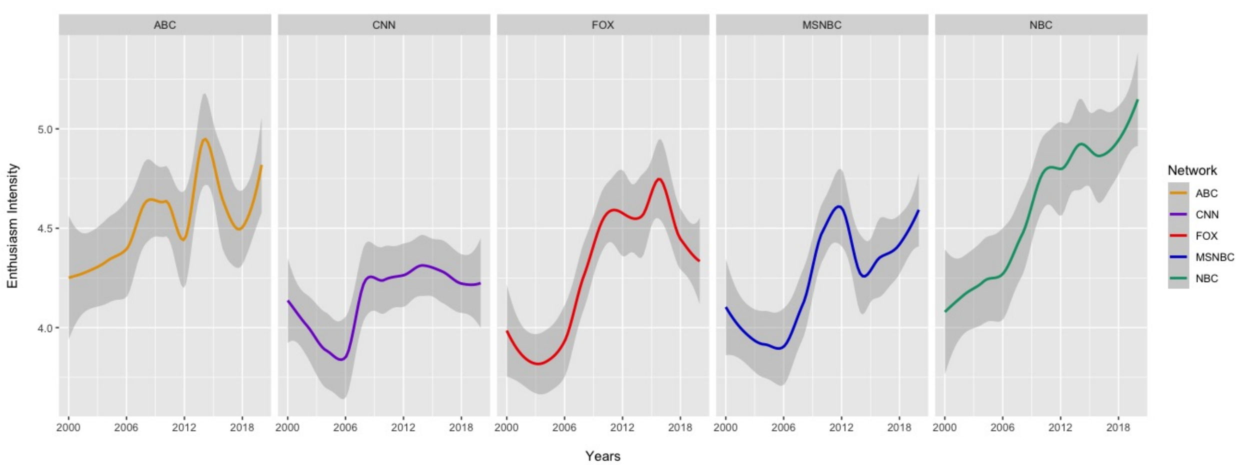


Figure E.63: Loess Plot of Emotional Intensity of Enthusiasm by Network Over Years Where Span = .25

E.4.2.2 Frequency

Figure E.64: Loess Plot of Frequency of Anger by Network Over Years Where Span = .75

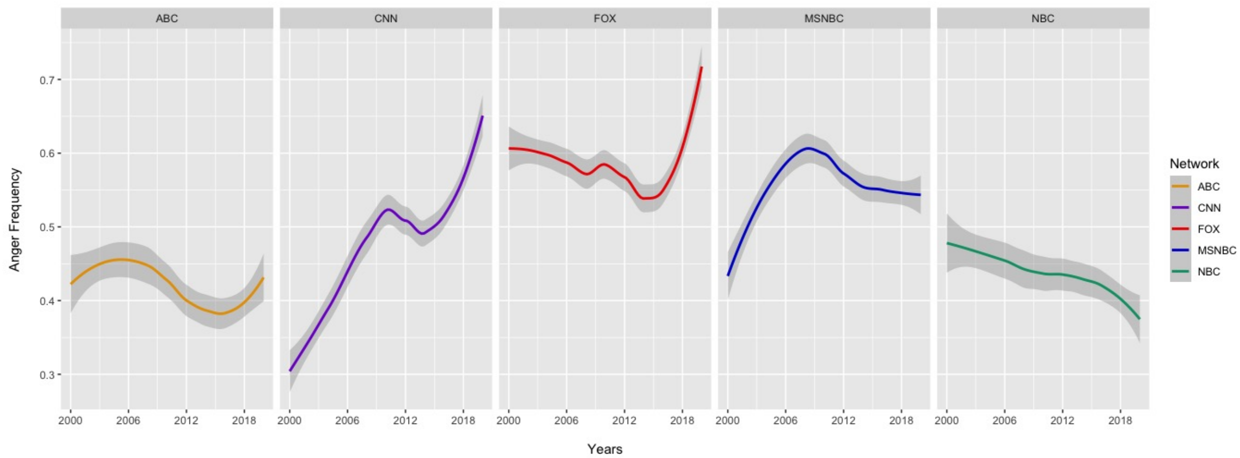


Figure E.65: Loess Plot of Frequency of Anger by Network Over Years Where Span = .5

