The New Media Frontier: How Social Media Affects Partisan Attachments, Candidate Evaluations, and Political Emotions

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DEDICATION

To my amazing wife, Sommer, and my beautifully smart and curious daughter, Genevieve.

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ABSTRACT

This dissertation seeks to further our understanding of how individual social media use affects polarization, evaluation of political candidates, and political emotions. Three separate articles are utilized to illuminate the effects of individual social media use. The first article presents a theory which argues that social media is uniquely positioned to affect partisan feelings due to its propensity to lead individuals into echo chambers—online places that reinforce their existing opinions and attitudes. The second argues that social media plays into the hyper-partisan nature of the American political landscape by fostering an atmosphere that leads individuals to harbor more favorable feelings toward in-party candidates, and more unfavorable feelings toward out-party candidates. The third and last article argues that emotions can be transferred from one person to another like a virus, and this can take place on computer mediated devices. Based on past research showing that a particular individual's news consumption can affect their emotional feelings about the political world, I anticipate seeing anger heightened for those interacting with political content on social media sites. In all, the articles show that the amount of time spent posting political content on social media has a significant effect on partisan attachments, candidate evaluations, and political emotions. However, in all three articles, the effect of time spent posting political content decreases as one's general social media use increased.

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INTRODUCTION

It was media scholar Marshall McLuhan (1964) who wrote that the medium is the message. With this argument, McLuhan was stating that the message being broadcasted to the masses is not as important to analyze as the medium through which the message is delivered. In my dissertation, I take McLuhan's advice and study one medium--*social media*. In particular, I study individuals' political social media use, which refers an individual engaging with political content through the lens of social media. To do this, this dissertation will feature three separate articles. These three articles seek to understand the effects that political social media use has on an individual's partisan attachments, candidate evaluations, and political emotions. All three articles utilize an interaction measurement of social media use, combining one's general time spent on Twitter and Facebook with the amount of time spent on these social media sites posting political content.

The first article examines how political social media use affects individual partisan attachments. Specifically, the article analyses if political social media use increases positive feelings one has toward their in-party (party they identify with) and negative feelings one has toward their out-party (the party opposing their in-party). I hypothesize that the more a respondent engages with political content on Facebook and Twitter, the higher they will rate their in-party and the lower they will rate their out-party. I theorize that the reason for this is that social media is uniquely positioned to affect partisan feelings due to its propensity to lead individuals into echo chambers—online places that reinforce their existing opinions and attitudes. Using data from the 2020 American National Election Survey, I show that individuals who post political content are ensconced in politically homogeneous bubbles, and those who do not engage in politics are likely often not confronted with politics on these social media sites.

The second article analyzes how political social media use affects political candidate evaluations. This article examines how political social media use affects how respondents rate their in and out-party presidential and House candidates. I hypothesis that there is a negative relationship between how often a person engages with political content on social media and their rating of presidential and House candidates from the opposing party, and that there is a positive relationship between how often a person posts engages content on social media and their rating of presidential and House candidates from their party. I theorize that this is because social media overly highlights the hyper-partisan nature of the American political landscape, and by way, putting forward an atmosphere which will lead individuals to harbor more favorable feelings toward in-party candidates, and more unfavorable feelings toward out-party candidates. The findings show that the more one posts political content, the lower they rate their out-party presidential and House candidate, and the higher they rate their in-party House candidate. Level of political social media posting did not affect how one rated their in-party presidential candidate.

The final article examines how political activity on Facebook and Twitter affects individuals' feelings about how things are going in the country politically. In particular, I look to see if one's anger and happiness is affected by political social media usage. I hypothesize that those who engage with political content on social media more often, will be more likely to feel angrier and less happy over how things are going within the country politically. I theorize this is the case because literature shows that emotions can be transferred from one person to another like a virus, and this can take place on computer mediated devices. In addition, past research shows that a person's news consumption can affect their emotional feelings about the political world. I find that the more one posts political content on Facebook and Twitter, the more anger they feel about the state of the country. However, this effect was lessened the more a respondent used social media in general. Social media use did not have any effect on the amount of happiness one felt. I will conclude by highlighting how these findings and overall articles add to the collective study of the media and its effects on our political world.

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CHAPTER I

NEGATIVE ECHO CHAMBERS: HOW THE USE OF SOCIAL MEDIA AFFECTS PARTISAN ATTACHMENTS

Abstract

Over half of Americans regularly get their news through social media. Yet our understanding of how social media use can affect American politics is still developing. Here, I test whether individuals' use of social media affects how they feel about the political party they identify with and the party they do not. This study uses the 2020 American National Election Study survey to test the relationship between political Twitter and Facebook use and an individual's partisan attachments. The results suggest that political social media use has a negative effect on how individuals rate their out-party but a positive impact on how they rate their in-party. These findings highlight the importance of analyzing *how* individuals use social media, not just *if* they use them.

Introduction

Marshal McLuhan (1964) posited that the medium is the message. In other words, the message itself is not as important to understand as the medium by which it is delivered. In recent years, social media use has increased dramatically. In 2005, the Pew Research Center reported that only 5 percent of American adults used social media sites. That percentage jumped to 50 percent in 2011 (Walker and Matsa 2021) and 72 percent in 2020. Moreover, Americans now use social media sites to get their news. In 2020, 59 percent of Twitter users reported they regularly get their news from social media sites, while 54 percent of Facebook users said the same. Many Americans also use social media to engage politically. One recent study suggests that only 44 percent of Republicans and 36 percent of Democrats who use social media never post political content (McClain 2021). In short, social media are now political.

Some recent studies analyze social media's effects on voter turnout and mobilization (Bond et al. 2012), and several address how politicians use social media (see, e.g., Wagner and Gainous 2009). But less is known about the effects of social media on political attitudes and opinions. Does social media use affect how users view their own party and the other party? Here, I address this question, arguing that it does. I *do not* argue that mere social media use affects partisan evaluations. Instead, I argue that *political* social media use affects partisan evaluations.

In what follows, I begin by highlighting the relevant literature on negative partisanship, focusing particular attention on how identifying with one political party leads people to harbor more negative feelings about the other. Next, I describe how social media is uniquely positioned to affect partisan feelings due to its propensity to lead individuals into echo chambers—online places that reinforce their existing opinions and attitudes. Individuals who post political content are ensconced in politically homogenous bubbles, and those who do not engage in politics are likely often not confronted with politics. From here, utilizing data from the 2020 American National Election Study (ANES), I turn to my quantitative analyses, exploring how engaging with political content on social media affects partisan evaluations. My findings indicate that the more an individual engages with political content on social media, the lower are their evaluations of their out-party, and the higher are their evaluations of their in-party. In particular, the more one spends posting political content on social media, the more their affective polarization increases. However, this effect lessens the more general time a respondent spends on social media. Furthermore, these patterns differ slightly by party. For Democrats, political social media use leads to a more favorable view of their own party. For Republicans, political social media use leads to a more unfavorable view of the Democratic Party and a more favorable view of their own party.

Partisan Attachments and Social Media

It is now the received wisdom that partisanship significantly influences political attitudes and behavior (Brader, Tucker and Duell 2013; Green et al. 2002; Dalton and Weldon 2007). Partisanship affects vote choice, individual reasoning, and political engagement (Campbell et al. 1960; Bartels 2002; Nicholson 2012). Many scholars (e.g., Mason 2014: Green et al. 2002) describe an individual's partisanship as a form of social identity. This means that partisans are emotionally connected to the well-being of their preferred party, and when their party is threatened, they tend to become angry (Mason 2014).

In recent decades, there has been an increase in negative partisanship (Iyengar et al. 2012; Huddy et al. 2015; Abramowitz 2015; Mason 2013, 2015; Greenberg 2004), broadly defined as the negative feelings a partisan has toward the other political party (Abramowitz and Webster 2016). Having a high level of negative partisanship means having very strong negative feelings towards the other party. Levels of negative partisanship have increased since the 1980s (Abramowitz and Webster 2016; Bafumi and Shapiro 2009; Iyengar et al. 2012; Mason 2014). One study showed that in 2019, 79 percent of Democrats and 83 percent of Republicans gave those in the opposite party a "cold rating"[1] on a 0-100 feeling thermometer (Pew Research Center 2019). In addition, 75 percent of Democrats and 64 percent of Republicans stated that people from the opposite party were "close-minded" (Pew Research Center 2019). In sum, the opposite party is not looked upon fondly by most Americans. Interestingly, levels of positive partisanship—that is, how favorably people feel about their party—have not changed much since the 1980s (Abramowitz and Webster 2016).

So what explains increases in negative partisanship? Past research points towards the effects of partisan identities and the media one consumes. Frey (2015) and Abramowitz (2013) argue that partisan identities are now well-aligned along political fault lines such as racial attitudes. Mason (2014) argues that due to this alignment of partisan identities around contentious political issues, partisans perceive the opposing party as much different than the one they support. This means that individuals now view the opposing party with hostility and suspicion (Mason 2014). But something

[1] A party rating between 0-49.

else affects negative partisanship: *media use*. Specifically, numerous studies show that levels of negative partisanship increase when individuals are exposed to media with a heavy partisan slant (Iyengar and Hahn 2009; Prior 2007; Mutz 2006; Levendusky 2013). In other words, when partisans reside within media echo chambers that push stories in line with their partisanship, their negative feelings toward the other party increase. Prior (2007) argues that partisans now more than ever reside in Internet news communities that further reinforce their partisan leanings and depict the opposing party negatively. Thus, more time online with political media leads to more negative partisanship. While Prior (2007) demonstrates that self-selection of media affects negative partisanship, they leave open the question of how negative partisanship is affected by an individual's social media use, which I seek to evaluate here.

Social media, which are websites and applications that allow users to create and share content or participate in social networking, has qualities that make it unique among media sources and is particularly prone to affecting party evaluations. Most importantly, social media leads users into echo chambers that have the potential to affect negative and positive partisanship profoundly. Studies have even found that in the rare cases when a person goes outside of their echo chamber and gets exposed to partisan criticism, there is *still* an increase in their negative feelings about the opposite party (Suhay et al. 2018; Banks et al. 2021). In addition to the echo chamber effect, many social media platforms' algorithms push negative posts to the top of users' newsfeeds due to them receiving the most engagement (Hao 2021).

People who use social media such as Twitter choose who they follow and get political information from. This leads users to create virtual "echo chamber" communities. Sunstein (2017) shows that these echo chambers are so insular that social media keeps people from learning about opposing viewpoints. This view is supported by studies of Twitter (Halberstam and Knight 2016) and Facebook (Bakshy et al. 2015).

However, attempts to create echo chambers notwithstanding, social media users sometimes cross paths with people who think differently than they do. Suhay et al. (2018) explore how political disagreements online affect social and political polarization in the United States, enhancing negative feelings toward the opposing political party. Two experimental surveys found that individuals exposed to online partisan criticism—that is, comments negative comments about their party—became more prejudiced toward their ingroup and against their out-group. Thus, if a Democrat is exposed to criticism of the Democratic party, they tend to become more partisan in their evaluations of both the Democratic and Republican Parties. This phenomenon may lead people exposed to partisan criticisms to think more negatively of the party they do not belong to and even more positively of their party.

Banks et al. (2021) evaluated whether exposure to certain tweets led individuals to perceive political candidates and parties as ideologically farther apart. The authors exposed respondents to tweets from the two major 2016 presidential candidates, Hillary Clinton, and Donald Trump, in a survey experiment. They used actual tweets with a *negative partisan connotation* sent by the candidates during the campaign. The authors found that those exposed to partisan tweets saw a greater ideological distance between the two major candidates than the control group. Again, if one believes the parties are farther apart, one might harbor more negative feelings towards the opposing party. Survey experiments such as this one help us establish a causal relationship between social media exposure and negative partisanship. But they can lack external validity. Not everyone uses social media, and people use it in different ways. Further, individuals are not exposed to political social media at random. In reality, they choose much of the content they see. In this paper, I plan to build on this work by extending these findings to the broader U.S. population and testing the relationship between political social media use and partisanship by using non-experimental data.

Social media algorithms increase the effects of political social media use. In 2021, former Facebook executives and outside analysts of the Facebook newsfeed showed that the site's algorithm sought to maximize engagement (Hao 2021). It did this by placing stories and content that received the most attention at the top of the newsfeed. Not surprisingly, the content that received the most engagement furthered controversy, misinformation, and extremism (Hao 2021). Twitter's algorithm works similarly. In analyzing emotional states present on Twitter, Choudhury et al. (2012) found that negative moods were more widely present than positive moods. This was especially the case for political tweets, which were disproportionately negative. Furthermore, Stieglitz and Dang-Xuan (2013) found that political Twitter posts that were emotionally charged were retweeted more often and more quickly than those that were not. In addition, the most influential political users (those within the top 50 most retweeted users) posted more emotionally charged tweets than the rest of the users within the dataset.

Social media algorithms do not simply place the most engaging posts at the top of users' newsfeeds. They also push to the top of newsfeeds information similar to information users have sought out in the past (Zimmer et al., 2019). Thus, the more political content a user posts or reads, the more political content they will see in their newsfeed. Furthermore, if the user interacts with political content that is more partisan and hostile to the opposite party—and this is the kind of political content most prevalent on social media—they will continue to see this type of content at the top of their newsfeed (Choudhury et al. 2012; Hao 2021; Pariser 2011; Flaxman et al. 2016). Therefore, those who post political content more often have more political content in their newsfeeds than those who use social media to escape politics.

Hypotheses, Data, and Methods

Because social media leads users into partisan "echo chambers" and because users exposed to partisan criticism online tend to be more prejudiced in favor of their ingroup and against the out-group, I propose the following hypotheses:

H1: There is a negative relationship between how often a person engages with political content on Twitter and Facebook and their rating of the opposing party.

H2: There is a positive relationship between how often a person engages with political content on Twitter and Facebook and their rating of their party.

Methodology and Data

I use data from the 2020 American National Election Studies (ANES) to test these hypotheses. The ANES is a nationally representative survey of Americans fielded every election cycle. The ANES in 2020 included questions about social media for the first time on their survey, which is why I focus on this wave in my analyses.

My key independent variables are social media use and political posting. *Social media use* is measured by asking respondents two questions: (1) "How often do you use Twitter?" and (2) "How often do you use Facebook?" The response set for both items is less than once a month (0), once or twice a month (1), about once a week (2), a few times a week (3), once a day (4), a few times every day (5), and many times a day (6). I add together the responses to these two questions, which have a Cronbach alpha of 0.84. The final variable ranges from 0 (uses Twitter and Facebook less than once a month) to 12 (uses Twitter and Facebook many times a day). Although the ANES asks about Reddit, Instagram and Snapchat, I focus on Twitter and Facebook because they are the most widely used social media sites for political content (Walker and Metsa 2021). *Political posting* is measured by asking respondents two questions: (1) “How often do you post political content on Facebook?” and (2) “How often do you post political content on Twitter?” The response set for both items is never (0), sometimes (1), about half the time (2), most of the time (3), and always (4). I add together responses to these questions, which have a Cronbach alpha of 0.93. Thus, the range of this variable is 0 (never posts about politics on social media) to 8 (always posts about politics on social media).

Figure 1.1 shows the full distribution of *Social media use*, while Figure 1.2 shows the distribution of *Political posting*. Over half of all respondents reported they have never posted political content on Twitter or Facebook, while only 12 respondents reported they “always” post political content on Twitter and Facebook. The distribution of scores on *Political posting* shows that 50 percent of individuals recorded a 0 on the variable. In contrast, only 100 respondents out of 2,043 reported they have never used social media in general, and 91 respondents reported the maximum amount of general social media use. Most respondents landed relatively evenly between these minimum and maximum values. Thus, general social media use is more common than political social media use. However, political social media use is not uncommon.

Dependent variables

I utilize three dependent variables. *Out-party rating* measures how respondents rated the party they do *not* identify with on a feeling thermometer scale of 0-100.[2] Figure 1.3 shows the distribution of values on this variable. The vast majority of respondents score below 50 on this variable, while

[2] Respondents were asked respectively, “How would you rate the Democratic Party” and “How would you rate the Republican party.” This variable includes how those identifying as Republican rated the Democratic party, and how Democrats rated the Republican party.

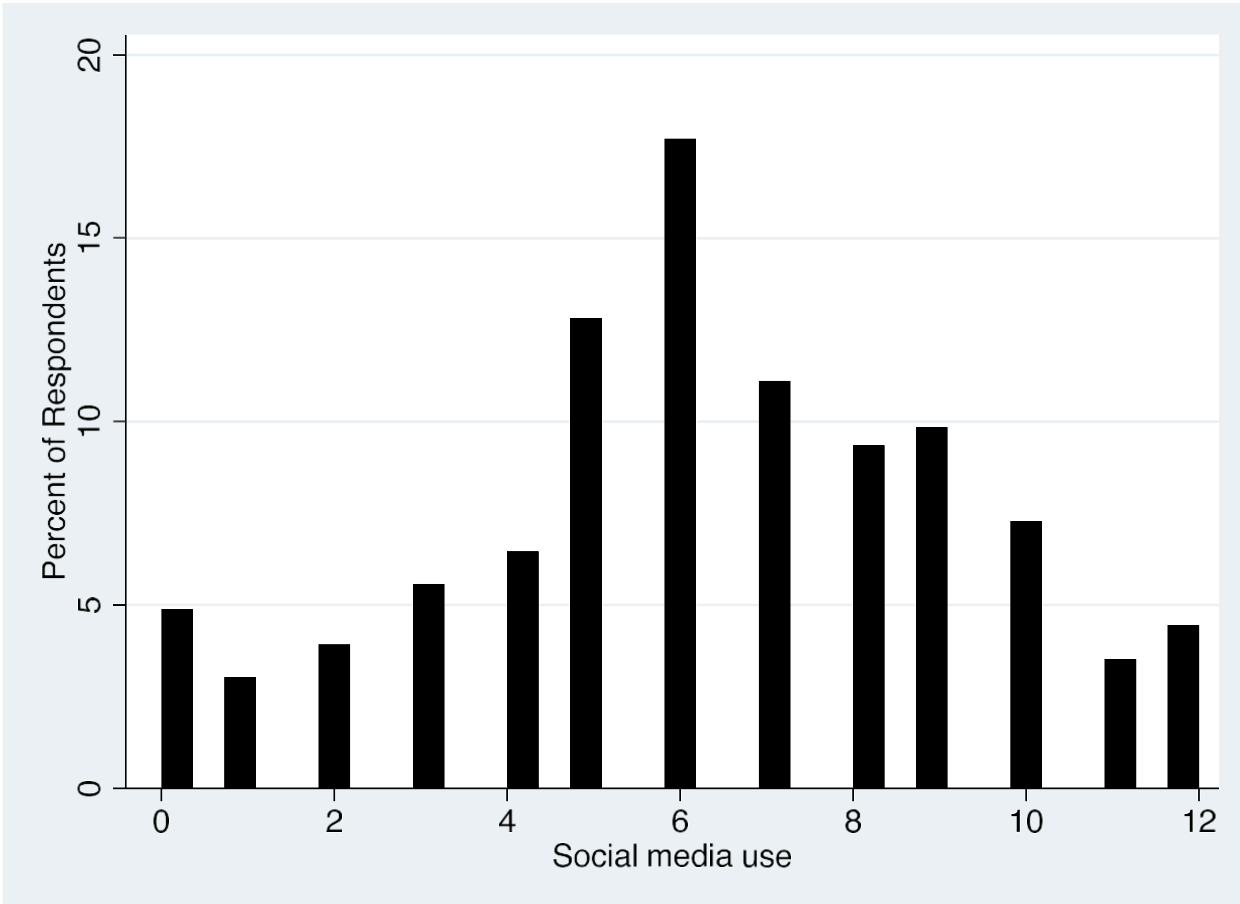

Figure 1.1. Distribution of Values on *Social media use*.

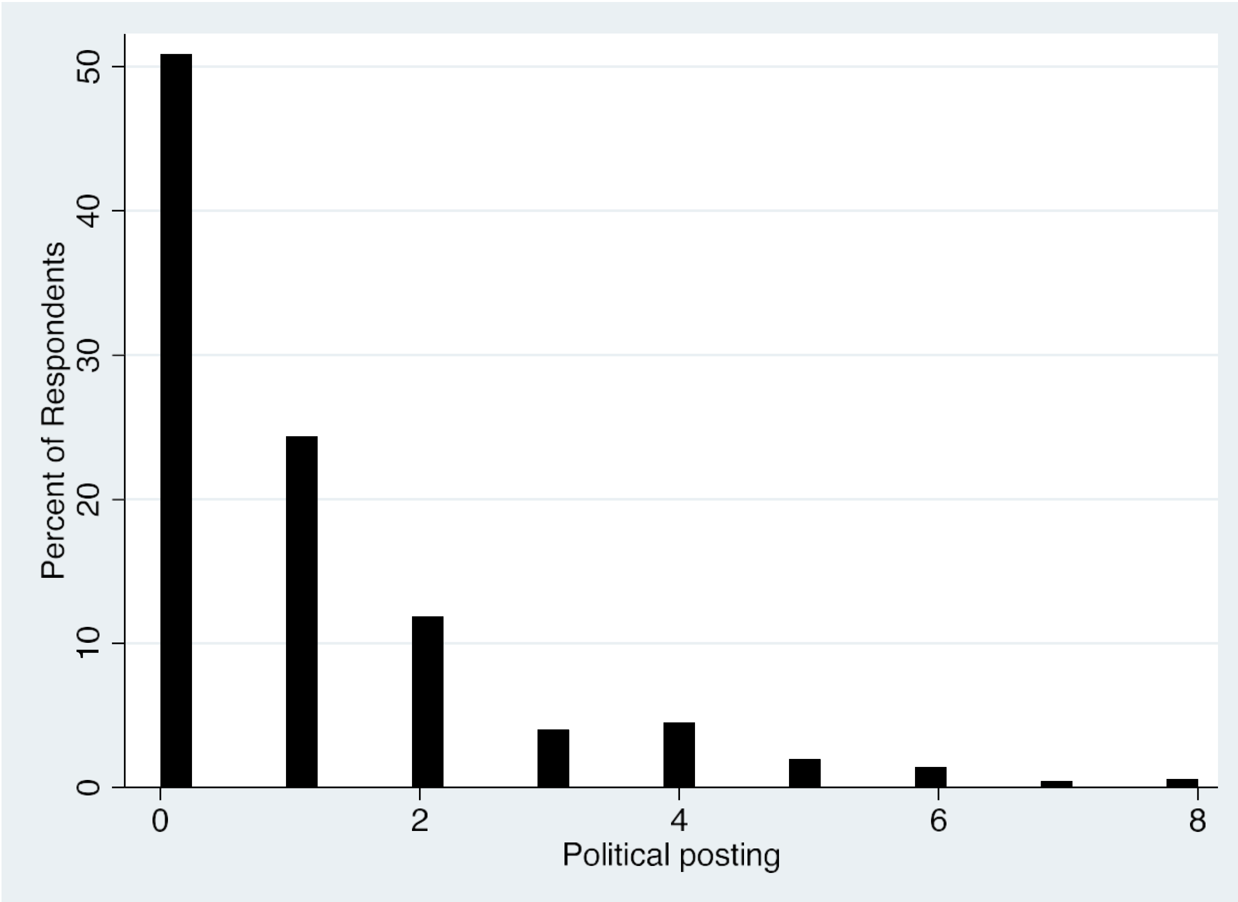

Figure 1.2. Distribution of Values on *Political posting*.

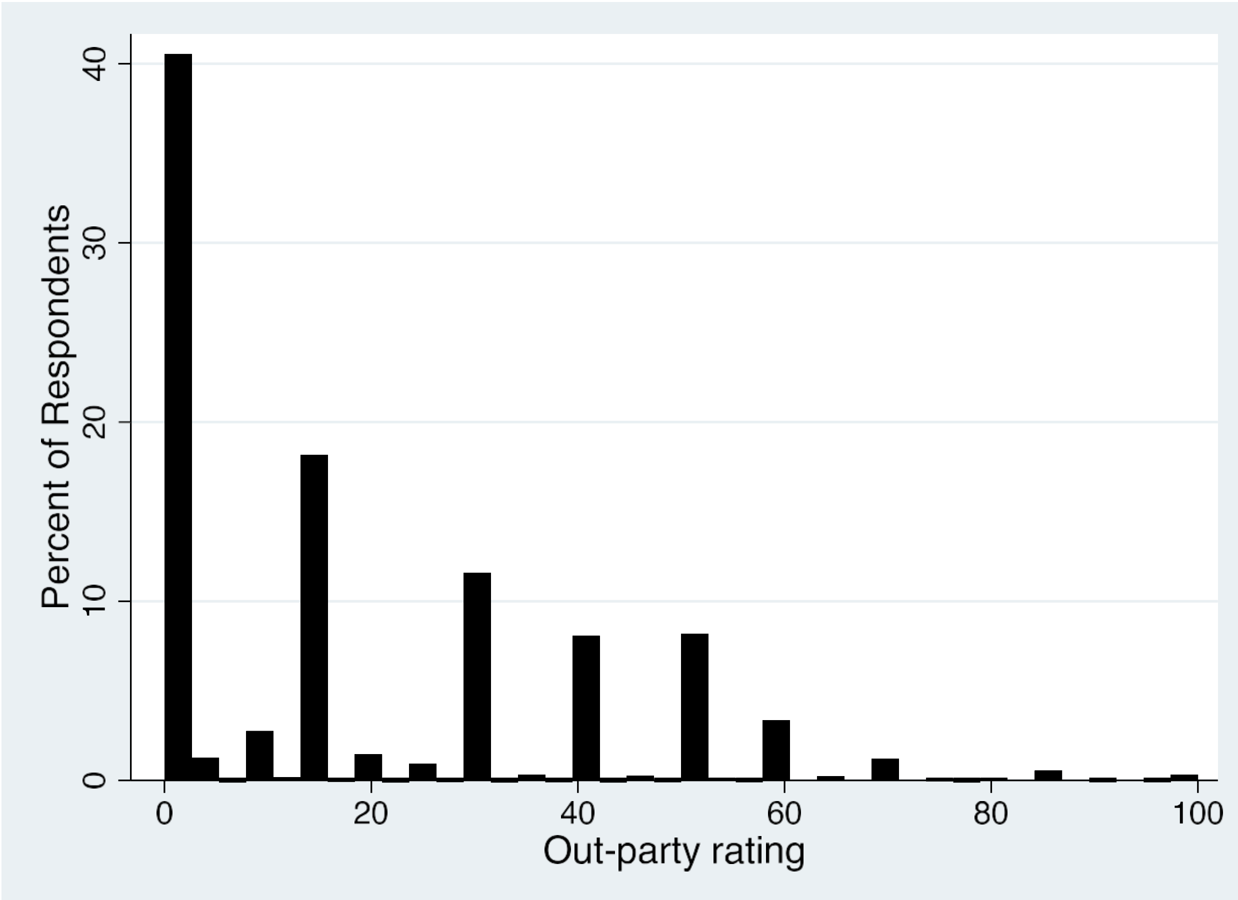

Figure 1.3. Distribution of Values on *Out-party rating*.

almost half gave a rating of 0. The mean for this variable is 18.80. *In-party rating* measures how respondents rated the party they identify with on a feeling thermometer scale of 0-100.[3] Figure 1.4 shows the distribution of values on this variable. Most respondents recorded a value of greater than 50 on this variable, with some even giving their in-party a rating of 100. The mean for this variable is 71.25. *Party-rating difference* is a respondent's score on *in-party rating* minus their score on *out-party rating*. This variable excludes independents. Figure 1.5 shows that this variable is relatively evenly distributed. The mean on *Party-rating difference* is 50.56.

To create these variables, I determined the out-party and in-party ratings by looking at the party identification of all respondents. Thus, the out-party rating of Democrats, would be how they rated the Republican Party, and the out-party rating of Republicans would be how they rated the Democratic Party. This includes all those who identify with the Democratic or Republican Parties, even the leaners. Independents were excluded from this analysis due to the reality of them not having a clean cut in-party and out-party candidate and the fact that this study is solely analyzing how partisans are being affected by their social media usage.

