#PolarizedFeeds: Two experiments on polarization and social media

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Abstract: Studies document the existence of information bubbles in social media, in which users exchange posts primarily with like-minded individuals. Little research, however, investigates whether exposure to social media polarizes users or simply sorts out like-minded voters who already have very different prior beliefs. In this paper, we conduct two survey experiments to test for the effect of exposure to tweets on perceived polarization of candidates and leading political figures. We show that subjects treated with negative tweets see presidential nominees and their parties as more ideologically distant from each other. We also demonstrate that this polarization effect is stronger among attentive respondents. Our results provide support for a social media effect on perceived polarization, beyond that due to the self-selection of likeminded users into different media communities. Exposure to tweets causes users to see candidates and political figures as further apart.

Are Americans who are exposed to information on Twitter becoming more polarized[1] or does the rancor on social media merely reflect users' prior existing divisions? This question could not be more important given politicians increasing use of social media to communicate their message to the public (Bhattacharya 2016, Gainous and Warner 2014, Kruikemeier 2014). As described by Lelkes, Sood, and Iyengar (2017), social networks today form the "backbone of many Americans' daily information environment", where "even the politically disinterested are exposed to nontrivial doses of partisan news" (Lelkes et.al. 2017: 6). For years, scholars have examined the dynamics of polarization. Consensus is that polarization among elites has been on the rise, even if its causes and consequences remain unclear (citation?). Where the public is concerned, however, there is still debate about whether Americans are more polarized today than in years past (citations?) and, crucially for this paper, regarding the role of social media. In this article, we conduct two survey experiments that measure the effect of exposure to partisan news in Twitter on perceived ideological distances between candidates and between candidates and respondents. Results provide evidence of increased perceived polarization among randomly assigned respondents that have not sorted themselves into groups of likeminded voters.

Most scholars have found growing policy polarization (Hetherington 2001, Kimball and Gross 2007, Abramowitz 2010, Layman et al 2010, Jacobson 2012) and affective polarization

[1] Researchers have distinguished different types of polarization, including policy polarization (the increase distance in the policy proposals of parties), affective polarization (the distance in likes-dislikes reported by voters), perceived polarization (the policy distance between candidates as perceived by voters). In this article, we take on the task of measuring changes in perceived polarization, measured by the ideological distance between candidates that is reported by voters.

among voters (Iyengar et.al. 2012, Mason 2015). Yet, prominent dissenters maintain that polarization remains an elite-level phenomenon (Fiorina, Abrams and Pope 2005, Fiorina and Abrams 2011). Evidence of change among voters has been documented, such as a stronger relationship between party identification and vote choice (Bartels 2000), reduced levels of split-ticket voting (Burden and Kimball 2002, Jacobson 2015), and a more negative assessment of the opposing party (Iyengar, Sood and Leikes 2012, Mason 2015). However, skeptics contend that not all political judgments have become more polarized. For example, some scholars argue that people's policy preferences are less polarized than their voting decisions, because the vote choices now offered by party elites are clearer (Mason 2015).

Scholars who find mass-level polarization agree that voters responded to elite cues. Once voters might have split tickets because they saw little ideological difference between a Republican presidential nominee and a Democratic Congressional candidate (Frymer, Kim and Bimes 1997), but growth in party-line voting in Congress led them to see a clear divide between the parties (Hetherington 2001, Burden and Kimball 2002).

However, voters' perceptions of policy polarization may stem not only from the actual positioning of parties but also from the way politicians' actions are communicated. There is a long scholarly tradition of studying the effects of media on voters' perceptions. Early studies of polarization and media focused on talk radio and cable channels, which are more partisan than traditional broadcast news (Prior 2006, Iyengar and Han 2009, Sobieraj and Berry 2011, Arceneaux and Johnson 2013, Levendusky 2013, Hopkins and Ladd 2015). When scholars turned their attentions toward online media, they focused initially on blogs and news websites (Lawrence, Sides and Farrell 2010, Stroud 2010).

Yet, the media does not stand still. The dramatic rise of social media in the past decade has significantly altered voters' information environment. By using Twitter and Facebook, candidates can bypass the traditional gatekeepers of the mainstream and even partisan media (Lelkes et.al. 2017; King et.al. 2017). Social media users increasingly access political information from trusted friends and acquaintances who post comments and share news on their walls (Halberstam and Knight 2014; Messing 2013; Arugete and Calvo 2018). The omnipresence of social media in both the 2016 presidential campaign and the subsequent revelations of Russian use of social media to intervene in elections around the world make an investigation of its effects especially timely.

Scholars of course have begun to explore the effects of emerging media technologies (King et.al. 2017; Vicario et.al. 2016; Bakshy et.al. 2015). Chaffee and Metzger (2001) and Bennett and Iyengar (2008) propose that new technologies which allow users to quickly indicate the content they want to read, may yield a new era of minimal effects. In this new era, traditional media organizations, already incapable of changing readers' minds, may also be unable to set the agenda (Artwick, 2012). Following their reasoning, polarization is mediated by networked peers that exchange information in social media. If selective exposure to congenial messages is frequent on social media networks (Messing and Westwood 2012, Barberá et al 2015), we should experimentally test the effect of such exposure on voter perceptions and preferences. The possibility that such exposure may contribute to polarization among voters is theoretically and substantively important and merits closer examination.