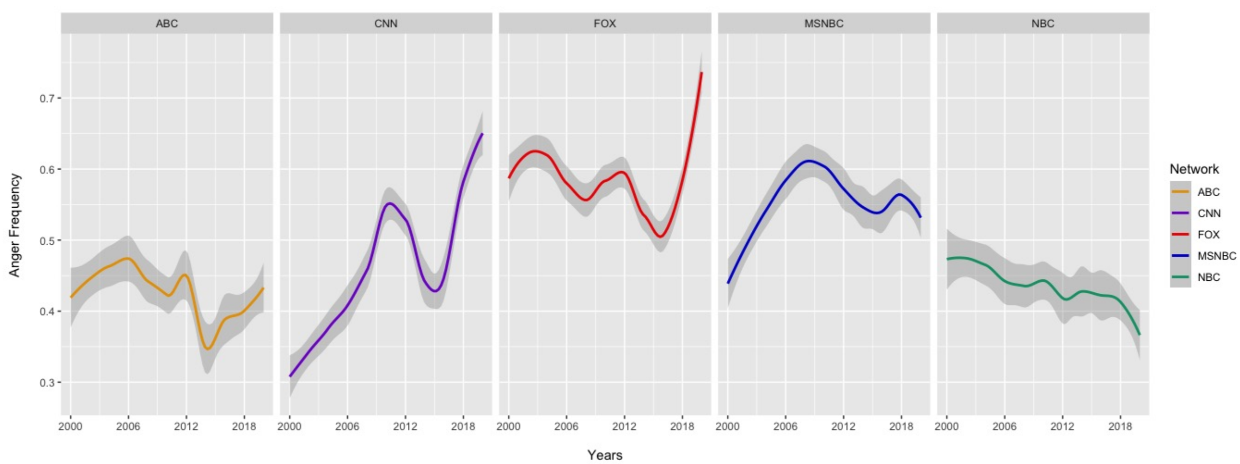


Figure E.66: Loess Plot of Frequency of Anger by Network Over Years Where Span = .25

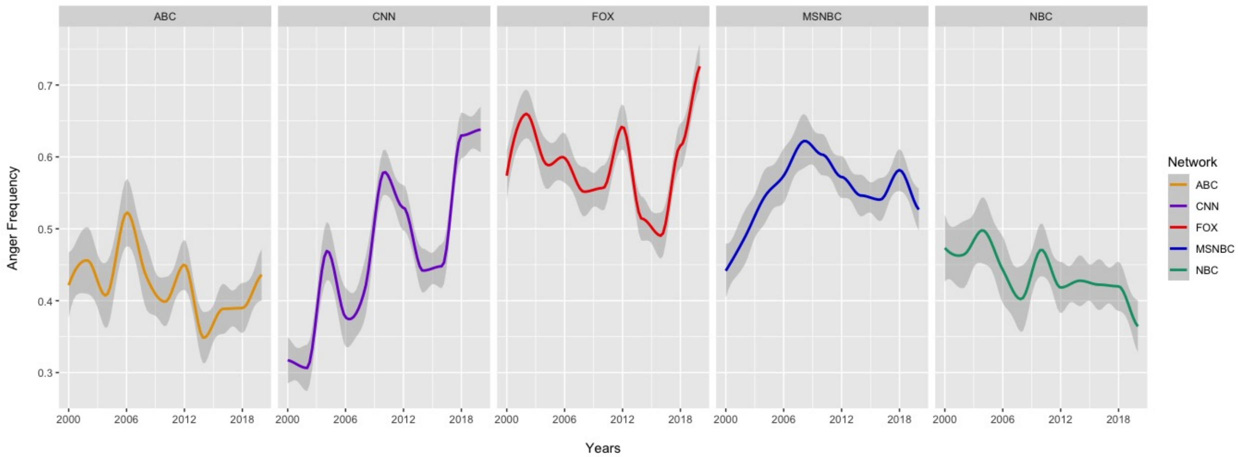


Figure E.67: Loess Plot of Frequency of Anxiety by Network Over Years Where Span = .75