Analytic Strategy

To assess the impact of *political social media use*, I estimate ordinary least squares regression models for each dependent variable using as key predictors social media use, political posting, and their interaction (*social media use x political posting*). This strategy allows me to determine how much political content an individual engages with on Facebook and Twitter shapes their partisan

[3] Respondents were asked respectively, "How would you rate the Democratic Party" and "How would you rate the Republican party." This variable includes how those identifying as republican rated the Republican party, and how Democrats rated the Democratic party.

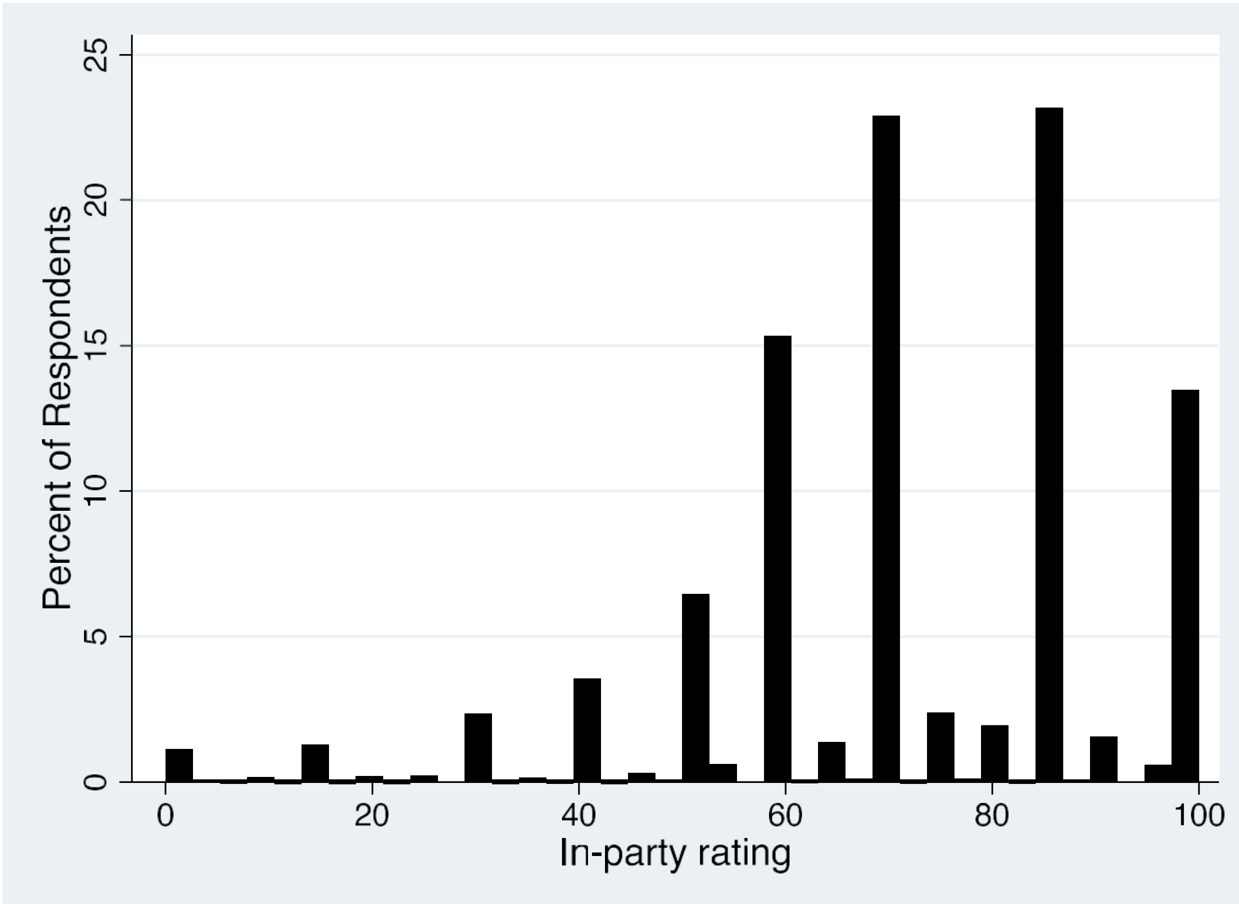

Figure 1.4. Distribution of Values on *In-party rating.*

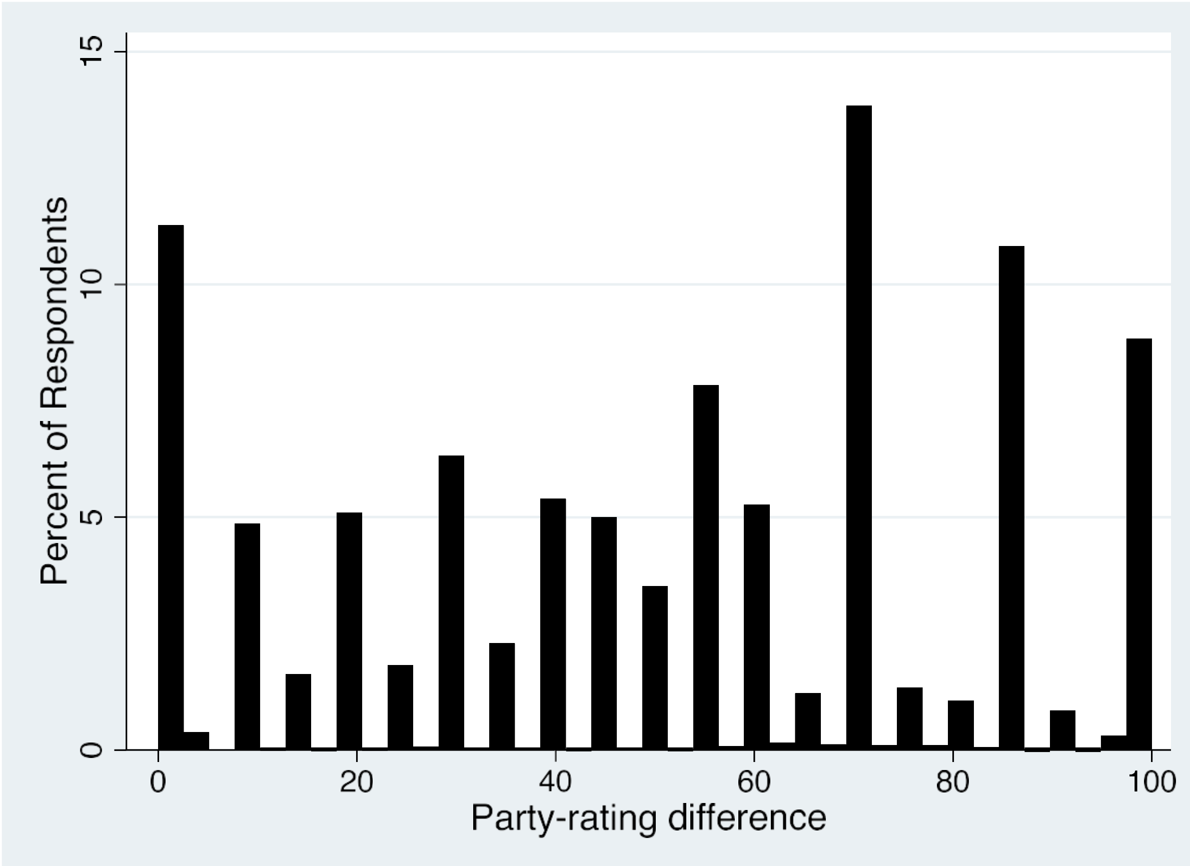

Figure 1.5. Distribution of Values on *Party-rating difference*.

views. In particular, the interaction term will indicate whether posting about politics is amplified when someone uses social media more frequently, or inversely, whether social media contributes to increased partisan views when it is dominated by more political usage.

Control variables

I include several control variables in my models. First, I include the basic demographic control variables *Age*, *Education*, *Race*, *Gender*, and *Income*. More information about how these demographic control variables are coded can be found in the appendix. I control for age because younger people are more likely to use social media (Auxier and Anderson 2021). I control for education because more educated citizens differ from their less educated counterparts regarding political behavior and levels of trust in media sources (Miller and Krosnick 2000). I control for race because racial groups have a different political history which could have the ability to affect polarization. I control for gender because past research shows that men and women differ in political attitudes and some political behavior (Coffe and Bolzendahl 2010). Lastly, I control for income because it affects political participation which includes one's inclination to post political content online. (Ojeda 2018).

I also include non-demographic control variables within the models. First, there is *Attention*, which measures how often a respondent pays attention to politics or elections (1 = "never," 2 = "some of the time," 3 = "about half of the time," 4 = "most of the time," 5 = "always"). I include this variable to ensure that the effects of political social media use on the party rating variables are not contingent on the level of attention one gives to politics. My last two control variables are *CNN* and *Fox*. These two control variables measure whether or not each respondent reported going to cnn.com or foxnews.com, respectively, to learn about the election of 2020. Both variables are binary, with 0 signifying the respondent did not go to the site in question and a 1 otherwise. I include these two variables to control for non-social media political news consumption.

Findings

Table 1.1 reports the results of the first three OLS models. Of most interest here is the significant coefficient on *Political posting* in Models 2 and 3. This indicates that political posting impacted respondents' scores on *In-party rating* and *Party rating difference,* respectively. In particular, Political *posting* does have a statistically significant effect on *In-party rating* and *Party rating difference.* This shows that the more a respondent's overall amount of time on social media was spent on posting political content, the more likely they are to have a larger gap between their in and out party ratings and a higher rating of their in party. To be more exact, a one unit increase in a respondent's time spent posting political content on social media is associated with a 3.709 point increase in the difference of the two party ratings. Further, since *Social media use* does not have a statistically significant relationship with any of the party rating variables, the model shows that the actual sheer amount of time someone spent on social media did not matter regarding the difference in party ratings, but the level at which someone posted political content when they did spend time on social media did matter. In fact, the more a respondent spent on social media actually negatively impacted the effect that *Political posting* had on *Party rating difference*. Table 1.2 gives greater detail to this relationship.

Table 1.1. OLS Regressions Predicting Party Ratings with Political Social Media Use Among All Respondents in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Rating**	**In Party Rating**	**Party Rating Difference**
Social Media Use	0.110	0.0107	0.112
	(0.250)	(0.297)	(0.399)
Political Posting	-0.403	2.032*	3.709**
	(1.060)	(1.210)	(1.652)
Social Media Interaction	-0.157	-0.108	-0.132
	(0.119)	(0.138)	(0.186)
Attention	-3.803***	1.451*	6.398***
	(0.697)	(0.872)	(1.280)
Party ID	0.217	0.224	0.0212
	(0.361)	(0.400)	(0.583)
Fox	2.607	1.457	0.658
	(1.937)	(1.964)	(2.803)
CNN	2.206	-0.185	-1.189
	(1.463)	(1.508)	(2.085)
Gender	-0.213	4.222***	3.479*
	(1.245)	(1.428)	(2.029)
Age	0.0357	0.0837	0.114
	(0.0430)	(0.0530)	(0.0742)
Black	1.855	5.572**	2.477
	(2.392)	(2.665)	(3.910)
Hispanic	4.734*	5.358*	-6.920
	(2.507)	(2.965)	(4.317)
Asian or NHOPI	2.156	1.052	-3.310

Table 1.1. Continued

Models:	**(1)**	**(2)**	**(3)**
	(3.311)	(3.535)	(4.876)
Native American	10.32	-9.144	-14.34*
	(6.826)	(6.496)	(7.564)
Multiple Races	-1.173	1.246	0.914
	(3.309)	(2.897)	(5.840)
Education	1.483**	-2.278***	-2.375**
	(0.661)	(0.798)	(1.088)
Income	-0.191*	-0.0599	0.410**
	(0.102)	(0.123)	(0.171)
Constant	24.22***	63.21***	20.36***
	(4.431)	(5.888)	(7.844)
Observations	1,387	1,388	1,521
R-squared	0.094	0.058	0.121

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 1.2 reports the marginal effects of *Political posting* at every level of *Social media use*. The table shows that *Political posting* had a positive and statistically significant effect on *Party rating difference* at every level of *Social media use*, but this effect waned as the amount of time spent on social media increased. At the lowest value of *Social media use*, as a respondent's *Political posting* score increased by one, their difference in the ratings of the two parties increased by 3.709, but at the highest value of *Social media use*, the difference in the ratings of the two parties only increased by 2.129, with a steady and consistent decline in the middle values of the *Social media use* variable. Thus, the results ultimately show that the sheer quantity of political content posted does not affect individual polarization, but the amount of time spent posting political content while one is on social media does affect individual polarization.

This finding could be highlighting the powerful impact of Facebook's and Twitter's algorithms which are used to reflect a user's interest within their newsfeed as described in the theory portion of this paper. Remember that algorithms are programmed to place user-driven interested content at the top of their newsfeeds, and the other type of content that does not get interacted a great deal with is placed lower down. Thus, it could be the case that an individual who spends their small amount of time on social media only posting political content and only viewing the top of the content on their news feeds is going to have more polarized feelings than someone who spends their large amount of time on social media posting political content and viewing more content buried farther down on their newsfeeds. Perhaps viewing less political content farther down on their news feeds, under the assumption that the more an individual scrolls down the less political content there is, is having a dampening effect on even viewing political content on their news feeds at all.

Table 1.2. Marginal Effects of Political Posting at Each Level of Social Media Use on Party Rating Difference.

Model:	**(1)**
Political Posting at each level of Social Media Use |	**Party Rating Difference**
0	3.709***
	(1.652)
1	3.577***
	(1.481)
2	3.445***
	(1.314)
3	3.314***
	(1.153)
4	3.182***
	(1.000)
5	3.050***
	(0.862)
6	2.919***
	(0.744)
7	2.787***
	(0.659)
8	2.655***
	(0.620)
9	2.524***
	(0.636)
10	2.392***
	(0.702)
11	2.260***

Table 1.2. Continued

Model:	**(1)**
	(0.807)
12	2.129***
	(0.938)
Observations	1,521

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Other variables in Table 1.1, including *Income*, *Gender*, *Attention*, *Black*, *Hispanic*, *Native American* and *Education*, produced significant coefficients in all three models. The coefficient on *Gender* was significant in Models 2 and 3, the coefficient on *Attention* was significant in all three models and the coefficient on *Income* is significant in models 1 and 3. The coefficient on *Black* was significant in Model 2, while *Hispanic* was significant in model 1 and 2 and the coefficient for *Native American* was significant in Model 3. Lastly, *Attention* was significant in all three models.

It makes sense that those more interested in politics feel more passionate about the political parties and thus rank their party higher and the other party lower. As for *Education and Income*, perhaps higher educated individuals and people in higher socioeconomic standings are more involved in politics and thus have stronger feelings about the two political parties. About *Gender* and *Black*, further research should be conducted to understand why gender interacts with in-party ratings and the absolute difference between the party ratings, and why Black, Hispanic and Native Americans partisanship differs from other racial groups.

Tables 1.3 and 1.4 model the data for Democrats and Republicans,[4] respectively. Table 1.3 shows that for Democrats, neither *Social media use* nor *Political posting* had a significant relationship with any of the party rating variables. Table 1.5 shows the effect of *Political posting* on *Out party rating* at each level of *Social media use* for Democrats to show the true interaction between *Political posting* and *Social media use*. *Political posting* only has a statistically significant effect on *Out party rating* at the largest values of *Social media use*. This shows that the effects of having a larger amount of time spent on social media posting political content increases as time

[4] Both of the Republican and Democratic groups contain those who identified themselves as either a Strong Democrat/Republican, Not Very Strong Democrat/Republican, or Independent-leaning Democrat/Republican.

Table 1.3. OLS Regressions Predicting Party Ratings with Political Social Media Use Among All Democrats in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Rating**	**In Party Rating**	**Party Rating Difference**
Social Media Use	0.253	0.0586	-0.287
	(0.315)	(0.415)	(0.514)
Political Posting	0.728	0.481	-0.709
	(1.141)	(1.473)	(1.825)
Social media interaction	-0.227*	-0.0117	0.266
	(0.126)	(0.166)	(0.197)
Attention	-4.119***	2.697**	6.561***
	(0.850)	(1.166)	(1.521)
Fox	18.84***	-9.529***	-22.40***
	(2.786)	(2.897)	(3.537)
CNN	-2.003	4.491***	5.355**
	(1.358)	(1.710)	(2.150)
Gender	1.029	3.464**	2.579
	(1.438)	(1.751)	(2.265)
Age	0.0638	0.122*	0.108
	(0.0503)	(0.0646)	(0.0876)
Black	1.057	9.038***	6.522*
	(2.164)	(2.710)	(3.910)
Hispanic	2.998	9.867***	5.758
	(2.549)	(3.548)	(4.739)
Asian or NHOPI	3.149	6.554	2.291
	(3.263)	(4.131)	(4.220)
Native American	4.783	-0.817	-7.076

Table 1.3 Continued

Models:	(1)	(2)	(3)
	(6.575)	(7.727)	(9.364)
Multiple Races	-1.584	5.944*	6.773
	(3.587)	(3.518)	(4.832)
Education	0.612	-1.014	-1.812
	(0.783)	(1.059)	(1.325)
Income	-0.229*	-0.0863	0.154
	(0.123)	(0.160)	(0.198)
Constant	26.89***	50.71***	25.07***
	(5.090)	(6.920)	(8.059)
Observations	846	847	845
R-squared	0.189	0.114	0.169

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 1.4. OLS Regressions Predicting Party Ratings with Political Social Media Use Among All Republicans in the 2020 ANES.

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Rating**	**In Party Rating**	**Party Rating Difference**
Social Media Use	0.0805	-0.0707	0.213
	(0.387)	(0.387)	(0.570)
Political Posting	-0.686	3.315*	6.965***
	(2.250)	(1.823)	(2.001)
Social media interaction	-0.215	-0.138	-0.421
	(0.314)	(0.240)	(0.305)
Attention	-2.638**	-0.400	2.666
	(1.022)	(1.220)	(1.650)
Fox	-8.333***	8.744***	11.29***
	(2.162)	(2.171)	(2.847)
Models:	**(1)**	**(2)**	**(3)**
CNN	14.35***	-12.89***	-15.18***
	(3.408)	(2.873)	(3.233)
Gender	-0.704	3.133	4.572
	(2.043)	(2.078)	(2.877)
Age	0.0308	-0.0501	0.0199
	(0.0696)	(0.0754)	(0.0987)
Black	-18.43**	9.812**	17.85
	(8.286)	(4.976)	(11.61)
Hispanic	7.051	-2.429	-3.638
	(6.262)	(4.836)	(8.431)
Asian or NHOPI	-0.349	-10.37	-12.18
	(6.768)	(6.470)	(10.80)
Native American	16.64	-17.75*	-26.03*

Table 1.4 Continued

Models:	**(1)**	**(2)**	**(3)**
	(10.78)	(9.463)	(13.71)
Multiple Races	4.148	-10.34*	-9.123
	(4.723)	(5.961)	(8.398)
Education	1.788*	-2.963***	-5.300***
	(1.071)	(0.959)	(1.376)
Income	-0.0164	-0.0757	0.165
	(0.160)	(0.173)	(0.229)
Constant	20.80***	81.78***	53.97***
	(5.763)	(6.248)	(9.386)
Observations	541	541	539
R-squared	0.172	0.161	0.208

Source: 2020 American National Election Studies Survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ (all two-tailed tests)

Table 1.5. Marginal Effects of Political Posting at Each Level of Social Media Use on Party Rating Difference for Democrats.

Model:	**(1)**
Political Posting at each level of Social Media Use |	**Party Rating Difference**
0	0.727
	(1.141)
1	0.501
	(1.023)
2	0.274
	(0.908)
3	0.047
	(0.797)
4	-0.178
	(0.690)
5	-0.405
	(0.590)
6	-0.631
	(0. 502)
7	-0.858**
	(0.433)
8	-1.085***
	(0.394)
9	-1.311***
	(0.392)
10	-1.538***
	(0.429)
11	-1.765***
	(0.496)
12	-1.991***

Table 1.5 Continued

Model:	**(1)**
	(0.582)
Observations	539

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

spent on social media increases. Thus, it seems that the amount of political content posted is having a larger effect on the decreasing of out party ratings amongst Democrats, than simply having a large amount of time spent on social media posting political content. At the largest value of *Social media use*, a one value increase in *Political posting* is associated with a 1.99 point decrease in the rating of a respondent's out party.

Table 1.4 shows quite different results for Republicans in the sample, which mirrors the results from the full sample analysis in Table 1.1 fairly well. *Social media use* did not have a statistically significant effect on the three dependent variables, but *Political posting* does have a significant effect on *In party rating* and *Party rating difference*. As Republicans increase their *Political posting* value by one, which means increasing their overall time spent on social media posting political content, we see a 6.965 point increase in the difference between their in and out party ratings. However, once again we see as time spent on social media increases the effect of the amount of time spent on social media posting political content on *Party rating difference* decreases. Table 1.6 showcases this relationship. At the smallest value of *Social media use*, as the amount of time spent posting political content increases, we see individuals having a 6.965 point larger gap in how they rated the two parties. This gap consistently decreases as we increase along values of *Social media use* until the significance level of *Political posting* dissipates completely within the last two greatest values of *Social Media Use*. Thus, the more a person is on Facebook and Twitter in general, the less of an effect one's overall time spent on these sites will have on the difference between how they rate the two political parties.

For the control variables In Table 1.3, *Attention*, *Income*, *Gender, Age*, *Black*, *Hispanic*, *Multiple Races*, *CNN,* and *Fox* produced significant results in at least one of the models. In Table 1.4, *Attention*, *Fox*, *CNN*, *Black*, *Native American*, *Multiple Races* and *Education* were significant

Table 1.6. Marginal Effects of Political Posting at Each Level of Social Media Use on Party Rating Difference for Republicans.

Model:	**(1)**
Political Posting at each level of Social Media Use |	**Party Rating Difference**
0	6.965***
	(2.001)
1	6.544***
	(1.735)
2	6.123***
	(1.484)
3	5.702***
	(1.257)
4	5.282***
	(1.070)
5	4.861***
	(0.945)
6	4.440***
	(0. 910)
7	4.019***
	(0.974)
8	3.598***
	(1.120)
9	3.177***
	(1.321)
10	2.757*
	(1.556)
11	2.336
	(1.812)
12	1.915

Table 1.6 Continued

Model:	**(1)**
	(2.081)
Observations	539

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

for at least one of the models. The most interesting of these relationships concern the variables *CNN* and *Fox*. For Democrats, Fox News viewership led to a 9.53 point decrease on *In-party rating* and an 18.84 increase on *Out-party rating*. For the same respondents, *CNN* viewership led to a 4.49 point increase on *In-party rating* and no effect on out-party rating. Among Democrats, watching Fox News decreased the party difference variable by 22.40 points, and watching CNN increased the *Party Rating Difference* by 5.355 points.

Table 3.1 shows that for Republicans, Fox News viewership led to an 8.74 point increase on *In-party rating* and an 8.33 point decrease on *Out-party rating*. For Republicans, CNN viewership led to a 14.35 point decrease on *In-party rating* and a 12.89 point increase on *Out-party rating*. Thus, it seems that a Republican who views a news source that challenges their in-party's narrative comes away feeling better about the other party and worse about their party. However, for Republicans, viewing a network that airs narratives supporting their in-party makes them like their in-party more and their out-party less. Moreover, there was a 15.18 point decrease in the party differential among Republicans who watched CNN. Thus, it seems that if partisans went outside their echo chambers, there would be less polarization. Therefore, one way to combat the increase in negative partisanship is to try to get partisans outside of their echo chambers, both online and offline. This directly contradicts past research, which has found that individuals exposed to divergent opinions increased their attachment to their current ideological position (Bail et al. 2018; Shore et al. 2018).

Conclusion

I set out to understand the effects of political social media use on positive and negative partisanship. Through an analysis of the 2020 ANES survey, I found mixed support for my hypothesis. It was also found that the amount of time spent posting political content online (*Political posting*) had a significant increase on the total difference between the rating of the two parties amongst all respondents analyzed as well as just within Republican respondents.

What is most interesting is that the effect of *Political posting* decreased the more time one spent on social media. Thus, it could be that those who spend the majority of their time posting political content on social media, and only stay on these sites to look at the first couple posts on their newsfeed could only be seeing the highly partisan political content that the algorithms place on the top of their newsfeeds. Therefore, these individuals might be affected more by their type of social media usage. However, those respondents who spend a good portion of their time posting political content, but also spend enough time scrolling through their feeds to not only see highly polarized political content but also see what their friends are up to as well as the other non-political content is on their newsfeeds, might not be affected by such social media usage as much.

These findings show that perhaps social media is not as strong of a force in the expansion of polarization has popular thought might assume. This could be due to social media user's informational intake on these sites do not drastically differ than their off-line information consumption. Studies of social media and politics need to further test this relationship in new innovative ways to get closer to the true relationship of political social media use and political opinions. These findings back up previous studies showing that the type of media one consumes perhaps does not change their beliefs drastically, but simply just reinforces their already held beliefs (Bolin and Hamilton 2018).

Subsequent separate analyses of Republicans and Democrats show some hopeful signs for battling polarization. The regression results displayed in Tables 3 and 4 show that Democrats who watched Fox News increased their out-party rating and a decrease in their in-party rating. The same was the case for Republicans who watched CNN. Getting social media users outside their echo chambers might help us battle increasing polarization and negative partisanship, which has been increasing in recent years. This contradicts past findings, which found evidence that exposure to divergent opinions and points of view either have only moderate effects or could create a polarizing backlash in the individual (Stroud 2010; Bail et al. 2018).

Of course, this study has some limitations that future work could seek to rectify. Here, I use an interactive measure of how often one posts political content on social media and how often they generally use social media. Thus, I may be missing some of the variations in social media use. Furthermore, I could not fully control what was actually on the newsfeeds of the respondents, as this was not an experimental study. Thus, my findings should be tested again when a better variable comes to light that considers the full nuances of social media use. Other studies should be conducted that analyze individual opinion change in viewing out-party narratives.

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CHAPTER II

PARTISANSHIP ON SOCIAL MEDIA: HOW POLITICAL SOCIAL MEDIA USE AFFECTS CANDIDATE RATINGS

Abstract

Recent surveys have highlighted the increasing partisan nature of the American electorate. It has been shown that more individuals than ever before have a more unfavorable view of their opposing political party's candidates for office. What could be driving this increasing hate toward politicians of the opposing party? Here, I test whether it is social media use that is causing individuals to have an increase dislike of their out-party's candidates for office. I use the 2020 American National Election Study to test whether one's political social media usage impacts their rating of presidential candidates, as well as candidates running for the House of Representatives. The results suggest that the more a respondent posts political content on social media, the more likely they are to have a dislike of the opposing party's House and presidential candidate.

Introduction

Since the mid-2000s, surveys have shown that we are in a much more hyper-partisanship political world than we were before the turn of the century (Pew 2014, 2017. 2019). More individuals now since 1992, state they have an unfavorable view of the opposite party which is causing them to have stronger partisan attachments (Pew 2016). Over the past couple of presidential elections, we have even witnessed an increase of partisan polarization, both at the elite and general electorate level (Christenson and Weisberg 2019; Fiorina et al. 2005; Jacobson 2007; Baufumi and Shapiro 2009; Iyenger et al. 2012). For instance, since 1984, there has been an increase in respondents giving the presidential candidate of the opposite party the most negative rating possible on a 0 – 100 feeling thermometer (Christenson and Weisberg 2019).

Furthermore, since 2004, and culminating in 2016, a large number of respondents in the American National Election Studies survey gave the presidential candidate from their out-party the most negative rating possible (Christenson and Weisberg 2019). In 2016, we saw 68% of Democrats and 59% of Republicans give Donald Trump and Hilary Clinton a "0" on a thermometer scale, respectively (ibid.). This clearly demonstrates that there is an increase in animosity towards the presidential candidates of the party in which individuals do not belong since the 1980s, and even since the turn of the century. Christenson and Weisberg (2019) argued the reason for this recent trend of negative ratings of out-party presidential candidates is due to the increase in partisan polarization within the electorate. However, this study did not go as far as to see if and how individuals' political social media use or even social media use in general had an effect on the animosity individuals held towards out-party candidates.

I show in *Paper I* how political social media use affects the feelings an individual has towards their political in-party and out-party. However, does political social media use affect how individuals feel about individual candidates in the same way? I argue that political social media use will affect how individuals evaluate political candidates as much as it does for evaluations of the political parties due to social media playing into the hyper-partisan nature of the American political landscape. Empirically answering this question, could help further our collective understanding of the effects of political social media use has on individuals' feelings, as well as what drives the partisan nature of the general electorate.

In what follows, I begin by highlighting the relevant literature on how the media, both traditional and social, has been able to affect the evaluations of political candidates and the political parties. Next, I describe how social media characteristics, specifically Facebook and Twitter play into and exacerbate the partisan nature of its users. From here, utilizing data from the 2020 American National Election Study (ANES), I turn to my quantitative analyses which explores how engaging with political content on social media affects candidate evaluations. My findings indicate that the more an individual engages with political content on social media, the more positively they rate the presidential candidate of their own party, while more negatively rating the presidential candidate of the party in which they do not belong. Furthermore, individuals who engage with more political content on social media also tend to rate their in-party House candidate more positively but does not affect how they rate their out-party House candidate.

Media and Partisanship Effects on Candidate Perception

Research shows thaty both traditional media and social media can affect individual candidate perceptions (Eberl et al. 2016; Kiousis 2004; Miller and Krosnick 2000; Norris et al. 1999). Eberl et al. (2016) analyzed survey data along with media reports and found that voters update their assessments of political candidates when viewing candidate portrayals in the media. In particular, the tone the media takes when speaking about candidates can both negatively and positively affect individual candidate perception. Wu and Coleman (2014) found evidence for this as well. However, in their analysis, they found that bad candidate portrayals were more effective in changing candidate impressions than good ones. This could mean that the media is better able to negatively affect candidate impressions more than they could positively affect them.

Pfau et al. (2001) found similar results when analyzing prospective voters three weeks prior to the 2000 presidential election. The authors differentiated between traditional media (newspapers, magazines, and television news) and what they call nontraditional communication forms of media such as political talk radio, television entertainment talk shows and television news magazines. The findings showed that while traditional media had a limited influence on candidate perception, these nontraditional media had the most influence on candidate perception. In particular, political talk radio was associated with a positive perception of George W. Bush, and a negative perception of Al Gore. However, television entertainment talk shows enhanced the perceptions voters had of Gore, while it did not significantly affect perceptions of W. Bush. Moy and Pfau (2000) found similar results.

These articles did not theorize why political talk radio negatively affected Gore and positively affected Bush, or why television talk shows positively affected Gore, but did not affect

Bush. However, I argue the reason for these findings could be due to individuals being able to self-select into the media they consume. We know from past research that individuals do self-select information which they tend to agree with (Bennett and Iyengar 2008; Feldman et al. 2011; Garrett et al. 2013; Smith and Searles 2014), and this self-selection has been found to be based on individuals' ideology, habit, and even topical interests (Bennett and Iyengar 2008; Baum 2002). Since the media has been found to affect individual opinions, in particular candidate perceptions, self-selection into media could be helping produce these effects as well. Social media provides its users the ability to self-select into who they follow, which in turn causes them to self-select into the information they have the ability to view on these sites and places them within an echo-chamber community. These echo-chambers then produce communities which could enhance an individual's feelings towards an out-party candidate, as well as an in-party candidate. As such, I argue that social media use, in particular political social media use, does affect the feelings an individual has towards political candidates.

In paper I, I showed how political social media use affects individuals' feelings about the political party they identified with, as well as the party they did not identify with; in particular, how it increases how much they like their in-group party and decreases how much they dislike the out-group party. I argued this is due to social media characteristics which seems to enhance the probability of individuals being within echo-chambers which contributes to these feelings due to the negative posts which are the most viewed and shared on sites such as Facebook and Twitter. While this study did show how political social media use affects feelings towards the parties, it did not analyze how it affects feelings towards individual political candidates.

Another variable that has been shown to affect how individual evaluate and feel about political candidates is partisanship. There is a large literature which aims to understand how partisanship at the individual level affects political opinions, feelings, and behaviors. For instance, partisanship has been found to increase voter turnout because group attachment is a strong motivator to act to in a way to benefit an individual's in-group (Binning et al. 2010; Dickerson and Ondercin 2017; Petersen et al. 2013; Terry and Hogg 1996). Furthermore, partisanship makes voting easier due to having an "R" or a "D" by a candidate's name helps voters choose between candidates easier due to the information it brings to them (Dhar 1996; Mogilner et al. 2008).

Partisanship also has a biasing effect on individuals' opinions. Cohen (2003) showed how individuals identifying with the Democratic party were more likely to show support for welfare policies as long as it had been introduced by a Democratic politician in comparison to if it was introduced by a Republican politician. The author found the same phenomenon taking place within Republican individuals towards policies introduced by politicians of their in-group. Not only does partisanship affect policy opinions, but it also affects individuals' opinions on political performances.

Research has shown that those identifying as Republicans held a more favorable view of George W. Bush's response to Hurricane Katrina than those identifying as Democrats (Huber et al. 2015; Malhotra and Kuo 2008). The same finding was discovered when asking Democratic and Republican individuals about the state of the economy under the same president. This was not only seen in issues directed towards personal opinions, but also towards facts. Republicans were even less likely to believe that the federal budget deficient decreased during the Clinton administration, which it did, than Democrats. It is quite clear that partisanship has an effect on individuals' behaviors and opinions. Since opinions can have an effect on how an individual feels about political candidates, partisanship will also have an effect on how individuals feel about certain political candidates. However, if these individuals are also within an environment which leads them into echo-chambers, as well as an environment that promotes political posts with heavy negative partisan connotations which increases negative and positive polarization, we could witness a scenario where this partisan candidate evaluation is even stronger.

Social media, in particular Facebook and Twitter, may fit in here. It has been highlighted that Facebook's algorithm seeks to place content which a user has engaged with in the past to the top of their individual newsfeed on the sight (Hao 2021; Zimmer et al. 2019; Pariser 2001; Flaxman et al. 2016). Thus, if an individual engages with political content more often, they will tend to see more political content more readily available to them when they open the app or website. However, if an individual does not engage with political content, they will be less likely to see such content on their Facebook newsfeed. Interestingly, the type of political content which is shared the most on this site tends to be those which have controversy, extremism and misinformation attached to its message (Hao 2021). Twitter's timeline acts in the same manner. The posts which are shared the most on this social media site are those with negative moods attached to them (Choudhury et al. 2012; Stieglitz and Dang-Xuan 2013). This was especially the case for political tweets.

Not only does political social media use leads individuals into a scenario where they are more likely to view negative political content, but it can also help place them into echo-chamber communities where they would tend to only see political content that supports their already existent beliefs and undermine beliefs which contradicts their own. For instance, Twitter allows their users to manually follow other users who they choose to get their political information from, and even block other users which they do not want to hear from. Sunstein (2017) showcased that these echo chamber communities can be such that individuals are kept from seeing opposing viewpoints. Other studies have supported this finding on both Twitter (Halberstam and Knight 2016) and Facebook (Bakshy et al. 2015).

Since this is the case, and we know that social media affects how individuals feel towards the two political parties even further, I believe that social media use, in particular, political social media use will have a positive effect on how individuals feel about presidential and House candidates belonging to their in-group, and negatively affect their feelings towards presidential and House candidates belonging to their out-group.

Hypotheses, Data, and Methods

Remember that particular media use can affect candidate evaluation and social media sites such as Facebook and Twitter, leads users into partisan "echo chambers". Due to this, and the notion that political candidates affect evaluations of political parties and I already showcased how political social media use affects the evaluation of the parties, I propose the following hypotheses:

H1: There is a negative relationship between how often a person engages with political content on social media and their rating of presidential and House candidates from the opposing party.

H2: There is a positive relationship between how often a person posts engages content on social media and their rating of presidential and House candidates from their party.

Methodology and Data

To test these two hypotheses, I use data from the 2020 American National Election Studies (ANES), which is a nationally representative survey of American fielded every election cycle.[5] The key independent variables are *Social media use*[6] and *Political posting*[7]. *Social media use* measures

[5] For this particular survey, the ANES conducted it using a contactless, mixed-mode design. Each respondent was given the survey via various forms such as a self-administered online survey, a telephone survey, or a live online video interview. Respondents were randomly chosen using an USPS computerized delivery sequence file, making it a probability sample, which is considered the gold standard for survey research. All residential addresses across all 50 states and Washington, DC had an equal chance of being chosen. The surveys were conducted between August 18, 2020 and November 3, 2020.

[6] Alpha coefficient: 0.8437

[7] Alpha coefficient: 0.9352

how often a respondent uses Facebook and Twitter in general. It is an additive scale which combines how each respondent answered the questions: (1) “How often do you use Twitter?” and (2) “How often do you use Facebook?” Both questions had a response set of: 1 = “less than once a month,” 2 = “once or twice a month,” 3 = “about once a week,” 4 = “a few times each week,” 5 = “once a day,” 6 = “a few times every day,” and 7 = “many times every day.” The value a respondent could get on this variable ranges from 2-14. However, I simplified this range by making it a range of 0-12. The Cronbach alpha of this variable is 0.8437. *Political posting* measures how often a respondent reported that they post political content on Facebook and Twitter. *Political posting* is also an additive scale which combines how each respondent answered the questions: (1) “How often do you post political content on Facebook?” and (2) “How often do you post political content on Twitter?” The response set for both of these questions are as follows: 0 = “never,” 1 = “sometimes,” 2 = “about half of the time,” 3 = “most of the time,” and 4 = “always.” The range a respondent could get on this variable ranges from 0-8. Political Posting has a Cronbach alpha of 0.9352.

The reason I solely focus on the social media sites Facebook and Twitter is that they are the most used social media sites for political content (Walker and Metsa 2021). The interaction term (*Social media use* x *Political posting*) provides the best readily available measure of how much an individual engages with political content on Facebook and Twitter. The highest value on this variable denotes an individual who spends a lot of their time engaging with political content on social media due to their time spent on these sites and their behavior in posting political content on those same sites. The lowest values denote an individual who does not spend a lot of their time engaging with political content due to their lack of time spent on social media as well as their lack of posting political content on these sites.

The distribution along the variable *Social media use* is showcased in Figure 2.1, and the distribution along *Political posting* is shown on Figure 2.2. These two figures show the stark contrast between these two variables. While over half of respondents stated they have never posted political content on Twitter or Facebook, only 0.05 percent of respondents reported they never generally used those same sites. Therefore, it is clear that general social media use is more common, but people using social media to post political content is not totally uncommon.

Dependent variables

I use four different dependent variables for this analysis. All four dependent variables pertain to the 2020 general election candidates. The first is *Out-party president*. It is a measurement of how respondents rated the presidential candidate of the party they do not identify with on a feeling thermometer scale of 0-100. The second is *In-party president*, and it is a measurement of how respondents rated their own party's presidential candidate on a feeling thermometer scale of 0-100. In order to create these variables, I determined the out-party and in-party candidates by looking at the party identification of all respondents. Thus, the out-party president rating of Democrats, would be how they rated the Republican candidate, and the out-party president rating of Republicans would be how they rated the Democratic presidential candidate. This includes all those who identify with the Democrat or Republican Parties, whether or not they reported they "lean" to one party or if they reported they had a strong identification with one of the parties. Independents were excluded from this analysis due to the reality of them not having a clean cut in-party and out-party candidate and the fact that this study is solely analyzing how partisans are being affected by their social media usage.

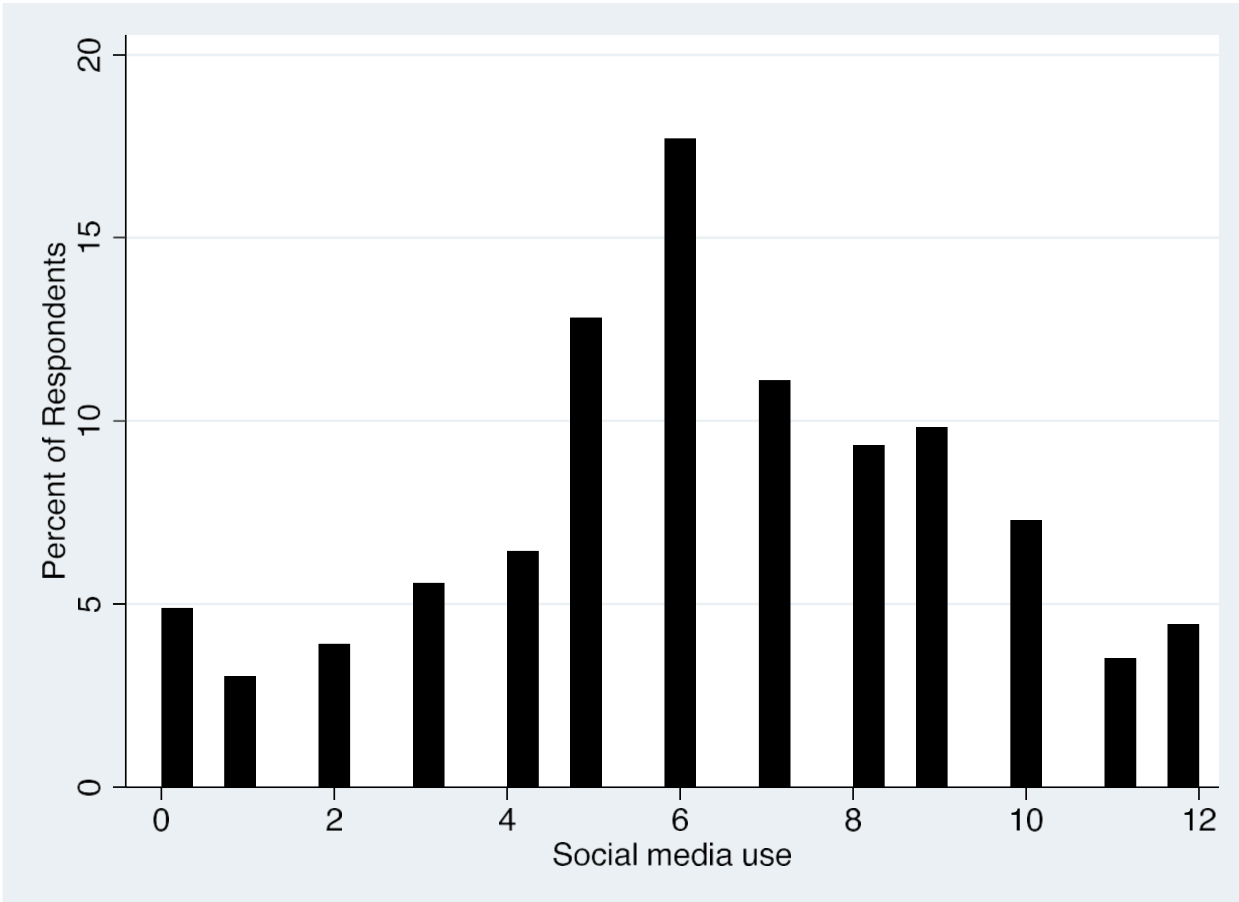

Figure 2.1. Distribution of Values on *Social media use*.

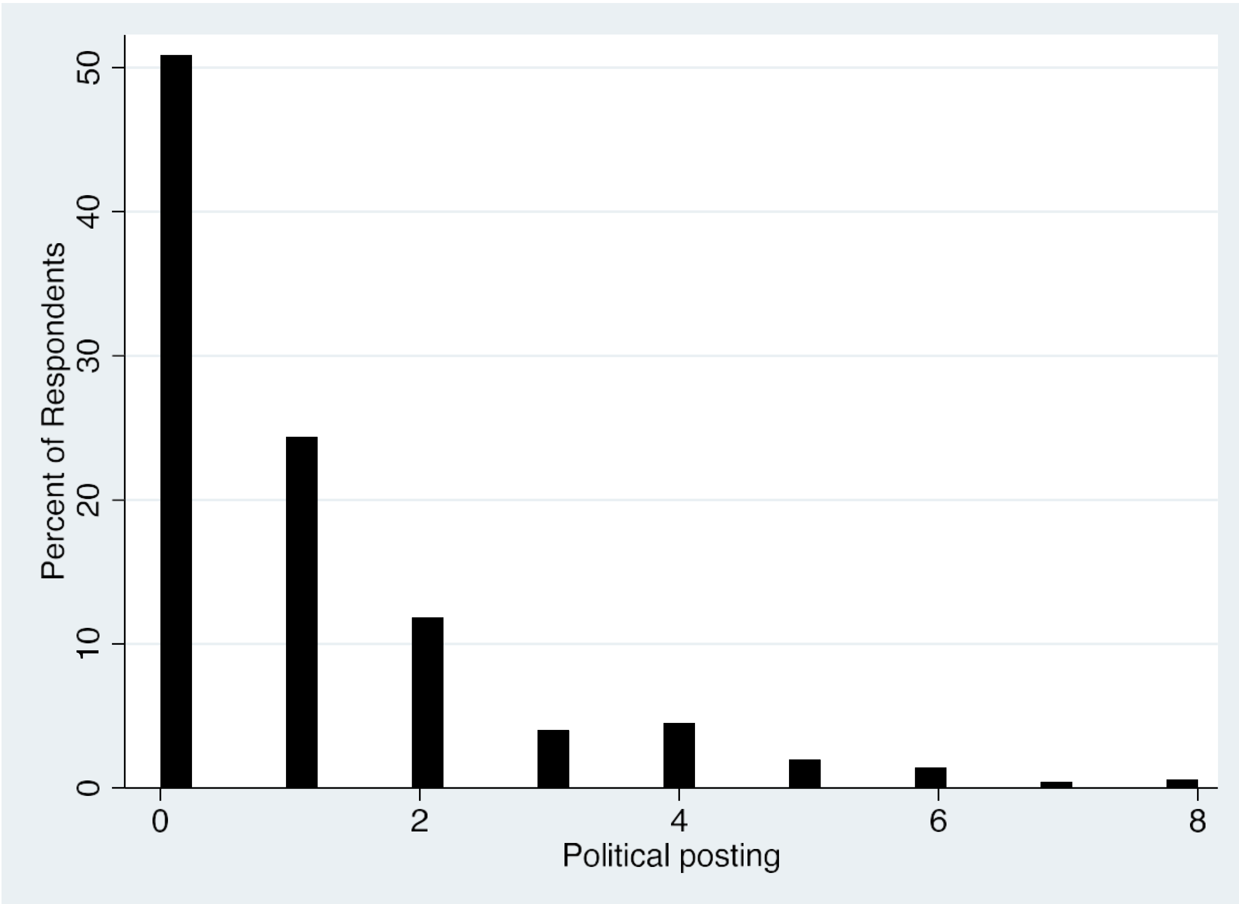

Figure 2.2. Distribution of Values on *Political posting*.

On both of these scales, the higher a respondent rated the candidate, the more favorable view they have of them. Figure 2.3 shows the distribution of values along *Out-party president*. As one might imagine, the values are heavily situated on the lower end of the scale. The mean for this variable is 15.5 which also highlights the fact that people tend to rate the opposite's presidential candidate very low. Figure 2.4 shows the distribution of *In-party president*. The distribution is similar to *Out-party president*; however, it seems as if respondents were more likely to rate their in-party candidate lower than rate their out-party candidate higher. The mean is 76.9.

The third dependent variable is *Out-party House* which measures how respondents rated the House candidate which ran under the party they do not identify with on a scale of 0-100. The fourth and last dependent variable is *In-party House* which measures how respondents rated the House candidate that ran under the party they do identify with on a scale of 0-100. Just as for the first two dependent variables, those who rate a House candidate higher signal that they had a more favorable view of the candidate in comparison to if they rated them lower. Figure 2.5 shows the distribution of *Out-party House*. The mean for this variable is 38.3. It is clear that there is a clear distinction in how respondents rated their out-party House candidate than how they rated their out-party presidential candidate. A good portion of respondents gave their out-party House candidate a middle value of 50. I believe this is due to the low amount of information that is generally out there about House candidates, especially when you compare the information that is readily available about presidential candidates. Similar findings can be found on Figure 2.6 which shows the distribution of values along *In-party House*. While the values seem to be rather evenly distributed within values 50 and above, the majority of these respondents gave their in-party House candidate a rating of 50. The mean for this variable is 67.4.

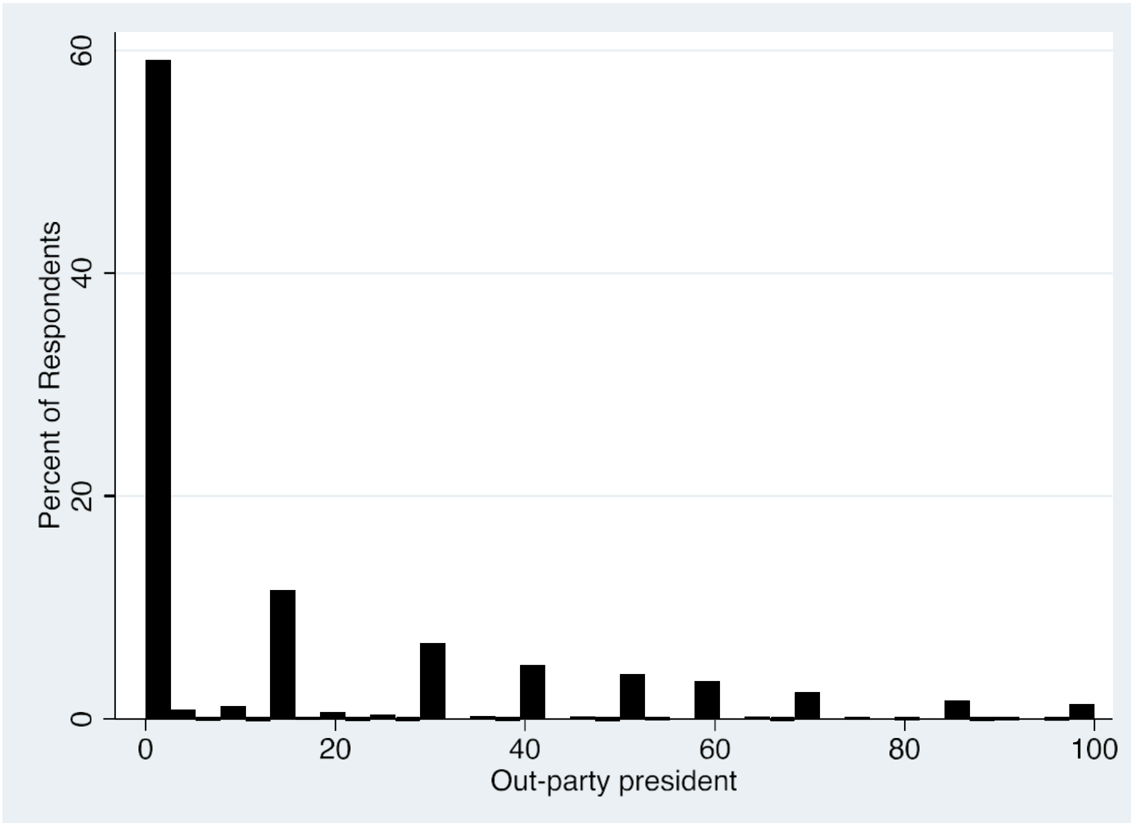

Figure 2.3. Distribution of Values on *Out-party president.*

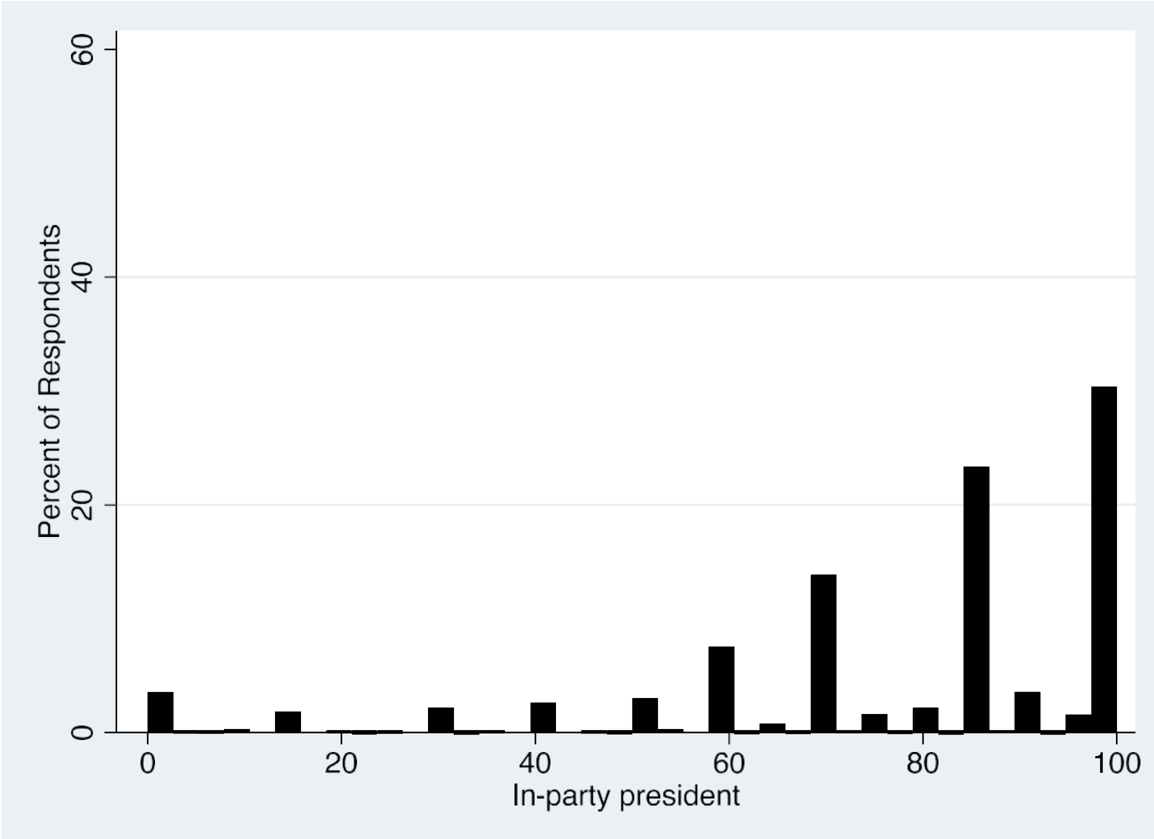

Figure 2.4. Distribution of Values on *In-party president*.