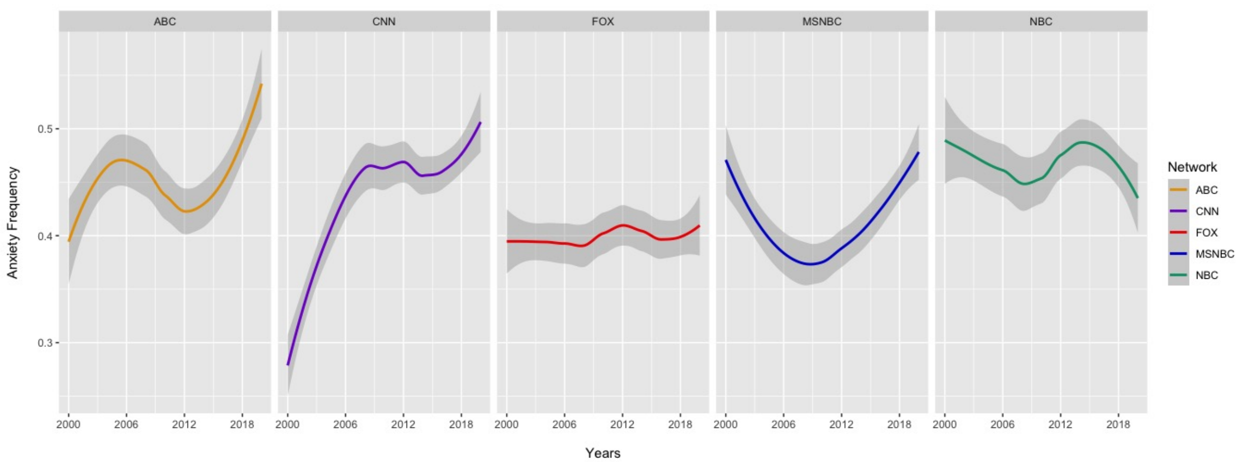


Figure E.68: Loess Plot of Frequency of Anxiety by Network Over Years Where Span = .5

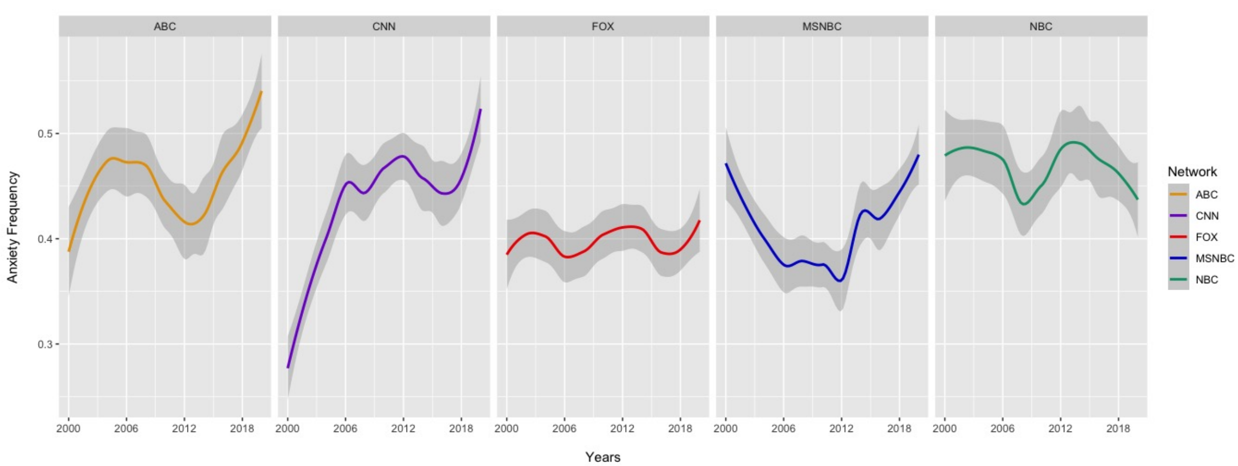


Figure E.69: Loess Plot of Frequency of Anxiety by Network Over Years Where Span = .25

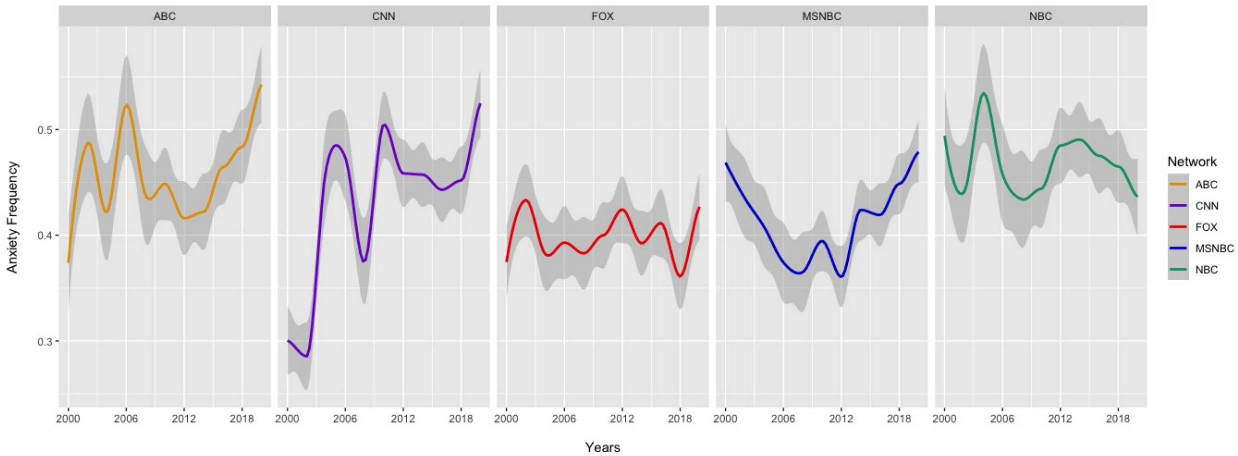


Figure E.70: Loess Plot of Frequency of Enthusiasm by Network Over Years Where Span = .75