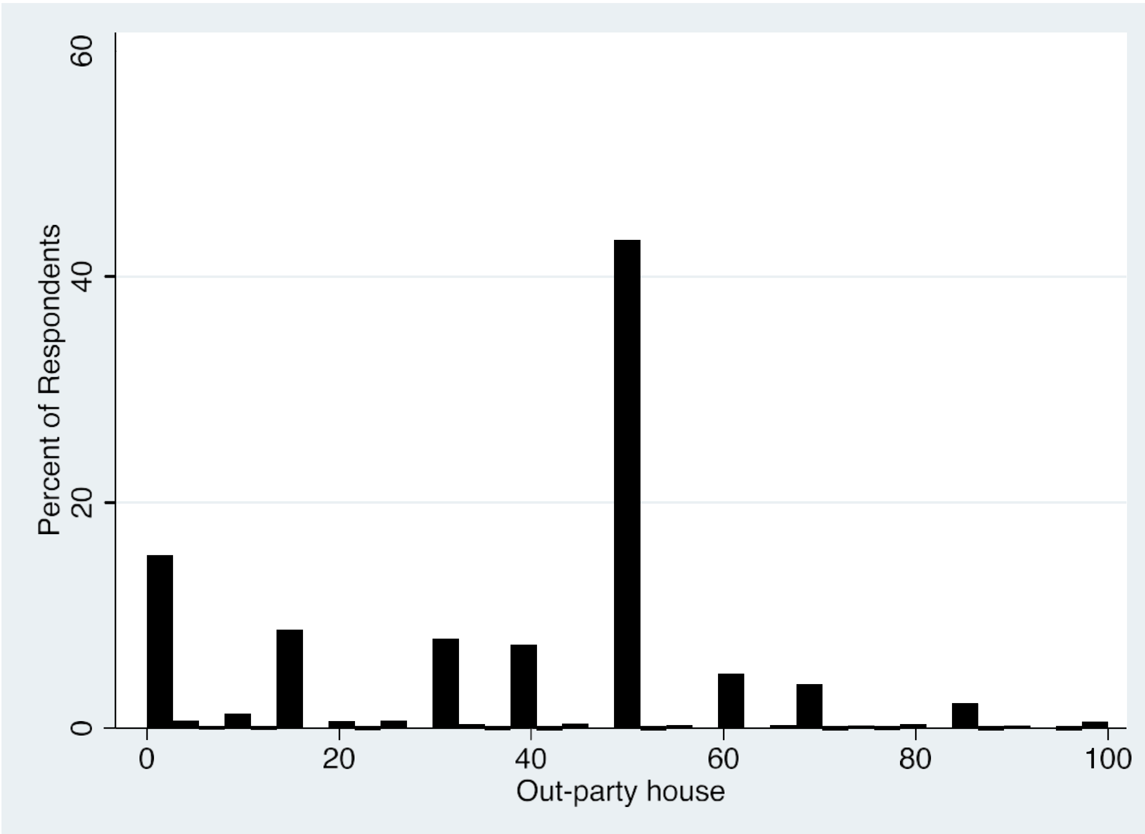

Figure 2.5. Distribution of Values on *Out-party House*.

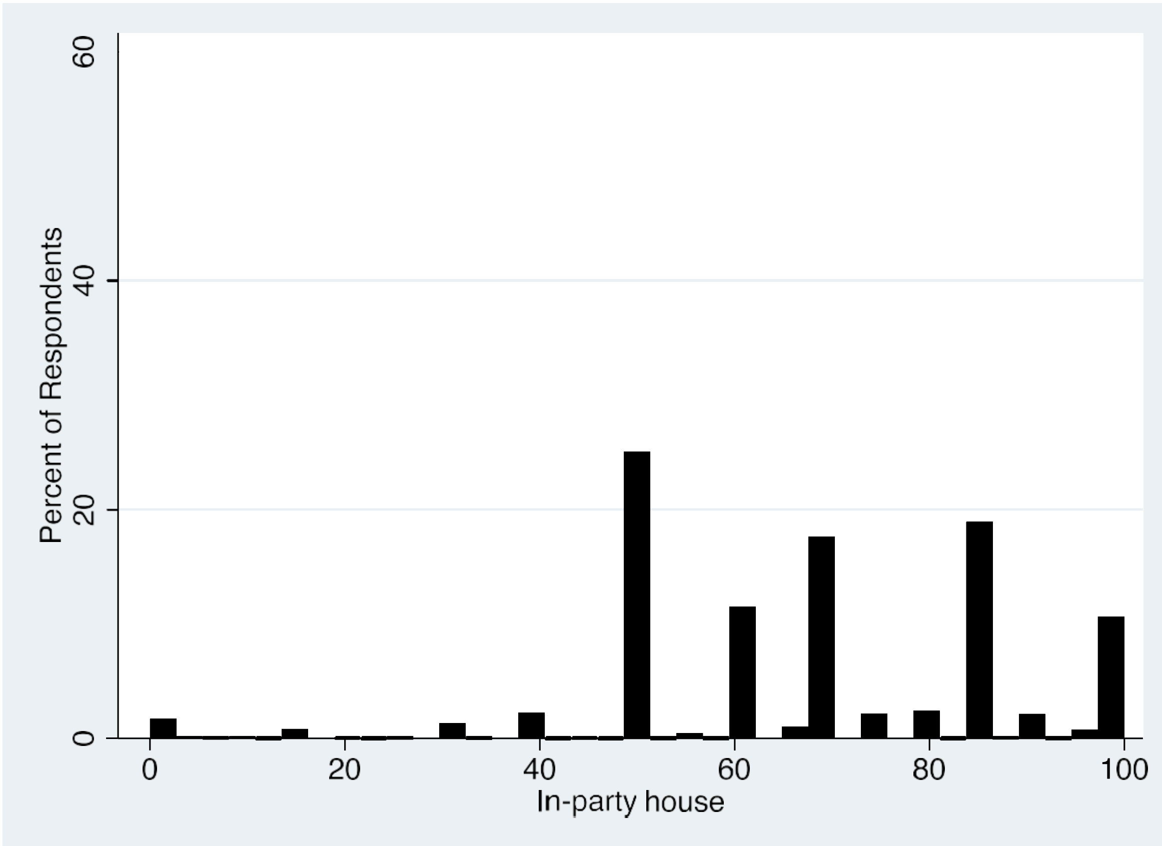

Figure 2.6. Distribution of Values on *In-party House*.

Analytic Strategy

To understand how Political social media use impacts candidate evaluations of partisans, I estimate an ordinary least squares regression model for each of the dependent variables with social media use, political posting, and their interaction (*Social media use x political posting*) as the key predictors. I chose an OLS regression due to both dependent variables being continuous, and the model acting in a linear fashion. This analytic strategy will give me the best opportunity to ascertain how much effect engaging with political content on Facebook and Twitter has on candidate evaluations. In particular, the interaction term will illuminate if the effect of posting political content online is increased when someone uses social media more often, or even if the effects of social media use is increased when their time on social media is dominated by posting political content.

Control variables

There are several control variables within these models. I include a series of demographic control variables: *Age*, *Race*, *Gender*, *Income*, and *Education*. Information on how these variables are coded can be found in the appendix. *Age* is controlled because younger people are more likely to use social media (Auxier and Anderson 2021), education is controlled because more educated citizens differ from their less educated counterparts regarding political behavior and levels of trust in media sources (Miller and Krosnick 2000), race is controlled for because racial groups have a different political history which could have the ability to affect polarization, gender is controlled for because past research shows that men and women differ in political attitudes and some political behavior (Coffe and Bolzendahl 2010), and lastly, income is controlled because it affects political participation (Ojeda 2018).

Other control variables are also included within these models that are not demographic in nature. The first is *Attention*. This measures how often a respondent claimed they paid attention to politics and elections (1- never, 2- some of the time, 3- about half of the time, 4- most of the time, 5- always). It could be the case that those who pay more attention to politics might feel more strongly about these two candidates which is the reason why this is controlled. The next two control variables will only be used in the models analyzing how political social media use affects how respondents rated their House candidates. The first of the two is *Dem House gender* which measures the gender of the Democratic House candidates. The second is *Rep House gender* which measures the gender of the Republican House candidates. The reason for these controls is because the gender of politicians has been known to affect how individuals evaluate political candidates (Aalberg and Jenssen 2007).

The last two control variables are *Fox* and *CNN*. These measure if a respondent reported they went to FoxNews.com or CNN.com respectfully. These two are included in the model to control for traditional media usage. Since I am concerned with how political social media use is affecting candidate ratings, I will need to make sure that no other media use behavior is also affecting these outcome variables. While it would be best to control for every single media that a respondent used in the lead up to the 2020 election, it would be unfeasible to have over 50 different traditional media variables within a model. Thus, I settled on what most consider to be the most traditional media used by individuals who are Republican and Democrat.

Findings

Table 2.1 reports the results of the OLS regressions for the first three models amongst all respondents in the 2020 ANES. All three models show that *Social media use* is not statistically significantly related to candidate evaluations. However, *Political posting* produced significant positive relationship with *President rating difference* and a significant negative relationship with *Out party president*. *Political posting* did not have a statistically significant effect in Model 2.

Table 2.1. OLS Regressions Predicting Presidential Candidate Ratings with Political Social Media Use Among All Respondents in the 2020 ANES.

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party President**	**In Party President**	**President Rating Diff**
Social Media Use	-0.190	-0.269	-0.110
	(0.293)	(0.338)	(0.562)
Political Posting	-2.541**	1.175	3.647*
	(1.089)	(1.233)	(1.929)
Social media interaction	0.0867	0.167	0.0971
	(0.119)	(0.142)	(0.217)
Attention	-2.161***	1.792**	3.957***
	(0.773)	(0.897)	(1.428)
Party ID	3.524***	-1.010**	-4.555***
	(0.418)	(0.444)	(0.740)
Fox	-3.654	3.863*	7.691**
	(2.231)	(2.198)	(3.852)
CNN	2.698*	-1.225	-3.736
	(1.437)	(1.697)	(2.598)
Gender	-0.810	1.090	2.006
	(1.492)	(1.521)	(2.511)
Age	0.0350	0.184***	0.150*
	(0.0524)	(0.0546)	(0.0898)
Black	-1.912	2.135	3.656
	(1.807)	(2.540)	(3.225)
Hispanic	3.723	-3.676	-8.187*
	(2.635)	(2.723)	(4.549)
Asian or NHOPI	0.606	1.504	0.917
	(3.720)	(4.703)	(7.706)
Native American	-3.250	4.168	7.401
	(6.676)	(5.326)	(10.93)
Multiple Races	-3.644	-0.992	2.615
	(3.299)	(3.375)	(6.079)
Education	0.686	-2.373***	-3.046**
	(0.821)	(0.780)	(1.339)
Income	-0.0305	0.0529	0.0878
	(0.122)	(0.129)	(0.211)
Constant	8.877*	70.99***	62.03***
	(4.783)	(5.496)	(8.835)
Observations	1,385	1,382	1,377
R-squared	0.177	0.081	0.130

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1

Table 2.2 provides the marginal effects of *Political posting* on *Out party president* at each level of *Social media use*. *Political posting's* effect on *Out party president* remained significant at the 99% confidence interval at all values of *Social media use*. However, the effect decreased as values of *Social media use* increased. Therefore, it seems that what affects presidential candidate evaluations the most regarding social media usage, is the overall time spent posting political content on social media sites, not the actual time spent on social media in general.

Table 2.3 reports the results for the OLS models analyzing House candidate ratings amongst all respondents in the 2020 ANES. Social media use once more did not record any significance by itself. However, *Political posting* was significant in all three models. Table 2.3 shows that as one's time spent posting political content on social media increases, the lower their rating of their out party House candidate, the higher their rating of their in party House candidate, and the bigger difference there is between their two House candidate ratings.

Table 2.4 reports the marginal effects of *Political posting* on *House rating diff* at all values of *Social media use*. *Political posting's* effect lessens as the values along *Social media use* increases until the effect of *Political posting* is no longer significant at the *Social media use* value of 10. Once again it seems that the overall amount of time spent posting political content on social media matters the most regarding social media's effects on candidate ratings. Furthermore, it seems that using social media in general more has a moderating effect on the posting of political content.

Table 2.5 reports the results of OLS regressions predicting presidential candidate ratings amongst only Democrats in the 2020 ANES and Table 2.6 reports regressions predicting House candidate ratings amongst the same respondents. The variable *Social media use* was once again not significant in either of the six different Models. For presidential candidate ratings, *Political posting* did not record significance in any of the models. For House candidate ratings, *Political posting* was significant with *In Party House candidates* and *House rating difference*.

Table 2.2. Marginal Effects of Political Posting at Each Level of Social Media Use on Out Party President

Model:	(1)
Political Posting at each level of Social Media Use |	**Out Party President**
0	-2.541***
	(1.088)
1	-2.454***
	(0.977)
2	-2.367***
	(0.868)
3	-2.281***
	(0.763)
4	-2.194***
	(0.661)
5	-2.107***
	(0.567)
6	-2.021***
	(0.485)
7	-1.934***
	(0.420)
8	-1.847***
	(0.382)
9	-1.760***
	(0.380)
10	-1.674***
	(0.413)
11	-1.587***
	(0.475)
12	-1.500***
	(0.556)
Observations	1385

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.3: OLS Regressions Predicting House Candidate Ratings with Political Social Media Use Among All Respondents in the 2020 ANES

Models:	(1)	(2)	(3)
VARIABLES	**Out Party House**	**In Party House**	**House Rating Diff**
Social Media Use	-0.406	-0.122	0.292
	(0.304)	(0.264)	(0.473)
Political Posting	-3.441**	3.212***	6.705***
	(1.539)	(1.190)	(2.287)
Social media interaction	0.357**	-0.211	-0.580**
	(0.175)	(0.146)	(0.264)
Attention	-4.718***	2.298***	6.990***
	(0.955)	(0.852)	(1.470)
Dem House Cand Gender	-3.474**	0.598	3.919
	(1.686)	(1.503)	(2.718)
Rep House Cand Gender	1.029	2.357	1.041
	(1.874)	(1.687)	(3.050)
Party ID	0.883*	0.287	-0.668
	(0.476)	(0.430)	(0.798)
Fox	-2.681	1.484	5.042
	(2.247)	(2.141)	(3.643)
CNN	1.299	-0.574	-1.216
	(1.942)	(1.622)	(2.948)
Gender	2.661	1.678	-1.309
	(1.709)	(1.461)	(2.703)
Age	0.0426	0.183***	0.120
	(0.0591)	(0.0490)	(0.0904)
Black	-2.817	1.104	2.807
	(3.453)	(2.785)	(4.958)
Hispanic	3.864	-4.445*	-8.605*
	(3.000)	(2.547)	(4.728)
Asian or NHOPI	8.120***	-3.903	-11.85***
	(2.765)	(2.557)	(4.411)
Native American	1.109	3.673	2.414
	(6.072)	(6.104)	(8.364)
Multiple Races	-2.893	1.055	3.747
	(5.277)	(3.141)	(7.694)
Education	2.034**	-2.314***	-4.701***
	(0.926)	(0.816)	(1.504)
Income	-0.0957	0.219*	0.300
	(0.147)	(0.124)	(0.221)
Constant	46.79***	52.15***	8.130

Table 2.3. Continued

Models:	(1)	(2)	(3)
	(6.277)	(6.092)	(10.39)
Observations	1,099	1,163	1,080
R-squared	0.095	0.097	0.119

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.4. Marginal Effects of Political Posting at Each Level of Social Media Use on House Rating Diff

Model:	**(1)**
Political Posting at each level of Social Media Use |	**House Rating Difference**
0	6.704***
	(2.286)
1	6.124***
	(2.042)
2	5.544***
	(1.804)
3	4.964***
	(1.573)
4	4.384***
	(1.355)
5	3.804***
	(1.157)
6	3.224***
	(0.990)
7	2.644***
	(0.872)
8	2.064***
	(0.825)
9	1.484**
	(0.860)
10	0.904
	(0.969)
11	0.324
	(1.130)
12	-0.255
	(1.325)
Observations	1080

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.5. OLS Regressions Predicting Presidential Candidate Ratings with Political Social Media Use Among All Democrats in the 2020 ANES.

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party President**	**In Party President**	**President Rating Diff**
Social Media Use	0.0556	-0.271	-0.373
	(0.302)	(0.363)	(0.566)
Political Posting	-0.630	-1.306	-0.743
	(1.173)	(1.396)	(2.080)
Social media interaction	-0.0389	0.312**	0.372*
	(0.124)	(0.153)	(0.224)
Attention	-0.836	1.464	2.359*
	(0.756)	(1.014)	(1.424)
Fox	5.753**	-6.486**	-11.87***
	(2.903)	(2.758)	(4.197)
CNN	-1.402	4.753***	6.449***
	(1.198)	(1.609)	(2.161)
Gender	-1.153	0.0665	1.431
	(1.306)	(1.690)	(2.430)
Age	0.0664	0.253***	0.191**
	(0.0532)	(0.0555)	(0.0873)
Black	-1.630	4.143	5.226
	(2.048)	(2.577)	(3.361)
Hispanic	2.547	-0.548	-4.049
	(2.289)	(2.612)	(3.608)
Asian or NHOPI	2.130	4.862	2.764
	(2.500)	(3.458)	(4.396)
Native American	-0.877	9.939*	10.68
	(4.345)	(5.809)	(7.783)
Multiple races	-1.284	0.926	2.245
	(2.558)	(3.606)	(5.342)
Education	-1.685**	0.970	2.687*
	(0.818)	(0.942)	(1.466)
Income	-0.217**	0.228	0.469**
	(0.111)	(0.147)	(0.205)
Constant	16.82***	52.96***	35.23***
	(4.324)	(5.747)	(8.198)
Observations	845	842	840
R-squared	0.086	0.136	0.145

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.6. OLS Regressions Predicting House Candidate Ratings with Political Social Media Use Among All Democrats in the 2020 ANES.

Models:	(1)	(2)	(3)
VARIABLES	**Out Party House Rating**	**In Party House Rating**	**House Rating Difference**
Social Media Use	-0.465	0.217	0.678
	(0.441)	(0.365)	(0.699)
Political Posting	-2.421	3.103**	5.656*
	(1.984)	(1.471)	(3.093)
Social Media Interaction	0.265	-0.247	-0.540
	(0.213)	(0.174)	(0.339)
Attention	-3.966***	2.943***	7.226***
	(1.242)	(1.049)	(1.979)
Rep House Cand Gender	2.846		0.418
	(2.280)		(3.568)
Fox	1.521	-6.204*	-7.902
	(3.553)	(3.266)	(5.692)
CNN	-0.851	0.456	2.266
	(2.205)	(1.796)	(3.423)
Gender	5.883***	0.913	-4.480
	(2.273)	(1.797)	(3.514)
Age	-0.0232	0.209***	0.194
	(0.0787)	(0.0584)	(0.118)
Black	-0.998	2.496	4.479
	(3.603)	(2.911)	(5.400)
Hispanic	2.572	-3.495	-5.253
	(4.012)	(2.942)	(5.787)
Asian or NHOPI	11.14***	-0.493	-12.14**
	(2.624)	(3.330)	(4.709)
Native American	7.808	14.28**	7.233
	(6.577)	(6.546)	(10.48)
Multiple Races	-4.420	3.081	7.933
	(5.927)	(3.656)	(9.399)
Education	2.031	-0.579	-3.131
	(1.319)	(0.977)	(1.982)
Income	-0.189	0.00293	0.293
	(0.195)	(0.153)	(0.291)
Dem House Cand Gender		1.984	6.388*
		(1.781)	(3.600)
Constant	45.37***	44.80***	-3.632
	(7.451)	(5.805)	(11.82)

Table 2.6. Continued

Models:	(1)	(2)	(3)
Observations	672	755	661
R-squared	0.098	0.110	0.124

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.7 is provided to look at the relationship between *Political posting* and *In party House rating* for Democrats a bit closer. This table reports the marginal effects of *Political posting* on *In party House ratings* for Democrats at all values of *Social media use*. Like the other marginal effects models have shown, *Political Posting* has the largest effect at the lower ends of the *Social media use* variable and the effects lessens as you move up in values on *Social media use* until the significance disappears at the value of 9.

Table 2.8 and 2.9 reports the OLS Regressions predicting presidential candidate ratings and House candidate ratings among Republicans in the 2020 ANES respectively. *Political posting* and *Social media use* both did not register any significance with any of the presidential candidate variables for Republicans However, for House candidate ratings, *Political posting* registered significance at the 95 percent confidence interval for *Out party House* and *House rating diff*. Table 2.10 reports the marginal effects of *Political posting* on *Out House rating* amongst Republicans at every level of *Social media use*. Once again, *Political posting*, or the amount of time spent posting political content on social media, has the greatest negative effect on *Out House Rating* at the lowest values of *Social Media Use*. The effects of *Political Posting*, again, lowers as one increase in values of *Social Media Use* until the significance goes away fully at the *Social Media Use* value of 7.

Conclusion

I sought to further our understanding of how political social media use affects how individuals view and rate candidates running for federal office. I explore this issue using data about the 2020 general elections. Using the 2020 ANES survey, I found mixed results regarding the effects of political social media usage. Amongst all respondents, the overall time spent posting political content on Facebook and Twitter was found to have a negative effect on how respondents rated their out-party presidential candidate. The time a respondent spent posting political content was also found to have a negative effect on one’s out-party House rating, a positive rating on in-party House rating, and the

Table 2.7. Marginal Effects of Political Posting at Each Level of Social Media Use on In Party House among Democrats.

Model:	**(1)**
Political Posting at each level of Social Media Use |	**In Party House**
0	3.103***
	(1.470)
1	2.856***
	(1.312)
2	2.610***
	(1.159)
3	2.363***
	(1.012)
4	2.116***
	(0.876)
5	1.869***
	(0.754)
6	1.623***
	(0.656)
7	1.376***
	(0.594)
8	1.129**
	(0.579)
9	0.882
	(0.614)
10	0.636
	(0.693)
11	0.389
	(0.802)
12	0.142
	(0.931)
Observations	755

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.8. OLS Regressions Predicting Presidential Candidate Ratings with Political Social Media Use Among All Republicans in the 2020 ANES.

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party President**	**In Party President**	**President Rating Diff**
Social Media Use	0.181	-0.763	-0.993
	(0.455)	(0.553)	(0.925)
Political Posting	-1.251	1.328	2.535
	(1.851)	(1.936)	(3.082)
Social media interaction	-0.272	0.433	0.718*
	(0.246)	(0.264)	(0.428)
Attention	-3.431***	1.520	5.001**
	(1.292)	(1.531)	(2.417)
Fox	-12.75***	13.46***	26.29***
	(2.740)	(2.512)	(4.513)
CNN	18.46***	-21.57***	-39.96***
	(3.116)	(3.895)	(5.963)
Gender	2.327	-1.477	-3.991
	(2.689)	(2.428)	(4.421)
Age	-0.0402	0.0485	0.0798
	(0.0866)	(0.0923)	(0.154)
Black	-26.06***	24.21***	50.31***
	(6.557)	(6.495)	(12.05)
Hispanic	3.418	-3.535	-6.854
	(6.737)	(8.318)	(14.62)
Asian or NHOPI	-0.565	-8.605	-7.864
	(8.691)	(11.98)	(19.76)
Native American	-3.868	-3.502	0.444
	(12.75)	(10.27)	(22.32)
Models:	**(1)**	**(2)**	**(3)**
Multiple Races	5.666	-10.49	-16.16
	(8.580)	(10.20)	(18.24)
Education	3.618***	-6.361***	-10.02***
	(1.365)	(1.128)	(2.140)
Income	0.233	-0.242	-0.500
	(0.219)	(0.208)	(0.376)
Constant	25.46***	91.88***	67.31***
	(7.056)	(7.001)	(12.08)
Observations	540	540	537
R-squared	0.197	0.255	0.266

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.9. OLS Regressions Predicting House Candidate Ratings with Political Social Media Use Among All Republicans in the 2020 ANES.

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party House**	**In Party House**	**House Rating Diff**
Social Media Use	-0.198	-0.372	-0.257
	(0.390)	(0.369)	(0.641)
Political Posting	-5.369**	3.535	8.515**
	(2.232)	(2.190)	(3.587)
Social Media Interaction	0.613**	-0.191	-0.788
	(0.287)	(0.323)	(0.502)
Attention	-4.587***	1.598	5.504**
	(1.414)	(1.276)	(2.214)
Dem House Cand Gender	-3.912*		2.980
	(2.344)		(3.886)
Fox	-8.841***	7.691***	17.70***
	(2.827)	(2.672)	(4.677)
CNN	10.07***	-5.647*	-15.48***
	(3.388)	(3.065)	(5.421)
Gender	-0.474	-0.0422	0.187
	(2.342)	(2.290)	(4.193)
Age	0.0824	0.0874	0.0366
	(0.0864)	(0.0750)	(0.138)
Black	-34.54***	-11.61**	24.50***
	(4.644)	(5.076)	(9.198)
Hispanic	7.755***	-7.377	-14.60*
	(2.863)	(5.180)	(7.684)
Asian or NHOPI	4.003	-8.180**	-11.43
	(4.970)	(3.859)	(8.470)
Native American	-5.489	-8.931	-3.625
	(11.67)	(7.034)	(11.64)
Multiple Races	4.958	-1.726	-8.522
	(6.646)	(5.284)	(10.66)
Education	1.901	-2.953**	-5.580***
	(1.190)	(1.202)	(2.103)
Income	0.0306	0.310	0.190
	(0.204)	(0.193)	(0.333)
Rep House Cand Gender		1.098	3.354
		(3.215)	(5.590)
Constant	51.28***	62.83***	17.19

Table 2.9. Continued

Models:	**(1)**	**(2)**	**(3)**
	(7.161)	(7.758)	(12.02)
Observations	453	462	419
R-squared	0.170	0.145	0.204

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 2.10. Marginal Effects of Political Posting at Each Level of Social Media Use on in Party House among Republicans.

Model:	(1)
Political Posting at each level of Social Media Use |	**Out Party House**
0	-5.369***
	(2.231)
1	-4.756***
	(1.967)
2	-4.142***
	(1.709)
3	-3.529***
	(1.462)
4	-2.916***
	(1.233)
5	-2.303***
	(1.032)
6	-1.689**
	(0.880)
7	-1.076
	(0.806)
8	-0.463
	(0.830)
9	0.150
	(0.944)
10	0.763
	(1.122)
11	1.376
	(1.338)
12	1.989
	(1.577)
Observations	453

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

absolute distance between the two House candidate ratings. However, one's general time on social media did not have an effect on how one rated House and Presidential candidates in the 2020 election.

This finding is perplexing. One might assume that presidential candidates getting the most attention on social media would cause their evaluations to be significantly affected by this increase in attention. However, it might be the case that any effect that social media use might have on presidential candidate evaluations might be lessened by all of the traditional media attention these candidates get, especially considering their monopolization of the public space. Thus, it makes sense that House candidate evaluations would be affected the most by social media usage, due to their lack of traditional media coverage, especially by the national media. Therefore, since individuals fail to get information on their House candidates from the traditional media, they are left to get this information from their social media newsfeeds.

The analysis separating Democrats and Republicans produced some interesting findings. There are some very notable similarities and differences between the two groups. For similarities, neither one of the partisan groups had their ordinary social media usage or the amount of time spent posting political content affect how they rated the presidential candidates. This is very similar to what we found when all respondents are lumped in together.

For differences, however, it seems the two partisan group's House candidate ratings are affected differently by social media use. The overall time spent posting political content negatively affected how Democrats rated their own party's House candidate but did not affect how they rate the other party's candidate. However, the same variable negatively affected how Republicans rated the other party's House candidate but did not affect how they rated their own party's House candidate. This difference between the two partisan groups is interesting. Was this finding produced because of a difference in social media usage between the two citizen partisan groups, or was it produced due to a difference in how the elites within the two political parties use social media? These questions should be explored in future research.

There are some limitations that future work should seek to rectify. For one, this analysis only encompasses one election cycle. While it would have been best to include multiple election cycles, the ANES only asked about social media posting habits on the most recent survey. If the ANES continues to ask these same questions, or possibly improves upon their social media questions, future work should analyze whether political social media use has the same effects spanning across multiple election years. Also, since I am not able to analyze the social media feeds of every single respondent here and I had to rely on self-reported behavior, I could very well be missing variation within social media use. As survey questioning becomes more exact, or maybe the ability to view individual’s social media feeds becomes available, future research should aim to fully understand how social media use, and political social media use in particular, affects how individuals view and rate political candidates across party lines.

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CHAPTER III

DOOM SCROLLING: HOW SOCIAL MEDIA CAN AFFECT YOUR EMOTIONAL POLITICAL STATE

Abstract

More and more Americans are stating that they feel anger when asked about how things are going within their country. Furthermore, Americans have been increasing their use of social media in general, and to obtain their news. Despite this trend, our collective understanding of how social media can affect individuals' emotional state is lacking. Here, I seek to understand the relationship between political social media use and how angry one feels about the state of the country. I show here that when individuals use social media for political purposes, in particular, Twitter and Facebook, they tend to feel angrier. These findings highlight the need to understand not only *if* someone uses social media, but *how* they use social media.

Introduction

Social media use has been increasing along with individuals using it to consume news. The Pew Research Center first started tracking social media use in 2005. Only 5 percent of American adults used social media sites during that year. However, that percentage jumped to 50 percent in 2011 (Pew Research 2021). The percentage of individuals using social media in 2020 jumped to 72 percent. Not only are individuals using these types of sites, but they are also using these sites to obtain their news. In 2020, 59 percent of Twitter users and 54 percent of Facebook users stated they regularly get their news from the respective social media sites. This large increase in using social media, as well as the act of using social media to get news highlights the importance of studying social media use and its effects on the political world.

In 2021, a Facebook whistleblower came forward to highlight the problems she saw with the current Facebook algorithm (Hao 2021). This whistleblower highlighted how Facebook's algorithm pushes posts that will receive the most engagement to the top of an individual's newsfeed, while suppressing posts which typically do not receive a lot of engagement. Recent studies have even shown that political posts on social media which tend to get the most engagement are ones with negative connotations attached to them (Hao 2021; Stieglitz and Dang-Xuan 2013). Therefore, if an individual interacts with political content on social media, they will see political content more often, and there is a good chance this content has a negative tone attached to it. Not only did individuals report higher social media use and higher amounts of using social media to obtain news in recent years, but individuals have also reported in high numbers that they are angry about the state of the country. In June of 2020, 73% of registered voters stated they were angry about the state of the country (Dunn 2020). In November of that same year, 59% of Trump supporters and 56% of Biden supporters reported that same anger towards the state of the country (Dunn 2020). It is clear that a large number of Americans feel anger towards where the country is currently at, and their party not being in control of the government is not the main cause.

This finding along with the recent headlines about Facebook, and the Pew Research surveys lead me to wonder: does political social media use affect an individual's feelings about how things are going within the country politically? In this paper, I argue that individuals who engage with political content more often on social media, will be more likely to feel more anger over how things are going within the country politically.

In what follows, I begin this study by highlighting the relevant literature on a phenomenon called emotional contagion. This literature essentially states that through face to face communication, and when confronted with computer generated messages, individuals can spread their emotional feelings to others like a virus. I also highlight how past media research has showcased how mass media is able to influence an individual's emotions and opinions. I then discuss what is known about the algorithms of both Facebook and Twitter in order to show, alongside the emotional contagion theory, that these algorithms could affect how individuals feel about how things are going within the country politically. I then test whether political social media use, in particular, Facebook and Twitter political use is positively correlated with the anger one might feel towards the state of the country. I use the 2020 American National Election Study to test these notions. The findings show the more an individual engages with political content on Twitter and Facebook, the angrier one feels about how things are going in the country. This indicates that future research should not only focus on if an individual's use social media, but how they use it as well.

Emotional Nature of Social Media

Research shows that social media can evoke strong emotions, whether by emotional contagion or other mechanisms. The theory of emotional contagion holds that emotions can be passed from one individual to another through the transfer of information (Hatfield and Cacioppo 1994). In this theory, emotions are likened to a virus passing from one individual to another. In one influential study, Fowler and Christakis (2008) analyzed 4,739 individuals over 20 years (1983-2003), seeking to discover if one person's happiness could "infect" another person. They found that having a friend living nearby (within one mile) who was happy increased a person's probability of reporting they were happy by 25 percent. In the same study, the scholars found that when a person claims to be happy, their neighbor's probability of being happy increases by 34 percent. In all, this study shows emotional contagion at work: being happy makes other people happy.

Emotional contagion has generally been viewed (and studied) as a face-to-face phenomenon. But several recent studies show that emotional contagion can occur even when face-to-face interaction does not. For example, Harris and Paradice (2007) find that readers of text messages can easily detect the emotions (negative or positive) of the sender. Thus, emotional contagion can take place via social media. Coviello et al. (2014) explored this notion by analyzing data from over 1 million Facebook users. They found that rainfall in one geological area directly contributed to Facebook users posting statuses with more negative emotions in that same area, and that this content affected their friends', who lived in other cities where there was no rainfall, statuses to have more negative emotions. In another analysis of Facebook posts, Coviello and Franceschetti (2014) found that a post expressing either a positive or a negative emotion could affect the emotional tenor of friends' posts. Overall, these studies show that social media posts can influence emotions, and emotional contagion can happen via social media.

To my knowledge, there are no extant studies of political, emotional contagion. But several studies suggest that emotional contagion may happen in the political realm. First, Hibbing and Theiss-Morse (1998) find that where people get their news affects their emotional and cognitive evaluations of Congress. Specifically, they find that people who get their news from television and radio experience more negative emotions than people who get their news from newspapers. Second, numerous studies show that mass media can "prime" media consumers (Iyenger and Kinder 1987; Krosnick and Kinder 1990; Krosnick and Brannon 1993; Kosicki 1993; Duyn and Collier 2018) and can directly affect opinions and worldviews (Shah et al. 2002; Tuchman 1978; Druckman et al. 2004; Entman 2004; Kinder and Sanders 1990; Jacoby 2000). Lastly, there has been numerous studies showcasing how even social media use can affect political opinions and even polarization which leads to the question if it can also affect political emotional states (Allcott et al. 2020; Bail et al. 2018; Lee, Shin, and Hong 2018; Jennings 2021; Valenzuela et al. 2019;).

Given this vast amount of research, I believe it is reasonable to hypothesize that social media can shape how individuals *feel* about what is happening politically. In other words, news consumption via social media can affect individuals' feelings about the political world through emotional contagion, or other media effects such as priming and opinion changing.

Social Media News Feeds

I believe that social media, in particular Facebook and Twitter, has qualities which will make its users feel angry and outraged about how things are going within the country. For one, the posts which receive the most engagement and are seen the most are those with negative emotions attached to them (Hao 2021). Since this is the case, individuals who are subjected to these posts, I believe, will be affected by these emotions and therefore, feel angrier about how things are going in the country. However, some individuals who use social media will not be subjected to these posts in high frequencies due to *how* they use social media. For instance, due to social media algorithms individuals will tend to only see content that they interacted with in the past (Hao 2021). If one does not interact with political content on Facebook, they will be very much less likely to see political content than someone who regularly interacts with them.

In 2021, Facebook's newsfeed algorithm made headlines. Former Facebook executives, along with outside analysis of the Facebook newsfeed, outlined how the algorithm seeks to maximize engagement (Hao 2021). This means that the algorithm will put stories and content which attracts the most engagement at the top of individuals' newsfeed while suppressing those which do not get a lot of engagement. These same studies show the content which receives the most engagement is content which furthers controversy, polarization, and extremism (Hao 2021). These posts even tend to be ones with angry overtones attached to them. If the posts which are getting the most engagement are ones which have negative attachments to them, or even have angry overtones, then it could be the case that users of this site might find themselves becoming angry due to past researched media effects or even emotional contagion.

Facebook is not the only site that sees angry content being spread the most; Twitter also sees this phenomenon. Choudhury et al. (2012) found tweets containing negative moods, in comparison to tweets with positive ones, were spread more widely on Twitter. Moreover, Stieglitz and Dang-Xuan (2013) found that emotionally charged political tweets were retweeted more often and quicker compared to tweets with neutral messages. This finding was even more pronounced for political tweets containing negative emotions. Not only that, but the most influential political users, which were the ones that were within the top 50 most retweeted users, sent more emotionally charged tweets compared to other users. All of this adds up to negative emotions being widely present on these social media sites.

However, just because individuals use social media does not mean that they are subjected to negative political posts. We also know that social media algorithms try to push forward content that is similar to the content a person has actually interacted with on their social media newsfeeds (Zimmer et al. 2019). If a person posts more political content and interacts with more political content, they will tend to see more political content on their newsfeed. Therefore, if an individual engages with partisan or negative political content, which we know is the political content that is most prevalent and gets the most engagement, then this content will continue to be on the top of this individual's newsfeeds (Choudhury et al. 2012; Hao 2021; Pariser 2011; Flaxman et al. 2016).

Hypotheses, Data, and Methods

The literature on emotional contagion shows that emotions can be transferred from one person to another like a virus, and this can take place on computer mediated devices. Furthermore, past research shows that a particular individual's news consumption can affect their emotional feelings about the political world. Due to the nature of Facebook's and Twitter's algorithms promoting emotionally charged negative content and along with it promoting content that each consumer already interacts with, I offer the following hypothesis.

H1: Individuals who engage with political content on Social Media more often, will be more likely to feel angrier and less happy over how things are going within the country politically.

Methodology and Data

To test my hypothesis, I will use data from the American National Election Studies (ANES) which was conducted in 2020[8]. The ANES used a contactless, mixed-mode design. Each respondent was

[8] The surveys were conducted between August 18, 2020 and November 3, 2020.

given and took the survey via various forms such as a self-administered online survey, a telephone survey, or a live online video interview. An USPS computerized delivery sequence file was used to randomly choose the respondents for this survey. All residential addresses in all 50 states, including Washington, DC, had an equal chance of being chosen.

The key independent variables are *Social media use*, which has a Cronbach alpha of 0.8437 and *Political posting*, which has a Cronbach alpha of 0.9352. *Social media use* measures how often a respondent uses Facebook and Twitter in general. I used two survey questions: (1) "How often do you use Twitter?" and (2) "How often do you use Facebook?" to create *Social media use*. The response set for these items were: 1 = "less than once a month," 2 = "once or twice a month," 3 = "about once a week," 4 = "a few times each week," 5 = "once a day," 6 = "a few times every day," and 7 = "many times every day." The variable had a range of 2-14. I recoded the variable to have a range of 0-12 to make the variable simpler to understand. *Political posting* measures each respondent's amount of time spent posting political content on social media. The variable is an additive scale of how each respondent answered these two questions: (1) "How often do you post political content on Facebook?" and (2) "How often do you post political content on Twitter?" The response set for both items was as follows: 0 = "never," 1 = "sometimes," 2 = "about half of the time," 3 = "most of the time," and 4 = "always." Thus, the range of this variable is 0-8.

Of course, the most obvious way to measure how much political content a person engages with on Facebook and Twitter is to ask them directly. Unfortunately, the ANES did not ask respondents how much they *engage* with political content on Twitter and Facebook but instead asked only the amount of time spent on social media posting political content on the two platforms. Because research shows that people who post the most political content on social media are also those who view, and thus engage with, the most political content on social media, I believe the interaction term between the two key independent variables will provide the best snapshot of a person engaging with political content (Lawson 2016).

Figure 3.1 shows how respondents are distributed along *Social media use*. Only around 100 respondents stated they never used Facebook or Twitter, and the overall distribution is rather evenly dispersed in comparison to *Political posting*. Figure 3.2 shows the distribution of values along *Political posting*. Over 50 percent of respondents stated they never post political content when on Facebook or Twitter and the distribution is heavily positively skewed.

Dependent variables

I utilize two dependent variables within this analysis. The first dependent variable is *Anger*, which measures the individuals' response to the question, "How angry do you feel about how things are going in the country?" It is a five point scale variable with "1" denoting not at all, "2" denoting a little, "3" denoting somewhat, "4" denoting very, and "5" denoting extremely. I expect to find a positive and statistically significant relationship between *Anger* and *Political social media use*. Figure 3.3 shows the distribution of respondents along *Anger*. It shows how the majority of respondents fell within a value of "3" and "5." The mean of *Anger* is 3.58. It is clear individuals tend to feel angrier when asked about the way things are going in this country politically. The second dependent variable is *Happy,* which measures the response to the question, "How happy do you feel about how things are going in the country?" The response set for this question was: 1 = not at all, 2 = a little, 3 = somewhat, 4 = very, and 5 = extremely. I expect to find a negative and statistically significant relationship between social media usage and *Happy*. Figure 3.4 shows the distribution of respondents along *Happy*.

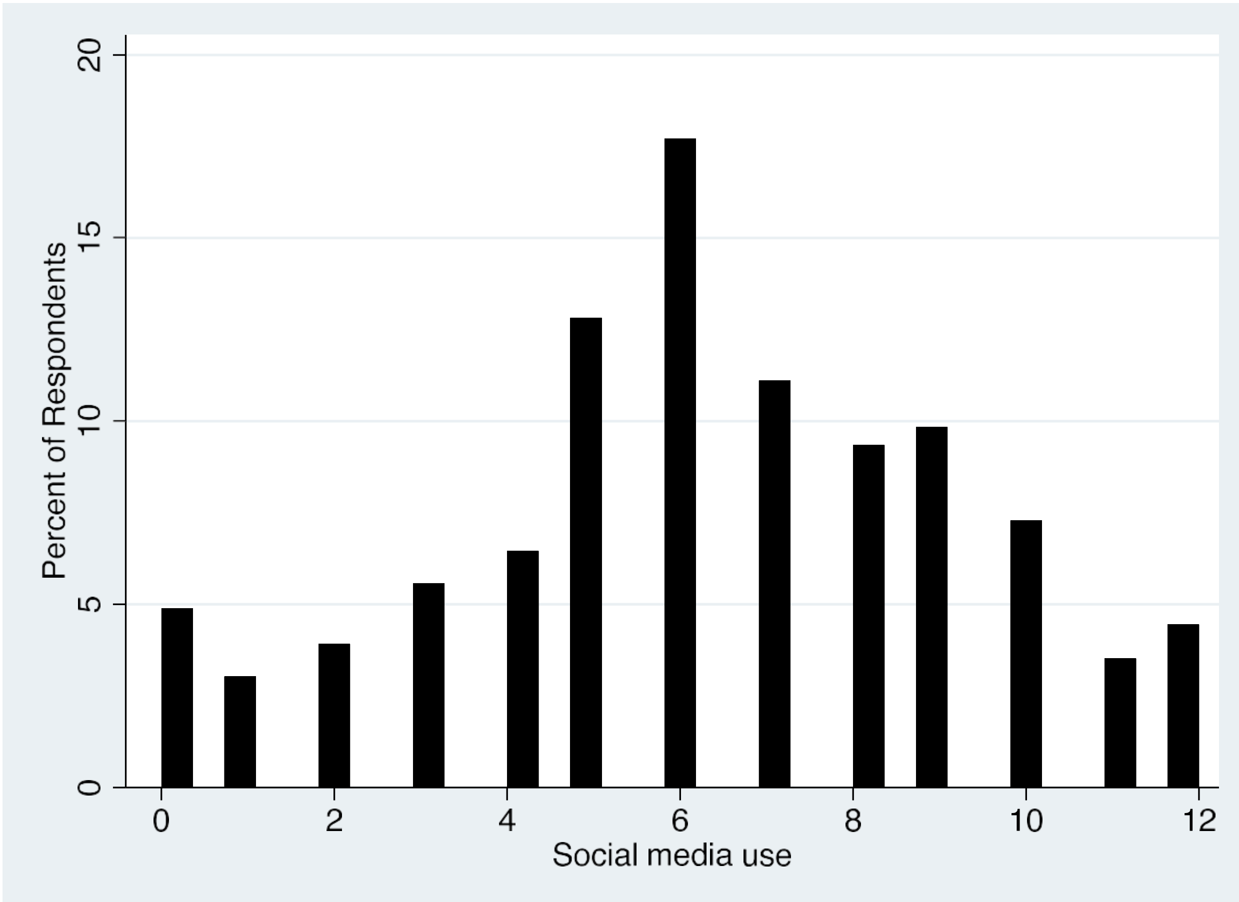

Figure 3.1. Distribution of Values on *Social media use*.

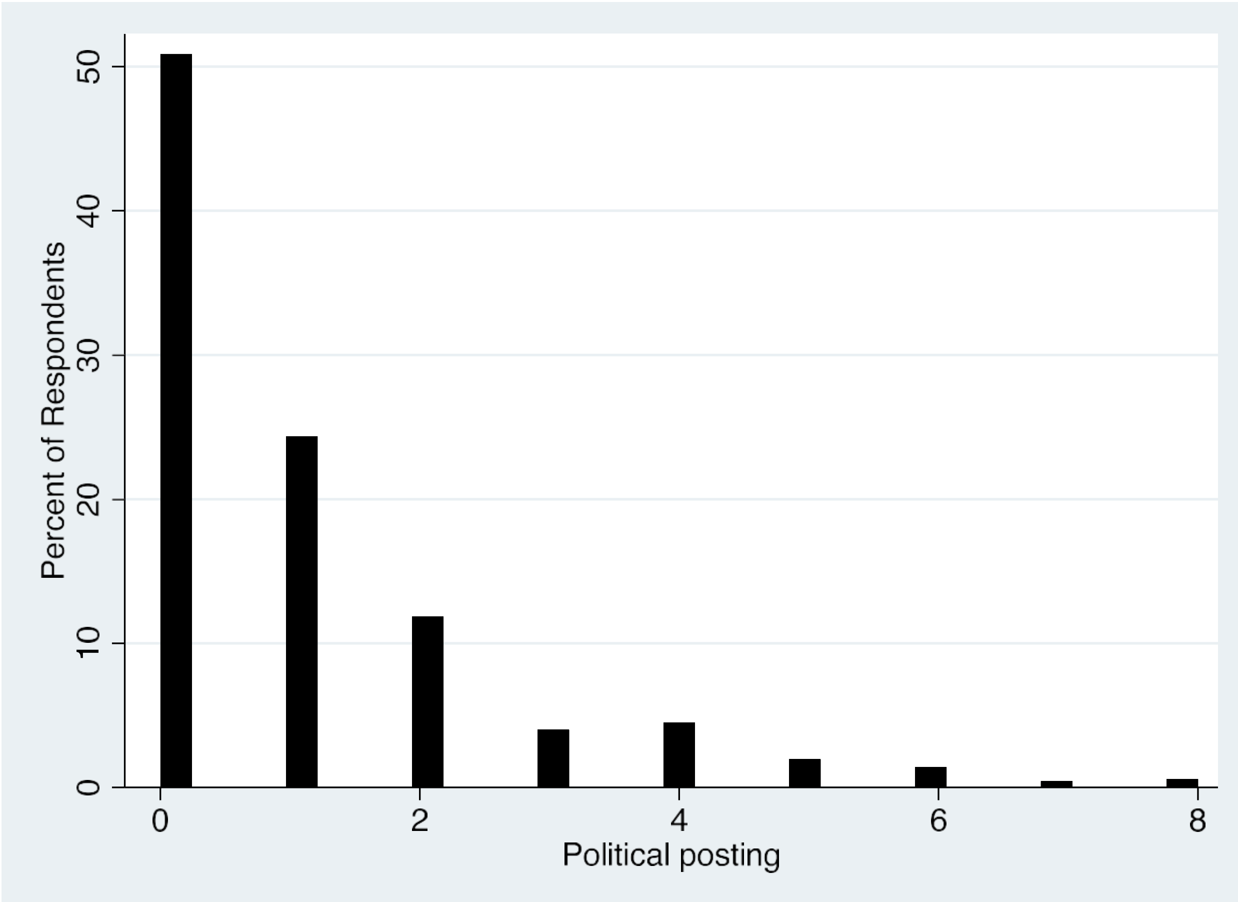

Figure 3.2. Distribution of Values on *Political posting*.

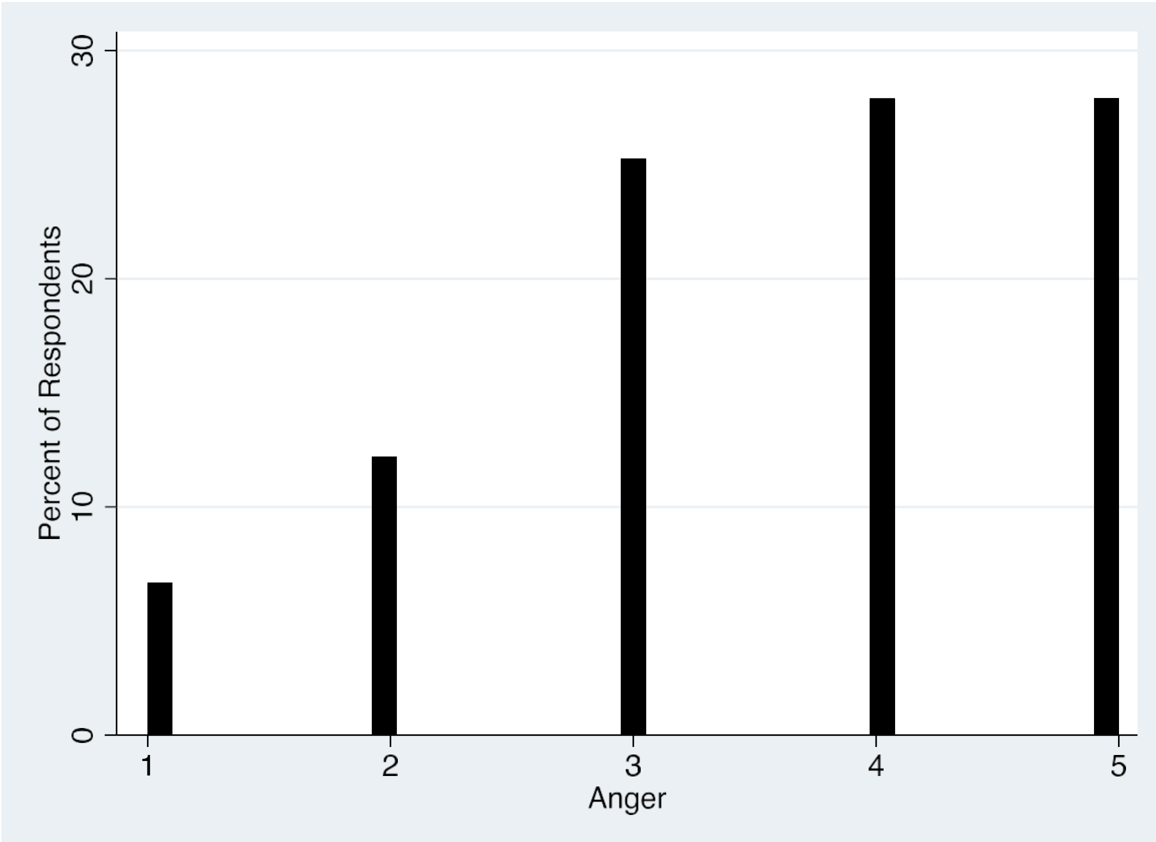

Figure 3.3. Distribution of values on Anger.

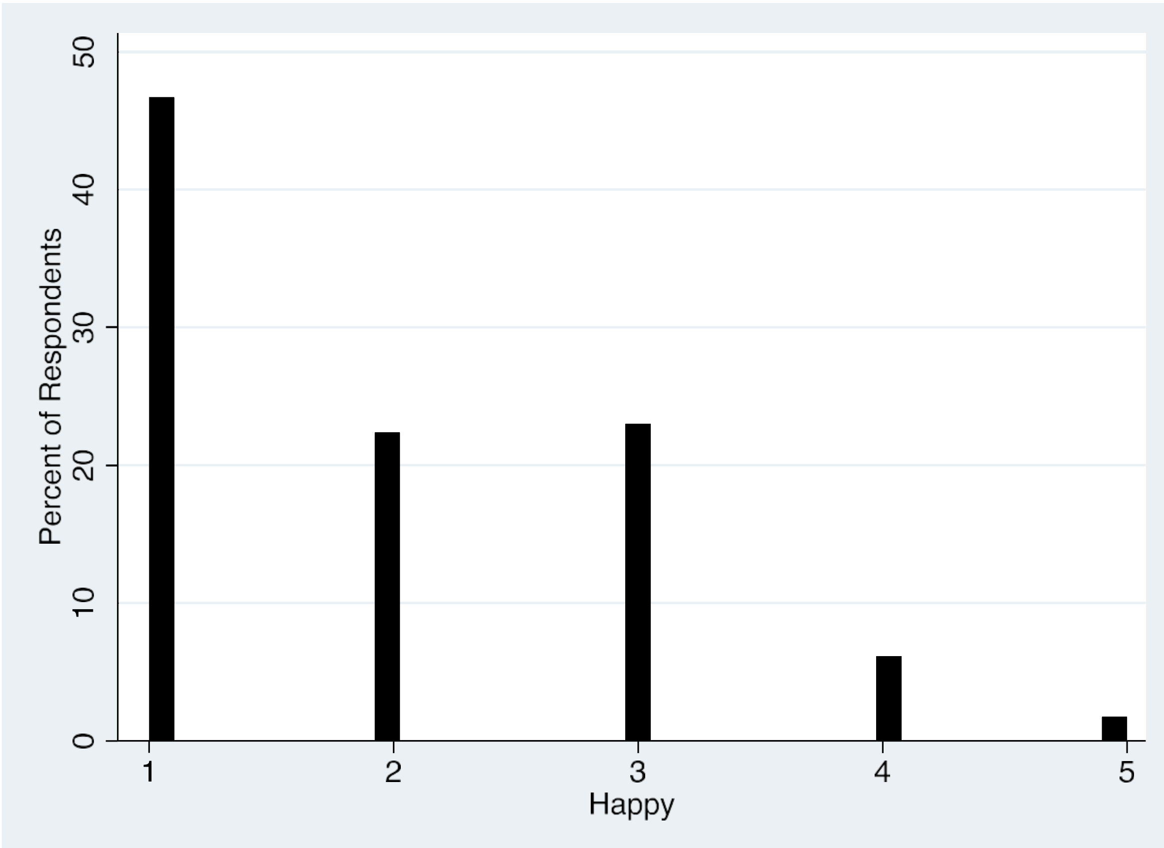

Figure 3.4. Distribution of values on Happy.

Analytic Strategy

To assess the impact of political social media use, I estimate ordered logistic regression models for each dependent variable using as key predictors *Social media use*, *Political posting,* and their interaction (*Social media use x Political posting*). The reason for the usage of an ordered logit regression due to the dependent variables being categorically ordered, I will be using an ordered logit regression to test my hypothesis. This will allow me to determine how much political content an individual engages with on Facebook and Twitter shapes their emotions regarding politics. In particular, the interaction term will indicate whether posting about politics is amplified when someone uses social media more frequently, or inversely, whether social media contributes to increased anger or happiness when it is dominated by more political usage.

Control variables

I include several control variables in my models. First, I include the demographic control variables *Age*, *Education*, *Race*, *Gender*, and *Income*. More information about these control variables can be found in the appendix. Age is controlled within this model due to younger generations more likely to reside on social media sites (Auxier and Anderson 2021). Educational attainment is controlled for because one's educational attainment affects trust in media and ordinary political behavior (Miller and Krosnick 2000). One's race is controlled for because racial groups simply have different history within this country which could have an effect on their political emotions. Gender is controlled for within the model due to men and women exhibiting different political attitudes and behavior (Coffe and Bolzendahl 2010). Lastly, one's income is controlled for because one's income is linked to their political opinions and behavior (Ojeda 2018).

I consider other theoretically motivated control variables as well. My last two control variables are *CNN* and *Fox*. These two control variables measure whether or not each respondent reported going to cnn.com or foxnews.com, respectively, to learn about the election of 2020.

Therefore, they are both binary, with 0 signifying the respondent did not go to the site in question and a 1 otherwise. I include these two variables to control for non-social media political news consumption. I include these two variables within the model to control for non-social media political news consumption. Even though these two variables are not able to control all of the traditional news consumption done by the respondents, my hope is that this will at least provide me with the best possibility to control for those types of behaviors. While the 2020 ANES did ask about other media consumption behaviors, I settled on just controlling for these two sites, due to them being the more stereotypical media usage for Democrats and Republicans. Since this is the case, I do believe just controlling for these two sites will provide me with the best chance of controlling for traditional media consumption behavior.

Findings

Table 3.1 shows the results of the ordered logit regression between *Anger* and the social media variables. *Political posting* did register statistical significance with *Anger*. Table 3.1 shows that those who had a higher amount of time spent on social media posting political content, had a higher probability of expressing more anger when asked about the political state of the country. What is interesting is that *Social media use* was not significant. Figure 3.5 highlights the interaction between *Social media use* and *Political posting*.

Figure 3.5 shows that the probability effects that *Political posting* has on the highest value of *Anger* dissipates slightly as one progresses along to the higher values of *Social media use*. The figure also shows that on the lower values of *Anger*, *Political posting* actually has a negative probability effect, but this effect dissipates as a respondent once again progresses along the higher values of *Social media use*.