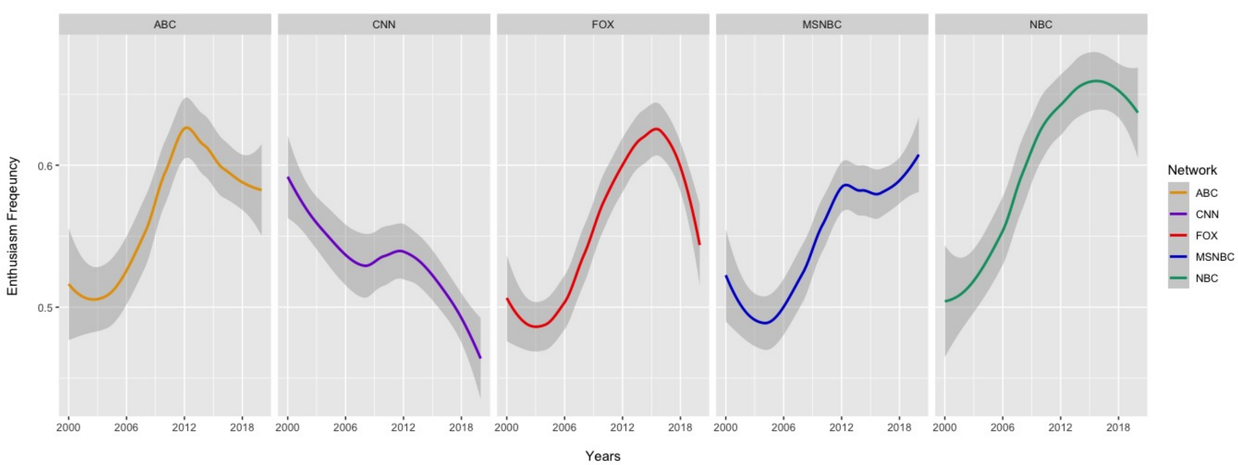
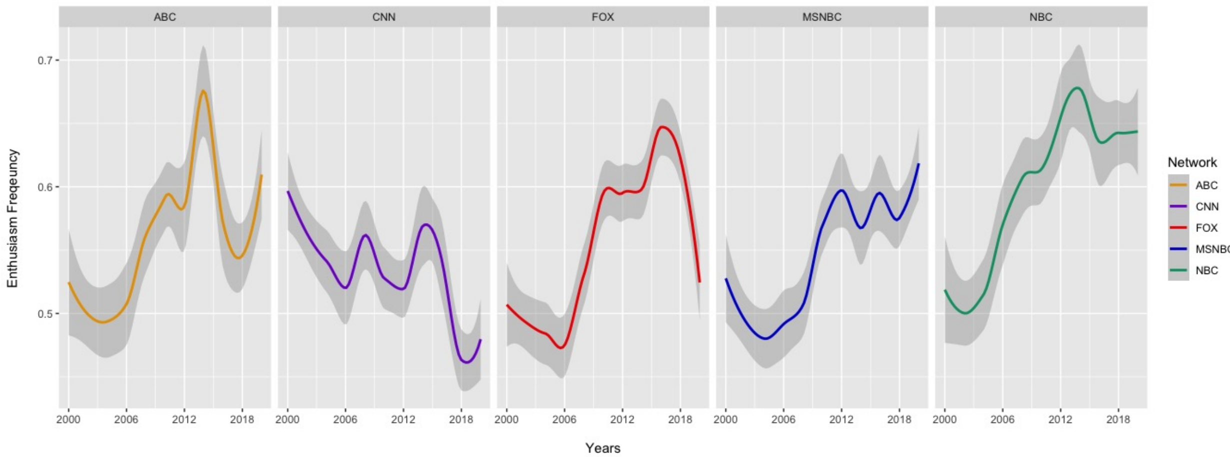


Figure E.71: Loess Plot of Frequency of Enthusiasm by Network Over Years Where Span = .5



Note: The plot for the frequency of enthusiasm by network over election years where the span = 0.25 results in near singularities and so the plot is omitted

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