Table 3.2 shows the results of an ordered logit regression between *Happy* and the social media variables for the whole 2020 ANES sample. This model reveals that neither *Social media use*

Table 3.1. Ordered Logit Regressions Predicting Anger Values with Political social media use Among All Respondents in the 2020 ANES

Model:	**(1)**
VARIABLES	**Anger**
Social media use	0.0282
	(0.0198)
Political Posting	0.213**
	(0.0997)
Social media interaction	-0.00534
	(0.0119)
Attention	0.416***
	(0.0557)
Fox	0.0710
	(0.129)
CNN	-0.211*
	(0.109)
Party id	-0.365***
	(0.0280)
Gender	0.408***
	(0.0982)
Age	-0.00571*
	(0.00339)
Black	-0.0415
	(0.206)
Hispanic	-0.0299
	(0.181)
Asian or NHOPI	-0.188
	(0.229)
Native American	-0.376
	(0.350)
Multiple races	0.500*
	(0.263)
Education	-0.0704
	(0.0520)
Income	0.00338
	(0.00806)
/cut1	-3.390***
	(0.359)
/cut2	-1.939***
	(0.341)
/cut3	-0.411
	(0.337)

Table 3.1. Continued

Model:	(1)
/cut4	1.087***
	(0.337)
Observations	1,533

Source: 2020 American National Election Studies Survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ (all two-tailed tests)

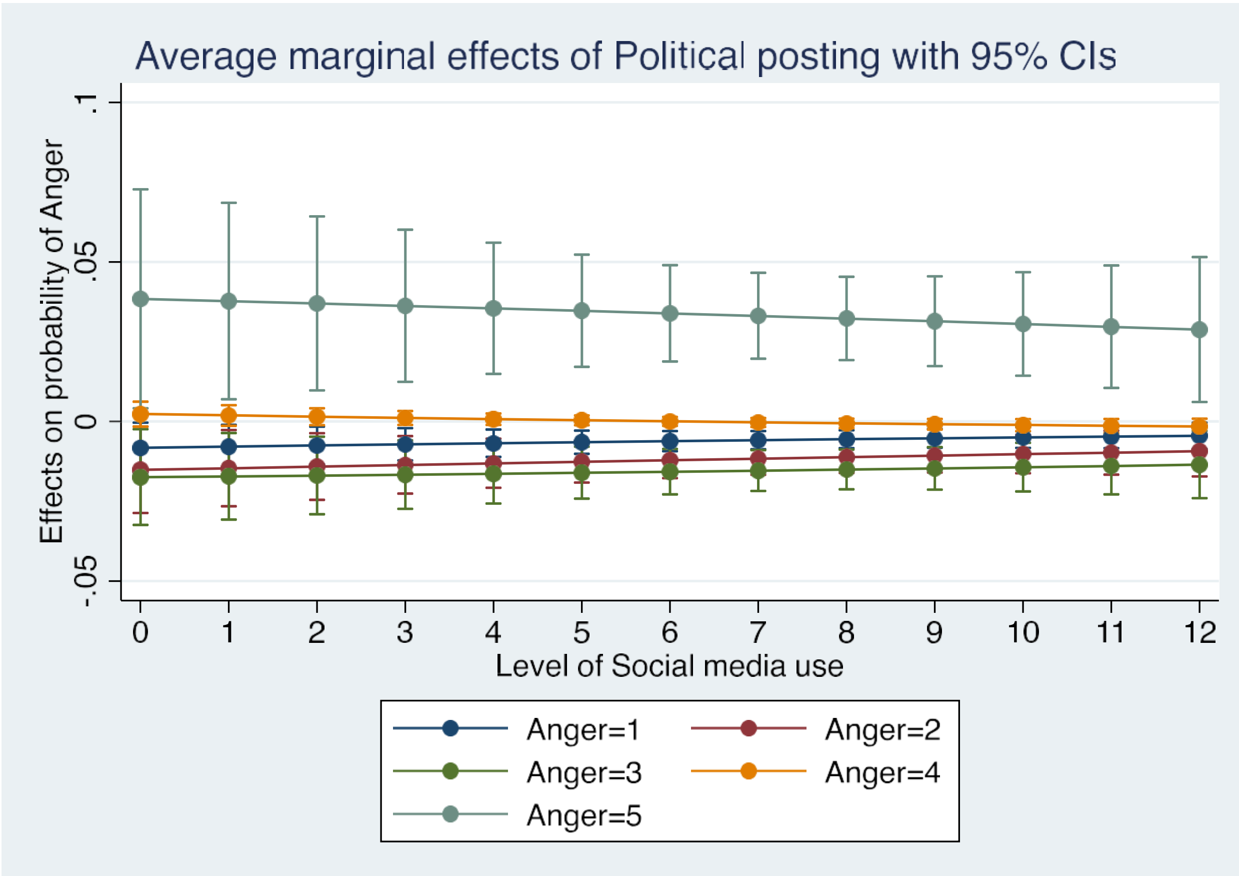

Figure 3.5. Margins plot of Political posting's, at each value of Social media use, effect on the probability of being at each level of Anger

Table 3.2: Ordered Logit Regressions Predicting Happy Values with Political social media use Among All Respondents in the 2020 ANES

Model:	**(1)**
VARIABLES	**Happy**
Social media use	-0.0287
	(0.0212)
Political posting	0.0643
	(0.106)
Social media interaction	-0.00571
	(0.0128)
Attention	-0.135**
	(0.0595)
Fox	0.476***
	(0.136)
CNN	-0.312***
	(0.121)
Party id	0.465***
	(0.0306)
Gender	-0.104
	(0.106)
Age	0.00151
	(0.00373)
Black	-0.407*
	(0.246)
Hispanic	0.255
	(0.193)
Asian or NHOPI	0.528**
	(0.250)
Native American	0.373
	(0.382)
Multiple Races	-0.0519
	(0.282)
Education	0.0732
	(0.0556)
Income	-0.00579
	(0.00860)
/cut1	1.278***
	(0.363)
/cut2	2.609***
	(0.369)
/cut3	4.486***
	(0.386)
/cut4	6.176***

Table 3.2. Continued

Model:	(1)
	(0.436)
Observations	1,533

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

or *Political posting* registered any sort of statistical significance. Therefore, while *Political Posting* has an effect on Anger, which dissipates the more one uses social media, a person's happiness toward the political state of the country is not affected by their social media usage.

Table 3.3 and 3.4 reveals the results of the logit regressions ran on only those identifying with Democrats within the sample. Table 3.3 shows the logit regression on *Anger* and Table 3.4 shows the logit regression on *Happy*. The results mirror the relationship examined above regarding the full sample. *Political posting* once again had a positive effect on Anger and was the only social media variable to record any statistical significance with *Anger* or *Happy*. Therefore, the overall time spent posting political content on social media seems to be the main aspect of social media usage that is affecting the emotional responses of the respondents when asked about the political state of the country. Figure 3.6 shows the effect of *Political posting* on the level of anger one feels about the political state of the country. The distribution is similar to Figure 3.5. However, it does contain a significant difference. It seems that among Democrats, the time spent posting political content on social media has a larger effect on anger than amongst the full sample in the 2020 ANES. Specifically, it seems that *Political posting* increased the probability of being located within the highest level of *Anger*. This probability declined as one's social media use increased.

Tables 3.5 and 3.6 shows the models ran above on just the Republican on the sample, with Table 3.5 containing the results for *Anger* and Table 3.6 contains results for *Happy*. Republicans within the sample show the opposite of what was displayed for all of the respondents sampled combined, and just within those identifying as Democrats. Amongst Republicans, the social media variables did not register a statistically significant relationship with Anger, but *Political posting* did register a positive significant relationship with *Happy*. Therefore, the higher amount of time spent posting political content on social media is associated with a higher level of happiness regarding the political state of the country.

Table 3.3. Ordered Logit Regressions Predicting Anger Values with Political social media use Among All Democrats in the 2020 ANES.

Model:	**(1)**
VARIABLES	**Anger**
Social media use	0.0289
	(0.0285)
Political posting	0.353**
	(0.140)
Social media interaction	-0.00993
	(0.0162)
Attention	0.476***
	(0.0816)
Fox	-0.123
	(0.228)
CNN	-0.0772
	(0.139)
Gender	0.575***
	(0.140)
Age	-0.00475
	(0.00474)
Black	0.0244
	(0.232)
Hispanic	-0.375
	(0.233)
Asian or NHOPI	-0.214
	(0.294)
Native American	-0.333
	(0.577)
Multiple Races	0.414
	(0.345)
Education	0.0114
	(0.0766)
Income	-0.00357
	(0.0112)
/cut1	-2.941***
	(0.626)
/cut2	-0.796*
	(0.468)
/cut3	0.802*
	(0.455)
/cut4	2.473***
	(0.463)

Table 3.3. Continued

Model:	**(1)**
Observations	848

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

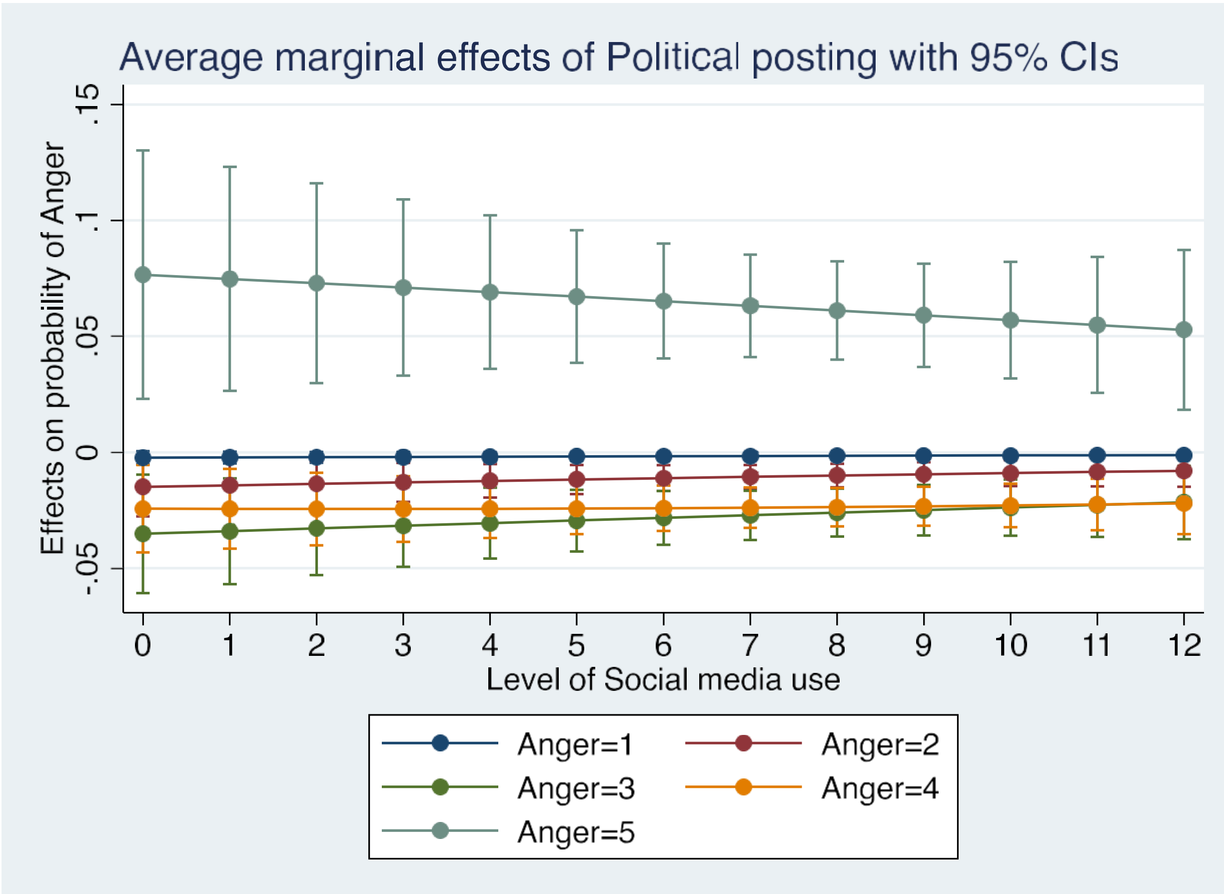

Figure 3.6. Margins plot of Political posting's, at each value of Social media use, effect on the probability of being at each level of Anger for only Democrats within the sample.

Table 3.4. Ordered Logit Regressions Predicting Happy Values with Political social media use Among All Democrats in the 2020 ANES.

Model:	**(1)**
VARIABLES	**Happy**
Social media use	-0.0191
	(0.0332)
Political posting	-0.0369
	(0.149)
Social media interaction	-0.00380
	(0.0175)
Attention	-0.251***
	(0.0908)
Fox	0.404
	(0.251)
CNN	-0.158
	(0.161)
Gender	-0.101
	(0.161)
Age	-0.00888
	(0.00565)
Black	-0.649**
	(0.301)
Hispanic	0.504**
	(0.257)
Asian or NHOPI	0.552*
	(0.314)
Native American	0.279
	(0.707)
Multiple races	-0.373
	(0.416)
Education	0.107
	(0.0897)
Income	-0.00714
	(0.0126)
/cut1	-0.366
	(0.522)
/cut2	1.495***
	(0.531)
/cut3	3.724***
	(0.655)

Table 3.4. Continued

Model:	**(1)**
Observations	848

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 3.5. Ordered Logit Regressions Predicting Anger Values with Political social media use Among All Republicans in the 2020 ANES.

Model:	**(1)**
VARIABLES	**Anger**
Social media use	0.000822
	(0.0314)
Political posting	0.00224
	(0.176)
Social media interaction	0.00489
	(0.0227)
Attention	0.284***
	(0.0887)
Fox	0.258
	(0.175)
CNN	-0.446**
	(0.208)
Gender	0.0693
	(0.159)
Age	0.000464
	(0.00550)
Black	-0.854
	(0.947)
Hispanic	0.0944
	(0.377)
Asian or NHOPI	-0.228
	(0.461)
Native American	-0.309
	(0.530)
Multiple races	0.188
	(0.488)
Education	-0.0906
	(0.0801)
Income	0.00404
	(0.0136)
/cut1	-1.617***
	(0.503)
/cut2	-0.293
	(0.490)
/cut3	1.245**
	(0.494)
/cut4	2.631***
	(0.504)

Table 3.5. Continued

Model:	**(1)**
Observations	544

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table 3.6. Ordered Logit Regressions Predicting Happy Values with Political social media use Among All Republicans in the 2020 ANES.

Model:	**(1)**
VARIABLES	**Happy**
Social media use	-0.0157
	(0.0312)
Political posting	0.449**
	(0.196)
Social media interaction	-0.0351
	(0.0258)
Attention	-0.0393
	(0.0909)
Fox	0.539***
	(0.179)
CNN	-0.592***
	(0.213)
Gender	-0.0325
	(0.160)
Age	0.00412
	(0.00561)
Black	0.447
	(0.911)
Hispanic	0.0777
	(0.365)
Asian or NHOPI	-0.0728
	(0.500)
Native American	0.275
	(0.525)
Multiple races	0.366
	(0.481)
Education	-0.0495
	(0.0810)
Income	-0.00606
	(0.0133)
/cut1	-1.245**
	(0.505)
/cut2	-0.154
	(0.501)
/cut3	1.708***
	(0.509)
/cut4	3.440***
	(0.552)

Table 3.6. Continued

Model:	**(1)**
Observations	544

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Figure 3.7 shows the full effect distribution of *Political posting* on *Happy* at every level of *Social media use*. It seems that having a higher level of *Political posting* increased the chances of being located within the three highest values of *Happy*, but this probability declined as one's time spent on social media use increased. *Political posting* had a negative probability effect with the lowest two levels of *Happy*, with that effect declining once more as one's time on social media increased.

Conclusion

This study analyzed how social media use affects individuals' feelings about how the country is going. Through the use of the 2020 ANES survey, I found mixed support for my hypothesis that the more an individual engages with political content on Twitter and Facebook, the more anger and less happiness they will feel about the state of the country, politically. While none of the social media variables have any significance with a respondent's happiness, the more time one spends posting political content online did have a significant effect on a person's anger. Thus, the higher the amount of time posting political content online, the more likely one is to express anger toward the political state of the country. However, this effect waned the more time one spent on social media in general.

However, when the respondents were separated into the two political party camps, we saw a stark difference in how engaging with online political content affects individuals. We saw Democrats' anger increased the more time they spent posting political content online, but neither of the social media variables had any effect on Democrat's happiness. The opposite was the case for Republicans within the example. While none of the social media variables had any effect on Republican anger, the results show that as the overall time spent posting political content online increased so did Republican happiness. This finding is quite perplexing.

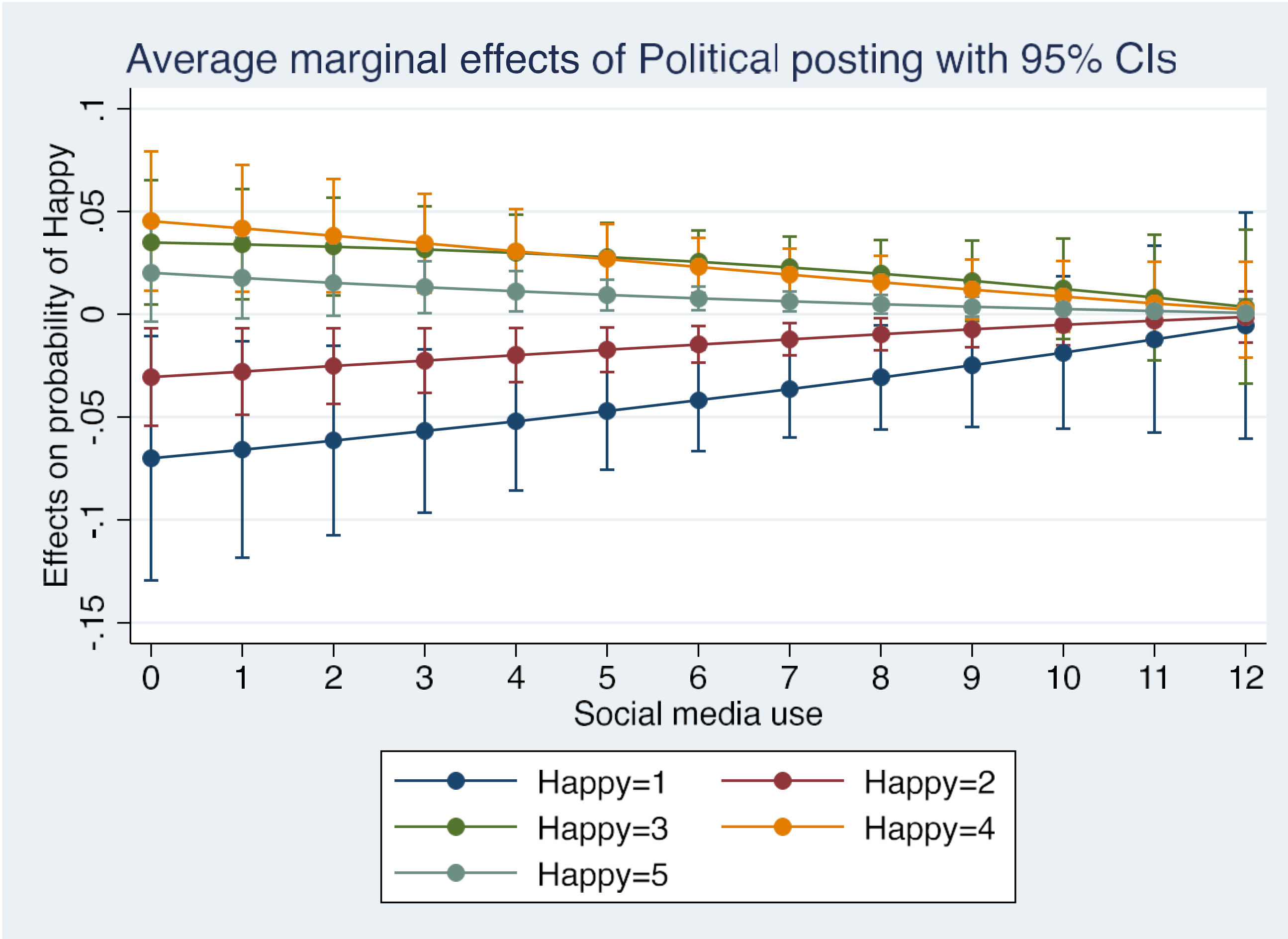

Figure 3.7. Margins plot of Political posting's, at each value of Social media use, effect on the probability of being at each level of Happy for only Republicans within the sample

This finding could have been produced due to differences in political narratives being used by the two different political party bases. Perhaps, the Democratic narratives centered around anger emotions more, and Republicans centered around happiness. Future studies should analyze the difference in emotions used online by the two different ideological camps.

More studies are needed to help us understand how political social media use affects public opinion and the overall political world. As the ability to understand how social media feeds are constructed, and our ability to analyze these feeds through social media company's API becomes stronger, then more studies should be conducted to further our knowledge on how social media affects individuals.

This study has limitations. For one, my measurement of political Twitter and Facebook use might not be 100% accurate. This is due to the statistics used being self-reported measures. Further, while I do believe that my measurement is accurate, it might not fully represent how people are using these two social media sites. It might be the case for some respondents that they go on social media to post political content, but they do not stay to read other posts. If this is the case, then they might not be affected by these types of posts as much as others who regularly get exposed to these posts. Future studies should seek to rectify these limitations and get closer to an individual's true social media behavior.

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CONCLUSION

With this dissertation, I set out to further our collective understanding of overall media effects by looking specifically at the newest form of media to take over the political world – social media. I did so by analyzing three distinctly different concepts. In particular, I analyzed how social media affects an individual's party evaluations, how individuals evaluate political candidates, and an individual's political emotions. These three concepts are both mathematically and theoretically different. Table C.1 shows that these variables are not closely correlated. Thus, each dependent variable likely measures something different. The highest correlation is between *In-party president* and *Out-party president* (- 0.60). All other correlations are just at or below 0.5. This correlation matrix shows that each paper examines a mathematically distinct political phenomenon.

To be clear, theoretically, these three concepts are also quite different. Polarization, in particular, affective polarization, measures the tendency of individuals who identify with a political party and view opposing partisans negatively and their fellow co-partisans positively. In contrast, an individual's candidate evaluation measures how respondents simply view and rate individual candidates for public office. Lastly, one's political emotion measures how one is feeling, within this dissertation these emotions are anger and happiness, toward politics. While an individual's polarization could affect their emotions and candidate evaluations, research shows that is not the only thing, meaning partisanship or polarization, that has a large effect on an individual's emotions or how they evaluate political candidates. As mentioned in Article III, while polarization could make one feel more anger toward the political state of the country, it certainly is not the only thing being affected by one's political emotions.

Table C.1. Correlation Matrix of Dependent Variables.

Variable	Out-Party Rating	In-Party Rating	Out-Party President	In-Party President	In-Party House	Out-Party House	Anger	Happy
Out-Party Rating	1							
In-Party Rating	-0.273	1						
Out-Party President	0.504	-0.296	1					
In-Party President	-0.391	0.548	-0.600	1				
In-Party House	-0.244	0.307	-0.249	0.411	1			
Out-Party House	0.325	-0.114	0.349	-0.218	-0.219	1		
Anger	-0.201	0.0324	-0.271	0.107	0.103	-0.105	1	
Happy	0.0257	0.131	0.166	0.0629	0.0257	0.0218	-0.471	1

The theory of emotional contagion suggests that the negative emotional tenor of social media posts could have an effect on individuals' emotions (Coviello et al. 2014). Not only that, but past media effects studied such as priming, framing, can also have a large effect on the emotions of the viewer of news, whether that is through radio, television, or social media (Krosnick and Brannon 1993; Kosicki 1993; Duyn and Collier 2018). While the theories highlighted in Article III put to light how polarization and political emotions are two different concepts, Article II highlights the difference between polarization and candidate evaluations. Again, polarization can have an effect on how individuals evaluate candidates, but this is not the only thing that could be causing that to happen. In particular, how the media one intakes portray candidates can have a large effect on how individuals evaluate political candidates (Eberl et al. 2016; Kiousis 2004; Miller and Krosnick 2000). Thus, if one takes in the majority of their candidate portrays through social media, then this could have an effect on how one evaluates and rates a candidate for public office, not just simply what their party identification is, or if they are highly polarized. Thus, this dissertation measures the effects of social media usage on candidate evaluations and political emotions, not the effects of polarization on evaluations and emotions as a by-product of their social media usage.

Not only did this dissertation measure how social media usage can affect three distinctly different political concepts, but it also added valuable knowledge to the overall discipline of Political Science, and to the study of media effects. Paper I showed that the more time spent posting political content online, the larger of a gap a respondent would have between their ratings of the Democrat and Republican parties. Furthermore, this posting effect, lessens the more time a respondent spent on social media in general. This adds a considerable amount of understanding of how the media, in particular social media, to the discipline. It is a common theme throughout the mass media that social media is increasing polarization. While some originally theorized that this polarization effect was due to echo-chambers being abundant on these platforms (Sunstien 2017), as more research is done on this topic it is becoming apparent that echo chambers are not as abundant as once thought (Dubois and Blank 2018). Due to these newly forming findings, it is of great interest to ponder once more to see why, how, and if social media is actually causing polarization to increase. Paper I has been able to help in this endeavor by showing how individuals use these platforms can cause variation in polarization within the general populace. Future studies should be able to use these findings to further test if and how social media is causing polarization to increase.

Paper II further helps the discipline along in its pursuit of knowledge regarding social media effects. In this paper it was found that as the overall amount of time spent posting political content online increases, the more likely a respondent is to rate the opposing party's presidential candidate lower. Once again, as the time one spends on social media in general increases, this posting effect lessens. Interestingly, this analysis showed that evaluations for candidates running for the House were more affected by one's social media usage in comparison to presidential candidate evaluations. The analysis showed that the amount of time spent posting political content on Twitter and Facebook positively affected one's rating of their in-party House candidate, negatively affected their rating of their out-party House candidate and even significantly increased the gap between these two ratings. However, much like the presidential ratings, the effect that posting political content had on candidate ratings lessened the more one spent on these sites in general.

Paper II's contribution is two-fold. For one, the notion that social media affects evaluations of House candidates more than evaluations of presidential candidates is a very interesting finding with huge ramifications for our political world. It is well known that local media used to be the number one source of information pertaining to members of Congress, while the national news was the number one source for news regarding the presidency. With the recent rumblings of the death and nationalization of local news, which brings with it less reporting on members of Congress, questions have been arising within Political Science asking what this new media atmosphere will mean for those running for Congress. For instance, Petrova, Sen and Yildirim analyzed how social media has affected the incumbency advantage and found that social media use by congressional challengers could help them increase their donations, which could put them in a better position to win over an incumbent. Furthermore, the notion of how social media would affect candidate perceptions was analyzed by Dimitrova and Bystrom (2013) and it was found that social media can drastically affect candidate perceptions in comparison to traditional news sources. The analysis within Paper II adds to this fast growing literature by showing that evaluations of House candidates seem to be affected more by social media use than evaluations for those running for president.

The second main contribution Paper II's analysis brings to the discipline is the notion of social media increasing the dislike of out-party presidential candidates more than social media is increasing the like of in-party presidential candidates. This finding adds to other findings within the discipline that shows social media containing more negative emotions than positive ones and provides a potential answer to what has been increasing anger toward political figures in recent years (Christenson and Weisberg 2019; Fiorina et al. 2005; Jacobson 2007; Baufumi and Shapiro 2009).

The third and last paper within this dissertation further adds to the discipline's knowledge just as the first two papers were able to accomplish. Paper III's analysis shows how as one's amount of time spent on social media posting political content increased, the more anger they felt regarding the political state of the country, but one's time spent posting political content did not affect one's happiness. Once again, this paper's analysis showed that while one's political posting habits were able to affect the anger a respondent feels, this effect was lessened the more time a respondent spent on social media in general. These findings not only add to Political Science by providing a possible answer to what has been causing political anger to be increasing in the United

States, but it also helped illuminate how the posts most abundant on Twitter and Facebook is affecting its users (Dunn 2020; Hao 2021; Stieglitz and Dang-Xuan 2013).

When put together, the three articles presented within this dissertation adds tremendous knowledge to the long-lasting study of media effects in Political Science by providing more support for the Cultivation Theory of media effects. There are various schools of thought on if and how the media is able to affect individual opinions. Originally there was the hypodermic needle theory that hypothesized that the media had tremendous persuasive effects that had the power to change minds almost instantaneously (Iyengar 2017). Then came the minimal effects theory which suggested that the media had little to no influence on opinions due to individuals bringing their predispositions and already held beliefs with them whenever they are exposed to media (Iyengar 2017). Then there is the Columbia school of thought which states that the media can influence opinions, but this is going to be mainly reliant on the interpersonal context between the giver of the information and the receiver. Not only will this interpersonal context affect how one takes in media information, but the selective exposure to like-minded information is also a huge factor within this school of thought (Iyengar 2017).

However, the findings presented within this dissertation sits best within the cultivation theory of media effects. This theory states that it takes time for the effects of the media to take hold within an individual (Gerbner et al. 2002). Thus, for the media to have any effect on the viewer, the viewer must be exposed to the media's content quite often and regularly. Per this theory then, an individual who watches Fox News once will not have their opinion altered by the media source, but an individual who watches Fox News every day for over a year could start to see their opinions being altered. This theory pairs nicely with what has been found within psychology. Much like the cultivation theory, studies within psychology have shown that with no exposure to media, there can be no persuasive effects of the media (McGuire, W.J. 1968).

The findings within the three papers of this dissertation supply supporters of the cultivation theory with more evidence to their position. All three articles highlighted how the more one posted political content online, the more effect social media had on the individual's polarization, candidate evaluation and political emotions. Thus, due to social media algorithms curating every newsfeed with content individuals have posted and interacting with in the past, it seems that those who post more political content will also see more political content. Therefore, per the cultivation theory, the more an individual was exposed to political content on social media, the more likely they were affected by said content. However, what is most interesting about this theory, is that these articles also show that the more time an individual spent on social media in general, lessened the effect that political social media use had on the respondents. This special finding might have been produced because the more one scrolls down their newsfeed, instead of just looking at the top content on said feed, the less curated information a social media user has. Thus, even if these individuals viewed the political content at the top of their feeds due to them interacting with such content, the witnessing of non-political content might actually lessen the effects that the original political content had. More research should be completed to see if the same phenomenon occurs in the traditional news. For instance, does the human interest story at the end of every nightly newscast take away the effects that the political information that aired at the top of the newscast had on the news viewer? Answers to these sorts of questions can further our collective knowledge on how social media, and the media in general, affects media viewers.

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APPENDIX

Coding of Variables for all three papers

Age (respondent's actual age).

Education (1-Less than high school diploma, 2-High school credential, 3-Some post-high, 4-Bachelor's degree, 5- graduate degree).

Race (1=White, non-Hispanic; 2=Black, non-Hispanic; 3=Hispanic; 4=Asian or Native Hawaiian/other Pacific Islander; 5=American Indian or Alaska Native 6=Multiple races, non-Hispanic).

Gender (0-Male, 1-Female).

*Incom*e (1= "below $9,999," 2= "$10,000-$14,999", 3= "$15,000-$19,999" 4="20,000-$24,999" 5="25,000-$29,999" 6="$30,000-$34,999" 7="$35,000-39,999" 8="$40,000-$44,999" 9="$45,000-$49,999" 10="$50,000-$59,999" 11="$60,000-$64,999" 12="$65,000-$69,999" 13="$70,000-$74,999" 14="$75,000-$79,999" 15="$80,000-$89,999" 16="$90,000-$99,999" 17="$100,000-$109,999" 18="$110,000-$124,999" 19="$125,000-$149,999" 20="$150,000-$174,999" 21="$175,000-$249,999" 22="$250,000 or more").

Auxiliary Models for Paper I

Tables A.1, A.2, and A.3 show the results of auxiliary regressions looking at *Political Twitter Use* and *Political Facebook Use*, instead of them combined as was the case with my main independent variable above in the main analysis. Since Twitter users differ in comparison to Facebook users in regard to age (Widner, Macdonald and Gunderson 2022) and the fact that Facebook is different than Twitter in major key areas such as look, length of posts, and even algorithmically, it is important to further test the relationship between political social media use on partisan evaluations, but this time separating the two social media sites within the analysis.

Table A.1. OLS Regressions Predicting Party Ratings with Twitter and Facebook Political Social Media Use Among All Respondents in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Rating**	**In Party Rating**	**Party Rating Difference**
Twitter Use	0.387	-0.0980	-0.284
	(0.526)	(0.631)	(0.923)
Twitter Posting	-0.183	2.846*	0.404
	(1.514)	(1.496)	(2.473)
Twitter Political Use	-0.253	-0.335	0.0999
	(0.256)	(0.281)	(0.453)
Facebook Use	0.955	0.152	-0.0658
	(0.752)	(0.829)	(1.043)
Facebook Posting	2.393	-0.0622	3.861
	(3.556)	(2.794)	(3.112)
Facebook Political Use	-0.773	0.231	0.158
	(0.553)	(0.473)	(0.551)
Attention	-3.763***	1.633*	6.446***
	(0.704)	(0.864)	(1.276)
Party ID	0.213	0.167	-0.0285
	(0.359)	(0.392)	(0.580)
Fox	2.778	1.169	0.203
	(1.907)	(1.933)	(2.765)
CNN	2.116	-0.00164	-1.172
	(1.405)	(1.478)	(2.081)
Gender	-0.231	3.973***	3.238
	(1.215)	(1.410)	(2.052)
Age	0.0346	0.0702	0.0951
	(0.0421)	(0.0514)	(0.0769)

Table A.1. Continued

Models:	(1)	(2)	(3)
Black	1.937	5.584**	2.260
	(2.405)	(2.630)	(3.977)
Hispanic	4.663*	5.427*	-6.818
	(2.504)	(2.956)	(4.266)
Asian or NHOPI	2.018	1.470	-2.886
	(3.341)	(3.507)	(4.904)
Native American	9.784	-8.588	-14.27*
	(6.754)	(6.552)	(7.626)
Multiple Races	-1.201	0.954	0.864
	(3.362)	(2.916)	(5.842)
Education	1.404**	-2.327***	-2.352**
	(0.663)	(0.776)	(1.081)
Income	-0.194*	-0.0373	0.442***
	(0.102)	(0.122)	(0.168)
Constant	21.81***	60.07***	17.03*
	(5.934)	(7.281)	(9.011)
Observations	1,387	1,388	1,521
R-squared	0.098	0.064	0.125

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.2. OLS Regressions Predicting Party Ratings with Twitter and Facebook Political Social Media Use Among All Democrats in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Rating**	**In Party Rating**	**Party Rating Difference**
Twitter Use	0.0452	0.383	0.000419
	(0.587)	(0.766)	(0.992)
Twitter Posting	0.806	2.664*	1.308
	(1.570)	(1.407)	(2.313)
Twitter Political Use	-0.224	-0.395	-0.0253
	(0.275)	(0.286)	(0.422)
Facebook Use	1.680**	0.589	-1.141
	(0.838)	(1.123)	(1.270)
Facebook Posting	3.254	1.053	-2.945
	(2.909)	(3.069)	(3.496)
Facebook Political Use	-0.937*	-0.167	0.851
	(0.494)	(0.554)	(0.632)
Attention	-3.994***	2.833**	6.550***
	(0.867)	(1.165)	(1.546)
Fox	18.81***	-9.914***	-22.84***
	(2.773)	(2.921)	(3.615)
CNN	-2.011	4.571***	5.427**
	(1.351)	(1.716)	(2.152)
Gender	0.610	3.382*	2.845
	(1.412)	(1.764)	(2.265)
Age	0.0546	0.110*	0.106
	(0.0524)	(0.0639)	(0.0927)
Black	1.113	9.132***	6.497*
	(2.189)	(2.660)	(3.874)

Table A.2. Continued

Models:	**(1)**	**(2)**	**(3)**
Hispanic	2.813	9.990***	6.053
	(2.562)	(3.520)	(4.757)
Asian or NHOPI	3.261	6.663	2.327
	(3.167)	(4.189)	(4.281)
Native American	4.521	-0.717	-6.547
	(6.843)	(7.873)	(9.571)
Multiple Races	-1.960	5.839*	6.921
	(3.615)	(3.521)	(5.002)
Education	0.492	-1.085	-1.738
	(0.768)	(1.042)	(1.327)
Income	-0.231*	-0.0832	0.155
	(0.122)	(0.161)	(0.202)
Constant	22.43***	45.60***	25.74***
	(6.441)	(8.805)	(9.523)
Observations	846	847	845
R-squared	0.195	0.117	0.170

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.3. OLS Regressions Predicting Party Ratings with Twitter and Facebook Political Social Media Use Among All Republicans in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Rating**	**In Party Rating**	**Party Rating Difference**
Twitter Use	0.766	0.123	0.923
	(1.027)	(1.063)	(1.518)
Twitter Posting	-3.748	4.823	7.203
	(3.448)	(3.621)	(4.561)
Twitter Political Use	0.149	-0.703	-1.507
	(0.615)	(0.697)	(0.943)
Facebook Use	0.104	-0.753	0.387
	(1.144)	(0.974)	(1.279)
Facebook Posting	3.561	-2.345	4.001
	(6.276)	(3.760)	(3.738)
Facebook Political Use	-0.861	0.888	0.371
	(0.911)	(0.612)	(0.671)
Attention	-2.734***	-0.473	2.606
	(1.035)	(1.212)	(1.634)
Fox	-8.390***	8.677***	11.17***
	(2.112)	(2.094)	(2.739)
CNN	13.35***	-12.27***	-14.03***
	(3.137)	(2.677)	(3.126)
Gender	-0.139	2.718	4.109
	(2.018)	(2.055)	(2.866)
Age	0.0206	-0.0302	0.0391
	(0.0633)	(0.0739)	(0.0966)
Black	-17.49**	9.744**	17.55
	(8.146)	(4.959)	(11.20)

Table A.3. Continued

Models:	**(1)**	**(2)**	**(3)**
Hispanic	6.764	-2.458	-3.702
	(6.416)	(4.876)	(8.595)
Asian or NHOPI	-2.229	-9.046	-9.896
	(6.487)	(6.382)	(10.59)
Native American	15.02	-16.31*	-24.03*
	(9.927)	(9.449)	(12.44)
Multiple Races	4.220	-10.10*	-8.595
	(4.627)	(5.879)	(8.227)
Education	1.766*	-2.838***	-4.999***
	(1.022)	(0.913)	(1.351)
Income	-0.0308	-0.0906	0.156
	(0.160)	(0.170)	(0.225)
Constant	23.66***	78.97***	40.04***
	(8.310)	(8.118)	(11.04)
Observations	541	541	539
R-squared	0.192	0.173	0.227

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Twitter Use is the amount of time a respondent spends on Twitter in general. It is the response each respondent gave to the question: "How often do you use Twitter?" The response set for both items was: 1 = "less than once a month," 2 = "once or twice a month," 3 = "about once a week," 4 = "a few times each week," 5 = "once a day," 6 = "a few times every day," and 7 = "many times every day." *Facebook Use* is the amount of time a respondent spends on Facebook in general and it is the response each respondent gave to the question: "How often do you use Facebook?" The response set for this item was: 1 = "less than once a month," 2 = "once or twice a month," 3 = "about once a week," 4 = "a few times each week," 5 = "once a day," 6 = "a few times every day," and 7 = "many times every day."

Twitter Posting measures how often an individual posts political content on Twitter and *Facebook Posting* measures how often an individual posts political content on Facebook. To contain values for both variables, each respondent was asked: (1) "How often do you post political content on Twitter?" and (2) "How often do you post political content on Facebook?" respectively. The response set for both items was as follows: 1 = "never," 2 = "sometimes," 3 = "about half of the time," 4 = "most of the time," and 5 = "always." Thus, the range of these variables are 1-5. *Twitter Political Use* is the interaction measure of *Twitter Use* and *Twitter Posting* and *Facebook Political Use* is the interaction measure of *Facebook Use* and *Facebook Posting*. The dependent and control variables within all three models are the same variables from the main regression analysis above.

Table A.1 shows that only *Twitter Posting* has a statistically significant effect on any of the three dependent variables and the only significant relationship it has is with *In Party Rating*. Neither *Twitter Use* nor the *Twitter Political Use* registered any significance with the dependent variables. Table A.4 shows the effects that *Political Twitter Use* has on *In Party Rating* within

Table A.4. Marginal Effects of Twitter Posting at Each Level of Twitter Use on Party Rating Difference

Model:	**(1)**
Twitter Posting at each level of Twitter Use |	**In Party Rating**
1	2.269*
	(1.187)
2	1.874*
	(1.002)
3	1.478*
	(0.872)
4	1.083
	(0.826)
5	0.688
	(0.876)
6	0.293
	(1.008)
7	-0.102
	(1.195)
Observations	847

every level of *Twitter U*se. *Twitter Posting* only has a positive significant effect on *In Party Rating* within the first three values of *Twitter Us*e. After that, the significance of *Twitter Posting* disappears. This once again highlights that the more time spent on a social media site, in this particular instance Twitter, is dampening the effect that the time spent on Twitter posting political content is having on an individual's rating of their in party.

Table A.5 analyzes *Twitter* and *Facebook Political Use* only within Democrats in the sample. Most notably within the table is Model 1. *Facebook Use* had a significant and positive relationship with *Out Party Rating*, showing that as one increases in value of *Facebook U*se, their rating of their out party actually increases by 1.68 points. Table A.6 shows the coefficients for the effects of *Facebook U*se at each level of *Facebook Posting*. The only level which shows a significant effect is when *Facebook Use* is at the largest value of *Facebook Posting*, which correlates to the largest amount of time spent on Facebook posting political content. Therefore, for Democrats, the more one uses social media and as their amount of time posting political content increases on Facebook, the lower the rating of the Republican Party.

Table A.7 shows the reverse relationship, *Facebook Posting's* effects on *Out Party Rating* at each level of *Facebook U*se. Similar to Table A.6, Table A.7 shows that *Facebook Posting* only has a significant effect on *Out Party Rating* at the two largest values of *Facebook Use*. Thus, for Democrats, the amount of political Facebook posts they make matter and not necessarily the amount of time spent posting political content on Facebook. Table A.3 shows the same analysis, but just amongst those identifying as Republicans in the sample. Neither of the Posting or Usage variables for Facebook and Twitter registered any significance. It is interesting that separating the analysis between Facebook and Twitter for Republicans erases any of the effects that social media posting, or usage has, but we did not see this within the Democrats in the sample.

Table A.5. OLS Regressions Predicting Party Ratings with Twitter and Facebook Political Social Media Use Among All Democrats in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	Out Party Rating	In Party Rating	Party Rating Difference
Twitter Use	0.0452	0.383	0.000419
	(0.587)	(0.766)	(0.992)
Twitter Posting	0.806	2.664*	1.308
	(1.570)	(1.407)	(2.313)
Twitter Political Use	-0.224	-0.395	-0.0253
	(0.275)	(0.286)	(0.422)
Facebook Use	1.680**	0.589	-1.141
	(0.838)	(1.123)	(1.270)
Facebook Posting	3.254	1.053	-2.945
	(2.909)	(3.069)	(3.496)
Facebook Political Use	-0.937*	-0.167	0.851
	(0.494)	(0.554)	(0.632)
Attention	-3.994***	2.833**	6.550***
	(0.867)	(1.165)	(1.546)
Fox	18.81***	-9.914***	-22.84***
	(2.773)	(2.921)	(3.615)
CNN	-2.011	4.571***	5.427**
	(1.351)	(1.716)	(2.152)
Gender	0.610	3.382*	2.845
	(1.412)	(1.764)	(2.265)
Age	0.0546	0.110*	0.106
	(0.0524)	(0.0639)	(0.0927)
Black	1.113	9.132***	6.497*
	(2.189)	(2.660)	(3.874)
Hispanic	2.813	9.990***	6.053
	(2.562)	(3.520)	(4.757)
Asian or NHOPI	3.261	6.663	2.327
	(3.167)	(4.189)	(4.281)
Native American	4.521	-0.717	-6.547
	(6.843)	(7.873)	(9.571)
Multiple Races	-1.960	5.839*	6.921
	(3.615)	(3.521)	(5.002)
Education	0.492	-1.085	-1.738
	(0.768)	(1.042)	(1.327)
Income	-0.231*	-0.0832	0.155
	(0.122)	(0.161)	(0.202)
Constant	22.43***	45.60***	25.74***
	(6.441)	(8.805)	(9.523)

Table A.5. Continued

Models:	**(1)**	**(2)**	**(3)**
Observations	846	847	845
R-squared	0.195	0.117	0.170

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.6. Marginal Effects of Facebook Use at Each Level of Facebook Posting on Out Party Rating

Model:	**(1)**
Facebook Use at each level of Facebook Posting |	**Out Party Rating**
1	0.743
	(0.465)
2	-0.193
	(0.468)
3	-1.129
	(0.842)
4	-2.066
	(1.298)
5	-3.002*
	(1.775)
Observations	846

Table A.7. Marginal Effects of Facebook Posting at Each Level of Facebook Use on Out Party Rating

Model:	**(1)**
Facebook Posting at each level of Facebook Use |	**Out Party Rating**
1	2.317
	(2.440)
2	1.381
	(1.983)
3	0.444
	(1.548)
4	-0.491
	(1.162)
5	-1.428
	(0.890)
6	-2.364***
	(0.849)
7	-3.301***
	(1.066)
Observations	846

Auxiliary Regressions for Paper II

Tables A.8 through A.13 show the auxiliary regressions computed looking at *Facebook Political Use* and *Twitter Political Use* separately to see how they affect candidate evaluations on their own. As mentioned in Paper I, past research has shown that these two social media sites differ in key fundamental ways which leads to the necessity to see if these differences change how political social media use affects candidate evaluations (Widner, Macdonald and Gunderson 2022).

Twitter Use and *Facebook Use* measures the amount of time each respondent spends on Twitter and Facebook respectively. To record values for these variables, each respondent was asked the questions: "How often do you use Twitter?" and "How often do you use Facebook?" The respondents could give one of the following answers for both questions: 1 = "less than once a month," 2 = "once or twice a month," 3 = "about once a week," 4 = "a few times each week," 5 = "once a day," 6 = "a few times every day," and 7 = "many times every day."

Twitter Posting and *Facebook Posting* measures how often each respondent posts political content on Twitter and Facebook when they do use each site. Each respondent was asked: "How often do you post political content on Twitter?" and "How often do you post political content on Facebook?" A respondent could give one of the following answers: 1 = "never," 2 = "sometimes," 3 = "about half of the time," 4 = "most of the time," and 5 = "always." All models also contain an interaction term for both Facebook and Twitter, labeled *Facebook Political Use* and *Twitter Political Use,* respectively.

Table A.8. OLS Regressions Predicting Presidential Candidate Ratings with Twitter and Facebook Political Use Among All Respondents in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Press Rating**	**In Party Press Rating**	**Party Rating Difference**
Twitter Use	0.582	-0.743	-1.408
	(0.564)	(0.661)	(1.054)
Twitter Posting	1.243	-0.166	-1.425
	(1.711)	(1.734)	(2.539)
Twitter Political Use	-0.368	0.348	0.747
	(0.293)	(0.308)	(0.459)
Facebook Use	0.163	-0.510	-0.702
	(0.781)	(0.802)	(1.325)
Facebook Posting	-1.445	1.422	2.735
	(2.703)	(2.507)	(4.402)
Facebook Political Use	-0.351	0.390	0.763
	(0.445)	(0.437)	(0.744)
Attention	-2.261***	1.832**	4.097***
	(0.787)	(0.888)	(1.417)
Party ID	3.555***	-1.043**	-4.616***
	(0.418)	(0.450)	(0.747)
Fox	-3.257	3.551	6.979*
	(2.202)	(2.175)	(3.781)
CNN	2.677*	-1.171	-3.655
	(1.415)	(1.688)	(2.563)
Gender	-0.540	0.936	1.573
	(1.478)	(1.531)	(2.516)
Age	0.0489	0.174***	0.126
	(0.0532)	(0.0548)	(0.0909)
Black	-1.657	1.859	3.098
	(1.769)	(2.550)	(3.219)
Hispanic	3.917	-3.594	-8.298*
	(2.668)	(2.744)	(4.594)
Asian or NHOPI	0.0545	1.856	1.844
	(3.765)	(4.676)	(7.704)
Native American	-3.626	4.366	8.020
	(6.533)	(5.305)	(10.74)
Multiple Races	-3.407	-1.019	2.341
	(3.317)	(3.359)	(6.087)
Education	0.631	-2.292***	-2.903**
	(0.827)	(0.770)	(1.329)

Table A.8. Continued

Models:	**(1)**	**(2)**	**(3)**
Income	-0.0596	0.0684	0.132
	(0.121)	(0.128)	(0.208)
Constant	8.508	69.62***	61.13***
	(5.936)	(6.932)	(10.69)
Observations	1,385	1,382	1,377
R-squared	0.184	0.084	0.137

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.9. OLS Regressions Predicting House Candidate Ratings with Twitter and Facebook Political Use Among All Respondents in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party House Rating**	**In Party House Rating**	**House Rating Difference**
Twitter Use	-0.706	0.142	1.176
	(0.729)	(0.639)	(1.172)
Twitter Posting	-3.406	2.846	6.947*
	(2.426)	(1.980)	(3.988)
Twitter Political Use	0.481	-0.270	-0.895
	(0.438)	(0.364)	(0.706)
Facebook Use	-0.259	-0.0320	0.0349
	(0.934)	(0.729)	(1.269)
Facebook Posting	-0.502	3.027	3.284
	(3.628)	(2.412)	(4.728)
Facebook Political Use	0.0719	-0.267	-0.318
	(0.585)	(0.427)	(0.788)
Attention	-4.756***	2.299***	6.954***
	(0.980)	(0.857)	(1.498)
Dem House Gender	-3.621**	0.599	3.993
	(1.694)	(1.494)	(2.708)
Rep House Gender	0.925	2.391	1.204
	(1.859)	(1.692)	(3.048)
Party ID	0.867*	0.287	-0.645
	(0.472)	(0.428)	(0.787)
Fox	-2.733	1.569	5.294
	(2.266)	(2.151)	(3.691)
CNN	1.301	-0.640	-1.274
	(1.924)	(1.629)	(2.934)
Gender	2.624	1.674	-1.188
	(1.722)	(1.496)	(2.754)
Age	0.0403	0.184***	0.126
	(0.0589)	(0.0502)	(0.0919)
Black	-3.106	1.237	3.240
	(3.439)	(2.781)	(4.982)
Hispanic	4.159	-4.588*	-9.092*
	(3.026)	(2.573)	(4.780)
Asian or NHOPI	8.264***	-4.016	-12.45***
	(2.854)	(2.554)	(4.442)
Native American	0.883	3.517	2.335
	(6.114)	(6.103)	(8.253)
Multiple Races	-2.576	0.944	3.362

Table A.9. Continued

Models:	**(1)**	**(2)**	**(3)**
	(5.324)	(3.151)	(7.696)
Education	2.126**	-2.348***	-4.815***
	(0.918)	(0.824)	(1.510)
Income	-0.0965	0.217*	0.287
	(0.145)	(0.123)	(0.220)
Constant	49.62***	47.68***	0.974
	(8.447)	(7.027)	(12.40)
Observations	1,099	1,163	1,080
R-squared	0.092	0.096	0.117

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.10. OLS Regressions Predicting Presidential Candidate Ratings with Twitter and Facebook Political Use Among All Democrats in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party Press Rating**	**In Party Press Rating**	**True Press Rating Diff**
Twitter Use	-0.228	-0.108	-0.00489
	(0.486)	(0.688)	(0.943)
Twitter Posting	-0.171	-1.104	-0.948
	(1.296)	(1.799)	(2.431)
Twitter Political Use	-0.0495	0.343	0.437
	(0.216)	(0.322)	(0.426)
Facebook Use	1.260	-0.475	-1.778
	(0.872)	(0.882)	(1.346)
Facebook Posting	2.063	1.508	-0.813
	(3.397)	(2.498)	(4.313)
Facebook Political Use	-0.625	0.0751	0.745
	(0.556)	(0.457)	(0.741)
Attention	-0.736	1.269	2.059
	(0.760)	(1.001)	(1.403)
Fox	5.433*	-6.246**	-11.32***
	(2.820)	(2.806)	(4.165)
CNN	-1.435	4.602***	6.323***
	(1.178)	(1.610)	(2.158)
Gender	-1.549	0.168	1.900
	(1.325)	(1.694)	(2.437)
Age	0.0556	0.267***	0.215**
	(0.0561)	(0.0567)	(0.0931)
Black	-1.709	3.964	5.091
	(2.126)	(2.568)	(3.421)
Hispanic	2.458	-0.367	-3.752
	(2.214)	(2.615)	(3.507)
Asian or NHOPI	2.340	4.856	2.561
	(2.440)	(3.550)	(4.404)
Native American	-0.976	9.676*	10.60
	(4.506)	(5.577)	(7.713)
Multiple Races	-1.612	1.369	2.982
	(2.449)	(3.602)	(5.270)
Education	-1.750**	1.084	2.880**
	(0.798)	(0.943)	(1.447)
Income	-0.221**	0.207	0.450**
	(0.111)	(0.150)	(0.210)
Constant	13.92**	51.68***	37.10***

Table A.10. Continued

Models:	**(1)**	**(2)**	**(3)**
	(5.941)	(7.462)	(10.64)
Observations	845	842	840
R-squared	0.094	0.136	0.149

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.11. OLS Regressions Predicting House Candidate Ratings with Political Social Media Use Among All Democrats in the 2020 ANES

Models:	(1)	(2)	(3)
VARIABLES	**Out Party House Rating**	**In Party House Rating**	**House Rating Diff**
Twitter Use	-1.765*	1.200	3.066**
	(0.918)	(0.732)	(1.431)
Twitter Posting	-2.876	3.617*	7.464*
	(2.741)	(2.015)	(4.409)
Twitter Political Use	0.644	-0.481	-1.311*
	(0.485)	(0.379)	(0.772)
Facebook Use	1.688	0.511	-1.360
	(1.241)	(0.996)	(1.773)
Facebook Posting	4.078	5.703*	0.146
	(4.148)	(3.334)	(5.997)
Facebook Political Use	-0.798	-0.901	0.135
	(0.687)	(0.580)	(1.004)
Attention	-3.864***	2.794***	6.983***
	(1.233)	(1.055)	(1.993)
Rep House Cand Gender	2.681		0.720
	(2.284)		(3.564)
Fox	0.567	-4.845	-5.763
	(3.554)	(3.267)	(5.658)
CNN	-1.043	0.375	2.373
	(2.167)	(1.785)	(3.393)
Gender	4.952**	1.066	-3.306
	(2.357)	(1.837)	(3.607)
Age	-0.0345	0.229***	0.219*
	(0.0775)	(0.0610)	(0.122)
Black	-1.344	2.697	4.995
	(3.681)	(2.949)	(5.607)
Hispanic	2.706	-3.480	-5.475
	(3.848)	(2.870)	(5.657)
Asian or NHOPI	12.23***	-1.267	-14.20***
	(2.887)	(3.395)	(4.963)
Native American	7.959	13.32**	6.275
	(6.256)	(6.592)	(10.23)
Multiple Races	-4.787	3.527	7.917
	(5.614)	(3.511)	(8.829)
Education	2.099	-0.643	-3.249*
	(1.276)	(0.965)	(1.936)

Table A.11. Continued

Models:	(1)	(2)	(3)
Income	-0.199	-0.0198	0.288
	(0.187)	(0.149)	(0.286)
Dem House Cand Gender		1.736	6.023*
		(1.779)	(3.584)
Constant	41.04***	37.01***	-6.461
	(9.965)	(7.440)	(14.52)
Observations	672	755	661
R-squared	0.107	0.123	0.133

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.12. Marginal Effects of Twitter Use at Each Level of Twitter Posting on House Rating Diff among Democrats

Model:	**(1)**
Twitter Use at each level of Twitter Posting |	**House Rating Diff**
0	3.065***
	(1.430)
1	1.754*
	(0.913)
2	0.444
	(0.902)
3	-0.866
	(1.409)
4	-2.176
	(2.086)
5	-3.487
	(2.812)
Observations	661

Source: 2020 American National Election Studies Survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ (all two-tailed tests)

Table A.13. OLS Regressions Predicting Presidential Candidate Ratings with Political Social Media Use Among All Republicans in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party President**	**In Party President**	**President Rating Diff**
Twitter Use	3.305**	-1.837	-5.159**
	(1.417)	(1.285)	(2.330)
Twitter Posting	7.149	2.051	-5.115
	(5.668)	(3.496)	(7.221)
Twitter Political Use	-1.654	0.550	2.211
	(1.114)	(0.778)	(1.554)
Facebook Use	-0.608	-1.620	-1.125
	(1.035)	(1.159)	(1.915)
Facebook Posting	-2.907	-3.067	-0.250
	(3.335)	(3.101)	(5.523)
Facebook Political Use	-0.525	1.330**	1.887**
	(0.518)	(0.521)	(0.888)
Attention	-3.624***	1.518	5.191**
	(1.274)	(1.570)	(2.457)
Fox	-12.50***	13.34***	25.91***
	(2.552)	(2.493)	(4.365)
CNN	16.77***	-20.63***	-37.35***
	(3.008)	(3.909)	(5.912)
Gender	3.101	-1.882	-5.164
	(2.548)	(2.430)	(4.333)
Age	-0.0243	0.0562	0.0721
	(0.0808)	(0.0945)	(0.152)
Black	-24.50***	23.74***	48.32***
	(4.663)	(5.912)	(9.367)
Hispanic	2.692	-3.255	-5.863
	(6.781)	(8.295)	(14.63)
Asian or NHOPI	-4.725	-6.968	-2.114
	(8.506)	(11.88)	(19.46)
Native American	-6.642	-1.781	4.908
	(12.04)	(9.789)	(21.00)
Multiple Races	6.852	-10.23	-17.04
	(8.652)	(10.28)	(18.34)
Education	3.313**	-6.281***	-9.628***
	(1.344)	(1.134)	(2.133)
Income	0.156	-0.233	-0.414
	(0.203)	(0.207)	(0.359)
Constant	25.95***	92.55***	67.70***
	(8.937)	(9.654)	(15.73)

Table A.13. Continued

Models:	**(1)**	**(2)**	**(3)**
Observations	540	540	537
R-squared	0.234	0.262	0.286

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.14. Marginal Effects of Twitter Use at Each Level of Twitter Posting on President Rating Diff among Republicans

Model:	**(1)**
Twitter Use at each level of Twitter Posting |	**President Rating Diff**
0	-5.390***
	(2.421)
1	-3.144***
	(1.317)
2	-0.898
	(1.727)
3	1.348
	(3.099)
4	3.594
	(4.648)
5	5.840
	(6.243)
Observations	453

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.15. Marginal Effects of Facebook Posting at Each Level of Facebook Use on in President Rating Diff among Republicans

Model:	**(1)**
Facebook Posting at each level of Facebook Use |	**President Rating Diff**
0	-2.698
	(6.035)
1	-0.567
	(5.175)
2	1.563
	(4.368)
3	3.695
	(3.650)
4	5.826*
	(3.084)
5	7.958***
	(2.765)
6	10.089***
	(2.779)
7	12.221***
	(3.120)
Observations	494

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.16. OLS Regressions Predicting House Candidate Ratings with Political Social Media Use Among All Republicans in the 2020 ANES

Models:	**(1)**	**(2)**	**(3)**
VARIABLES	**Out Party House Rating**	**In Party House Rating**	**True House Rating Diff**
Twitter Use	0.337	-1.542	-1.450
	(1.223)	(1.319)	(2.166)
Twitter Posting	-5.640	-1.017	6.490
	(5.160)	(5.402)	(9.451)
Twitter Political Use	0.593	0.313	-0.595
	(0.961)	(1.071)	(1.783)
Facebook Use	-2.001*	0.250	1.938
	(1.180)	(0.951)	(1.715)
Facebook Posting	-4.501	3.413	6.386
	(4.853)	(3.299)	(6.930)
Facebook Political Use	0.949	0.0187	-0.831
	(0.766)	(0.567)	(1.158)
Attention	-4.898***	1.763	5.901***
	(1.424)	(1.224)	(2.159)
Dem House Cand Gender	-4.047*		3.753
	(2.338)		(3.866)
Fox	-9.392***	7.436***	18.20***
	(2.740)	(2.535)	(4.534)
CNN	10.01***	-5.033*	-15.02***
	(3.208)	(3.035)	(5.402)
Gender	0.294	-0.428	-0.981
	(2.281)	(2.274)	(4.097)
Age	0.0825	0.0853	0.0366
	(0.0875)	(0.0725)	(0.134)
Black	-32.69***	-13.01**	21.88*
	(6.540)	(6.160)	(12.20)
Hispanic	7.704**	-7.072	-14.40*
	(3.145)	(5.335)	(8.195)
Asian or NHOPI	2.607	-5.980	-8.778
	(5.360)	(4.049)	(9.038)
Native American	-6.278	-7.212	-1.306
	(11.60)	(7.527)	(11.05)
Multiple Races	7.174	-2.682	-11.43
	(6.684)	(5.424)	(10.76)
Education	1.994*	-2.879**	-5.620***
	(1.187)	(1.177)	(2.068)

Table A.16. Continued

Models:	**(1)**	**(2)**	**(3)**
Income	0.00978	0.368**	0.266
	(0.204)	(0.184)	(0.314)
Rep House Cand Gender		1.123	3.724
		(3.133)	(5.397)
Constant	63.22***	58.77***	1.085
	(10.09)	(9.367)	(15.72)
Observations	453	462	419
R-squared	0.177	0.158	0.211

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.8 reports the results from the Models analyzing presidential candidate ratings among all respondents in the 2020 ANES. Neither of the Twitter or Facebook variables registered any significance with the presidential candidate rating variables. Table A.9 reports the OLS regressions predicting House candidate ratings with Twitter and Facebook Political Use among all respondents. The only social media variable that registered any significance is Twitter Posting and it was only significant at the 90 percent confidence interval. It seems that when the two social media sites pulled apart and analyzed separately, that neither one had the ability to strongly affect presidential or House candidate ratings.

Table A.10 reports the results of OLS Regressions predicting presidential candidate ratings only amongst Democrats within the sample. Much like the Models in Table A.8 and A.9, not one of the individual Twitter or Facebook variables registered any significance with the presidential candidate rating variables. However, Table A.11 shows a little bit of a different picture for *Twitter Use* and the House candidate ratings. Table A.11 shows that *Twitter Use* is significant with *Out Party Rating* and *House Rating Diff*, and *Twitter Posting* is significant with *In Party House Rating* and *House Rating Diff*. Table A.12 reports the marginal effects of *Twitter Use* on *House Rating Diff* at each level of *Twitter Posting*. At the lowest value of *Twitter Use*, as one increases their time spent posting political content on Twitter increases, the more likely they are to have an increased difference of their two House rating variables. This effect loses all significance at the *Twitter Use* value of 2.

Lastly, Table A.13 and A.16 reports the OLS regression results for both presidential and House candidate ratings for only Republicans in the 2020 ANES. While Table A.16 only shows *Facebook Use* having barely a significant effect on *Out Party House Rating*, Table A.13 highlights several important relationships between Twitter and Facebook usage and presidential candidate ratings. Among Republicans, Twitter Use had the most significance with *Out Party President* and

President Rating Diff. No other social media variable had any significant relationship with the president rating variables. To analyze these relationships a bit closer, Table A.14 and A.15 are given.

Table A.14 reports the marginal effects of *Twitter Use* at each level *Twitter Posting* on *President Rating Diff*. Twitter Use at the largest negative effect on *President Rating Diff* at the lowest Political Posting with this effect losing significance at the *Political Posting values* of 2. Thus, if one simply used Twitter and used less of their Twitter time posting political content, the smaller the difference would be between their presidential candidate ratings. Table A.15 shows the marginal effects of *Facebook Posting* at each level of *Facebook Use* on *President Rating Diff*. *Facebook Posting* did not record any significance until *Facebook Use* reaches a value of 4, and the effects do not become significant at the 95 percent confidence interval until a *Facebook Use* value of 5. Thus, the more a Republican identifying individual uses Facebook and their time spent posting political content on Facebook increases, the more likely they are to have a larger gap in their presidential candidate ratings.

Auxiliary Regressions for Paper III

Tables A.17 through A.22 below reveal the results of auxiliary regressions ran with separated social media variables for Facebook and Twitter respectively. Due to the fundamental differences between the two sites such as character limits for posts, look, and algorithmically, and because the users of the two sites differ, it is best to understand how the effects of these two sites differ (Widner, Macdonald and Gunderson 2022).

My first key independent variable is *Twitter Political Use,* a composite variable I created by multiplying three variables, *Twitter Use*, *Twitter Posting*, and *Attention*. *Twitter Posting* measures how often a respondent posts political content on Twitter. It is an additive scale of how each respondent answered the question: “How often do you post political content on Twitter?” The response set for both items was as follows: 1 = "never," 2 = "sometimes," 3 = "about half of the time," 4 = "most of the time," and 5 = "always." Thus, the range of *Political posting* is 1-5. *Twitter use* measures how often a respondent generally uses Twitter. To create this variable, I used the survey question: (1) "How often do you use Twitter?" The response set for was: 1 = "less than once a month," 2 = "once or twice a month," 3 = "about once a week," 4 = "a few times each week," 5 = "once a day," 6 = "a few times every day," and 7 = "many times every day." *Twitter use* has a range of 1-7. *Attention* measures how often a respondent pays attention to politics or elections (1 = "never," 2 = "some of the time," 3 = "about half of the time," 4 = "most of the time," 5 = "always"). I believe these three variables will give me the best opportunity to capture how often an individual views political content on Twitter.

My second key independent variable is *Facebook Political Use*, which is also a composite variable I created by multiplying three variables, *Facebook Use*, *Facebook Posting*, and *Attention*. *Facebook Posting* measures how often a respondent posts political content on Facebook. It is a scale of how each respondent answered the question: "How often do you post political content on Facebook?" The response set for this item is as follows: 0 = "never," 1 = "sometimes," 2 = "about half of the time," 3 = "most of the time," and 4 = "always." Thus, the range of *Facebook posting* is 0-5. *Facebook use* measures how often a respondent generally uses Facebook. To create this variable, I used the survey question: (1) "How often do you use Facebook?" The response set for was: 1 = "less than once a month," 2 = "once or twice a month," 3 = "about once a week," 4 = "a few times each week," 5 = "once a day," 6 = "a few times every day," and 7 = "many times every day." *Facebook use* has a range of 1-7.

Table A.17 reports the results of the ordered logit regression predicting *Anger* values for both Twitter and Facebook social media variables for all respondents in the 2020 ANES. None of the Twitter variables produced any significant relationships with *Anger*. Only *Facebook posting* had any significant relationship with *Anger*, however, it was only significant at the 90 percent confidence interval. Table A.18 reports the results of the ordered logits regression that predicted *Happy* values for the individual social media variables. Twitter once again did not produce any statistically significant relationships with the dependent variable. However, both Facebook variables produced a significant relationship, with Facebook posting having a relationship with *Happy* at the 99% confidence interval..

Figure A.1 highlights the probability effects of *Facebook posting* on *Happy* at each level of *Facebook use*. At the lowest level of *Facebook use*, as one increases their time spent posting political content on Facebook, the less likely they would have been given the lowest value of *Happy*. This negative probability effect slowly decreased toward zero as one's time spent on Facebook increased. At the highest value of *Facebook use*, *Facebook posting* actually had a positive effect on the probability of being located in the lowest value of *Happy*. Therefore, if a respondent spends the vast majority of their time posting political content on Facebook, but overall spends very little time on social media, then they will be most likely to say they do not feel happy at all about the political state of the country.

Table A.19 shows the results of the logit regressions predicting *Anger* values amongst only Democrat identifying respondents in the sample and Table A.20 has the results of the logit regressions predicting *Happy* values for the same respondents. Table A.21 and A.22 has the results of the logit regressions predicting *Anger* and *Happy* values respectively for Republican identifying respondents. Once again, none of the Twitter variables had any significant relationship with *Anger* or *Happy* for Democrats and Republicans alike. However, *Facebook posting* had a positive and significant relationship with *Anger* for Democrats.

Table A.17. Ordered Logit Regressions Predicting Anger Values with Twitter and Facebook political use Among All Respondents in the 2020 ANES

Model:	**(1)**
VARIABLES	**Anger**
Twitter use	0.0210
	(0.0459)
Twitter posting	0.0772
	(0.146)
Twitter political use	0.00494
	(0.0275)
Facebook use	0.0619
	(0.0562)
Facebook posting	0.425*
	(0.221)
Facebook political use	-0.0307
	(0.0366)
Attention	0.419***
	(0.0561)
Fox	0.0596
	(0.130)
CNN	-0.207*
	(0.109)
Party id	-0.365***
	(0.0280)
Gender	0.407***
	(0.0995)
Age	-0.00614*
	(0.00340)
Black	-0.0546
	(0.206)
Hispanic	-0.0215
	(0.181)
Asian or NHOPI	-0.181
	(0.229)
Native American	-0.403
	(0.352)
Multiple races	0.500*
	(0.263)
Education	-0.0692
	(0.0520)
Income	0.00382

Table A.17. Continued

Model:	**(1)**
	(0.00807)
/cut1	-2.813***
	(0.478)
/cut2	-1.361***
	(0.465)
/cut3	0.169
	(0.464)
/cut4	1.668***
	(0.465)
Observations	1,533

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.18. Ordered Logit Regressions Predicting Happy Values with Twitter and Facebook political use Among All Respondents in the 2020 ANES

Model:	**(1)**
VARIABLES	**Happy**
Twitter use	-0.0833
	(0.0507)
Twitter posting	-0.138
	(0.165)
Twitter political use	0.0271
	(0.0307)
Facebook use	0.116*
	(0.0598)
Facebook posting	0.635***
	(0.231)
Facebook political use	-0.101***
	(0.0384)
Attention	-0.131**
	(0.0598)
Fox	0.471***
	(0.136)
CNN	-0.312***
	(0.121)
Party id	0.465***
	(0.0307)
Gender	-0.139
	(0.108)
Age	0.00109
	(0.00375)
Black	-0.421*
	(0.246)
Hispanic	0.269
	(0.193)
Asian or NHOPI	0.540**
	(0.250)
Native American	0.354
	(0.382)
Multiple Races	-0.0602
	(0.282)
Education	0.0733
	(0.0558)
Income	-0.00531
	(0.00863)
/cut1	1.840***
	(0.498)

Table A.18. Continued

Model:	**(1)**
/cut2	3.176***
	(0.503)
/cut3	5.058***
	(0.517)
/cut4	6.756***
	(0.559)
Observations	1,533

Source: 2020 American National Election Studies Survey. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ (all two-tailed tests)

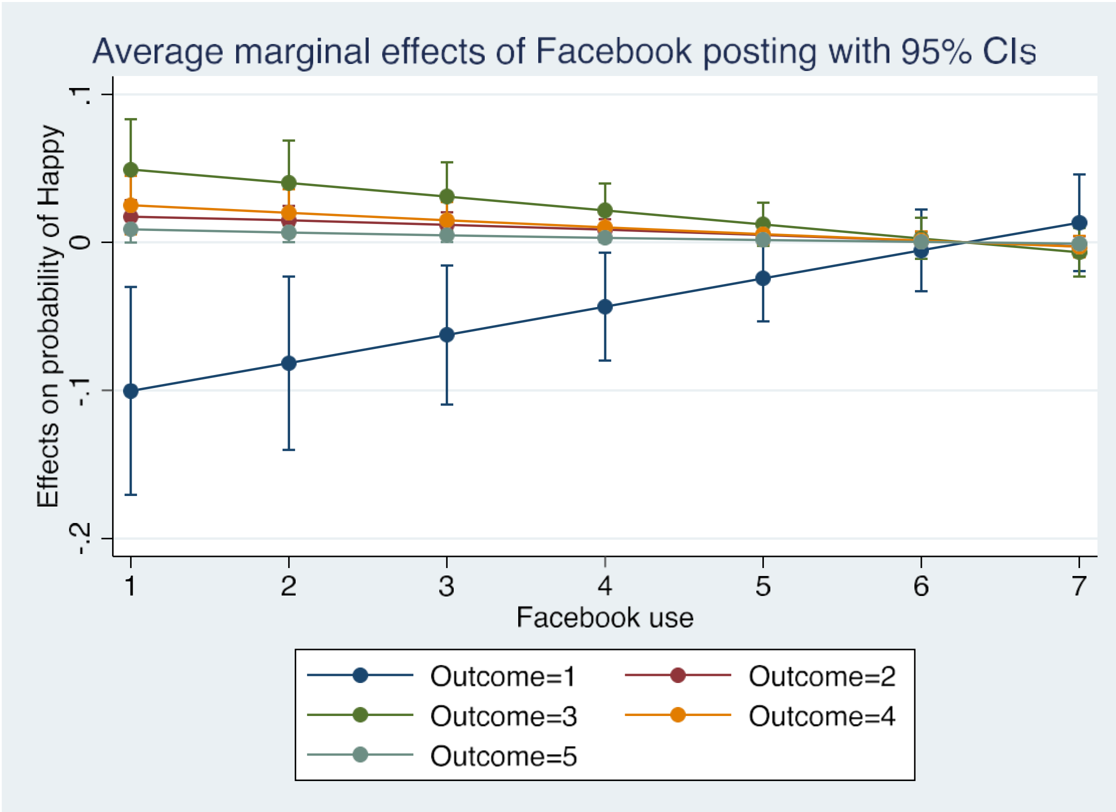

Figure A.1. Margins plot of Facebook posting's, at each value of Facebook use, effect on the probability of being at each level of Happy for all respondents

Table A.19. Ordered Logit Regressions Predicting Anger Values with Twitter and Facebook political use Among All Democrats in the 2020 ANES

Model:	**(1)**
VARIABLES	**Anger**
Twitter Use	0.0151
	(0.0615)
Twitter political use	0.204
	(0.187)
Twitter political use	0.00495
	(0.0349)
Facebook use	0.118
	(0.0869)
Facebook posting	0.756**
	(0.353)
Facebook political use	-0.0735
	(0.0580)
Attention	0.481***
	(0.0827)
Fox	-0.149
	(0.229)
CNN	-0.0701
	(0.140)
Gender	0.556***
	(0.142)
Age	-0.00514
	(0.00481)
Black	0.0135
	(0.233)
Hispanic	-0.372
	(0.234)
Asian or NHOPI	-0.195
	(0.294)
Native American	-0.368
	(0.576)
Multiple races	0.416
	(0.346)
Education	0.00935
	(0.0767)
Income	-0.00354
	(0.0112)
/cut1	-1.884**
	(0.787)

Table A.19. Continued

Model:	(1)
/cut2	0.262
	(0.669)
/cut3	1.862***
	(0.662)
/cut4	3.536***
	(0.671)
Observations	848

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.20. Ordered Logit Regressions Predicting Happy Values with Twitter and Facebook political use Among All Democrats in the 2020 ANES.

Model:	**(1)**
VARIABLES	**Happy**
Twitter use	-0.0798
	(0.0702)
Twitter posting	-0.139
	(0.209)
Twitter political use	0.0320
	(0.0383)
Facebook use	0.163*
	(0.0944)
Facebook posting	0.527
	(0.335)
Facebook political use	-0.123**
	(0.0579)
Attention	-0.257***
	(0.0921)
Fox	0.420*
	(0.255)
CNN	-0.160
	(0.161)
Gender	-0.150
	(0.164)
Age	
	-0.00820
Black	(0.00572)
	-0.636**
Hispanic	(0.302)
	0.500*
Asian or NHOPI	(0.258)
	0.570*
Native American	(0.314)
	0.281
Multiple races	(0.714)
	-0.370
Education	(0.417)
	0.113
Income	(0.0898)
	-0.00934
/cut1	(0.0127)
	0.135
/cut2	(0.719)
	2.004***

Table A.20. Continued

Model:	(1)
/cut3	(0.728)
	4.233***
	(0.822)
Observations	
	848

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.21. Ordered Logit Regressions Predicting Anger Values with Twitter and Facebook political use Among All Republicans in the 2020 ANES.

Model:	**(1)**
VARIABLES	**Anger**
Twitter use	-0.0363
	(0.0871)
Twitter posting	-0.298
	(0.312)
Twitter political use	0.0383
	(0.0615)
Facebook use	0.0437
	(0.0845)
Facebook posting	0.364
	(0.319)
Facebook political use	-0.0336
	(0.0525)
Attention	0.288***
	(0.0894)
Fox	0.257
	(0.175)
CNN	-0.417**
	(0.207)
Gender	0.0919
	(0.162)
Age	-0.000460
	(0.00552)
Black	-0.784
	(0.958)
Hispanic	0.143
	(0.377)
Asian or NHOPI	-0.197
	(0.466)
Native American	-0.349
	(0.530)
Multiple races	0.193
	(0.493)
Education	-0.0827
	(0.0805)
Income	0.00502
	(0.0137)
/cut1	-1.448*
	(0.740)
/cut2	-0.122

Table A.21. Continued

Model:	**(1)**
	(0.731)
/cut3	1.422*
	(0.735)
/cut4	2.815***
	(0.744)
Observations	544

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

Table A.22. Ordered Logit Regressions Predicting Happy Values with Twitter and Facebook political use Among All Republicans in the 2020 ANES

Model:	**(1)**
VARIABLES	**Happy**
Twitter use	0.0710
	(0.0953)
Twitter posting	0.524
	(0.348)
Twitter political use	-0.102
	(0.0706)
Facebook use	0.122
	(0.0837)
Facebook posting	0.895***
	(0.322)
Facebook political use	-0.108**
	(0.0526)
Attention	-0.0290
	(0.0914)
Fox	0.538***
	(0.178)
CNN	-0.595***
Gender	(0.214)
	-0.0303
Age	(0.163)
	0.00408
Black	(0.00562)
	0.569
Hispanic	(0.910)
	0.109
Asian or NHOPI	(0.369)
	-0.0423
Native American	(0.498)
	0.186
Multiple races	(0.529)
	0.384
Education	(0.482)
	-0.0434
Income	(0.0811)
	-0.00573
/cut1	(0.0134)
	0.309
/cut2	(0.748)

Table A.22. Continued

Model:	**(1)**
	1.405*
/cut3	(0.747)
	3.279***
/cut4	(0.760)
	5.039***
	(0.807)
Observations	
	544

Source: 2020 American National Election Studies Survey. *** p<0.01, ** p<0.05, * p<0.1 (all two-tailed tests)

For Republicans, not any of the Facebook variables had a significant relationship with Anger, but *Facebook posting* and *Facebook political use* had a significant relationship with *Happy*. Figure 2 reveals the probability effects of *Facebook posting* on every category of *Happy* as one progresses through the values of *Facebook use*. The biggest finding within the Figure is that at the lowest level of *Facebook use*, as one increases their time spent posting political content on Facebook, the least likely they were to report “not at all” when asked how happy they are about the political state of the country. This negative probability decreases the more a respondent increases their overall Facebook usage.

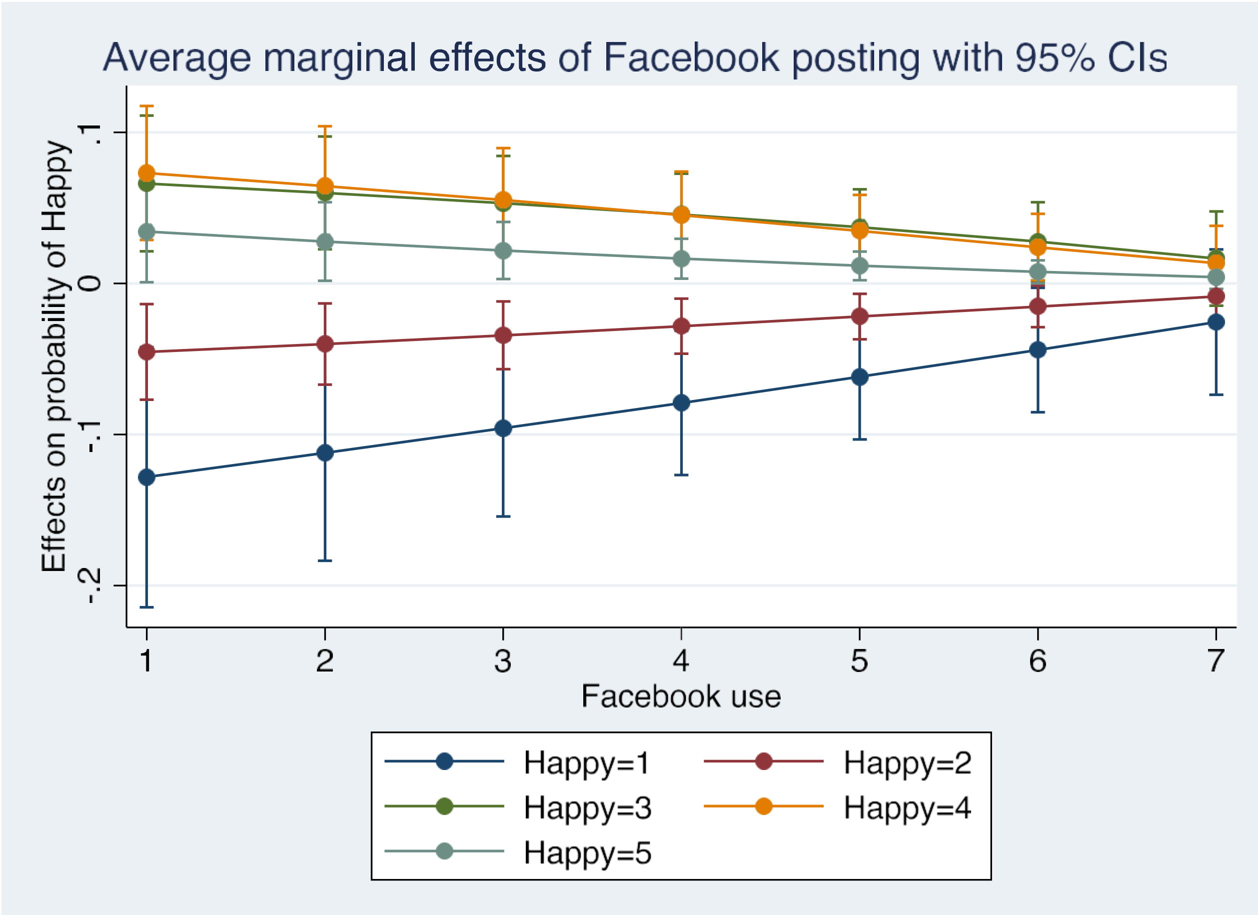

Figure A.2. Margins plot of Facebook posting's, at each value of Facebook use, effect on the probability of being at each level of Happy for all Republicans

VITA

Originally from Fredericksburg, Virginia, Justin Allen Rose developed a passion for history at a very early age which eventually led him to gain an interest in the political world. After graduating high school, he attended Cameron University where he received a Bachelor of Arts degree in Journalism and Media Production with a minor in Political Science. In his last two semesters at Cameron, Justin fell in love with Political Science and decided to pursue a Doctor of Philosophy degree in the field. In 2019, he was accepted to the Political Science PhD program at the University of Tennessee, Knoxville where he would end up graduating from in 2023. His research interests include how the media and religion affects American politics. After graduation, he will continue his position as an assistant professor at his undergraduate institution, Cameron University.