In this paper, we offer original evidence from two survey experiments that allow us to assess the impact of exposure to tweets on voters' perceptions of candidates and policies. The polarizing effect of Twitter exposure suggests that social media is fueling the partisan divisions so prominent in contemporary American politics. We test for the effect of social media on polarization using two survey experiments. Our experimental findings show that subjects treated with negative campaign tweets from either Donald Trump or Hillary Clinton perceive each presidential candidate as being further apart ideologically, even when messages have no associated policy content. In a second experiment on the dismissal of Acting Attorney General Sally Yates, we show that the time users spend reading a tweet (attention) increases perceived polarization.

The organization of this paper is as follows: in the first section, we review the literature on social media and perceived polarization. In the second section, we introduce our experimental designs, one of them focusing on messages by the presidential candidates and the second one focusing on messages by traditional media outlets (NYT, Fox, and AP). In the third and fourth sections, we present experimental results showing that (1) exposure to tweets increases polarization and the (2) time of exposure (attention) increases polarization. We conclude in the fifth section.

1. Social Media and Perceived Polarization

Social media users are polarized, but does social media polarize them further? In the last few years, a significant consensus has emerged that voters *read*, *click*, and *share* political information in segregated social media communities (Bakshy, Messing, & Adamic, 2015; Barberá, 2015; Bhattacharya, Yang, Srinivasan, & Boynton, 2016; Calvo, 2015; Romero, Meeder, & Kleinberg, 2011; Vaccari et al., 2013). These social media bubbles expose voters to starkly different political narratives, which raises the question: is social media not only a conduit but also responsible for increased polarization? While the self-sorting of individuals into politically homogenous online communities ensures that voters received augmented versions of their own prior beliefs, we have little evidence of a direct and unconditioned effect of social media posts on perceived polarization. Indeed, high segregation of users in social media provides researchers with excellent left-right discrimination in observational data, but provides no direct link of social media posts on polarization among its users (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015; Calvo, 2015; Lansdall-Welfare, Dzogang, & Cristianini, 2016)

The existence of information bubbles ensures that users receive very different information about candidates and their parties. However, this could be explained as the result of users sorting themselves in communities of like-minded peers, as the result of attitude change, or some combination of both (Bakshy et al., 2015). In the former case, voters that think alike post alike. In the second case, voters exposed to distinct types of information change their attitudes in regards to the candidates and parties reported in social media. To test for a direct effect of social media posts on attitude change, we created a survey experiment that selectively exposes respondents to negative social media tweets. Results show that users exposed to tweets perceived a larger ideological distance between candidates as well as between parties. That is, exposure to tweets resulted in a change in the perceived distance between the candidates rather than simply reinforcing respondents' prior attitudes.

Perceived Polarization as a Framing Issue

Changes in the perceived ideological distance between candidates may take place through a number of different processes. First, users may perceive that candidates' polarization differs significantly across issues. For example, users may see candidates as being ideologically distant from each other on immigration issues yet less differentiated on foreign policy. If, as proposed by the agenda melding literature (Shaw, McCombs, Weaver, & Hamm, 1999; Weaver, McCombs, & Shaw, 2004), social media provides a frame for issues that a community of users find most important, high levels of polarization on twitter may reflect attention to different issues in each community rather than changes in attitude after users are exposed to political messages.

A case for polarization as an issue selection problem is described in two recent articles by Barberá et.al. (2015) and Bakshy et. al.(2015). In both cases, polarization in Twitter networks is measured by analyzing social media posts by the same groups of users while selecting on a variety of political and non-political issues. Polarization in social media is apparent on political issues, but those same users happily exchange posts with the opposing political community on issues unrelated to politics. Therefore, perceived polarization in social media may be simply the result of data selection rules by researchers rather than reflecting changes in political attitudes by users.

In our experiments, we control for sorting effects in two different ways. Our first experiment seeks to rule out issue-selection as a source of bias, randomly assigning users to Twitter posts and selecting on valence issues with no policy content. As our experimental design will show, the two tweets frame the difference between Trump and Clinton exclusively in terms of character. Given that valence issues should not affect the perceived ideological location of candidates, the design allows us to measure attitude change driven by political tweets with no policy content. Results show that these non-policy treatments affect the perceived ideological distance between candidates.

Second, we provide experimental results indicating that more prolonged attention to social media posts increases perceptions of polarization. Berinsky et al. (2014) find a stronger treatment effect among respondents who are most attentive to the political stimuli. Accordingly, in our second experiment, we measure the time respondents spent reading a Tweet on the firing of Acting Attorney General Sally Yates after President Trump signed his first executive order restricting travel by foreign citizens of seven majority Muslim countries. Here we measure attention with time exposed to the tweet. Holding issue selection constant and controlling for different media sources, we show that more prolonged attention to tweets increases perceptions of polarization.

Perceived Polarization as an Assimilation and Contrast Issue

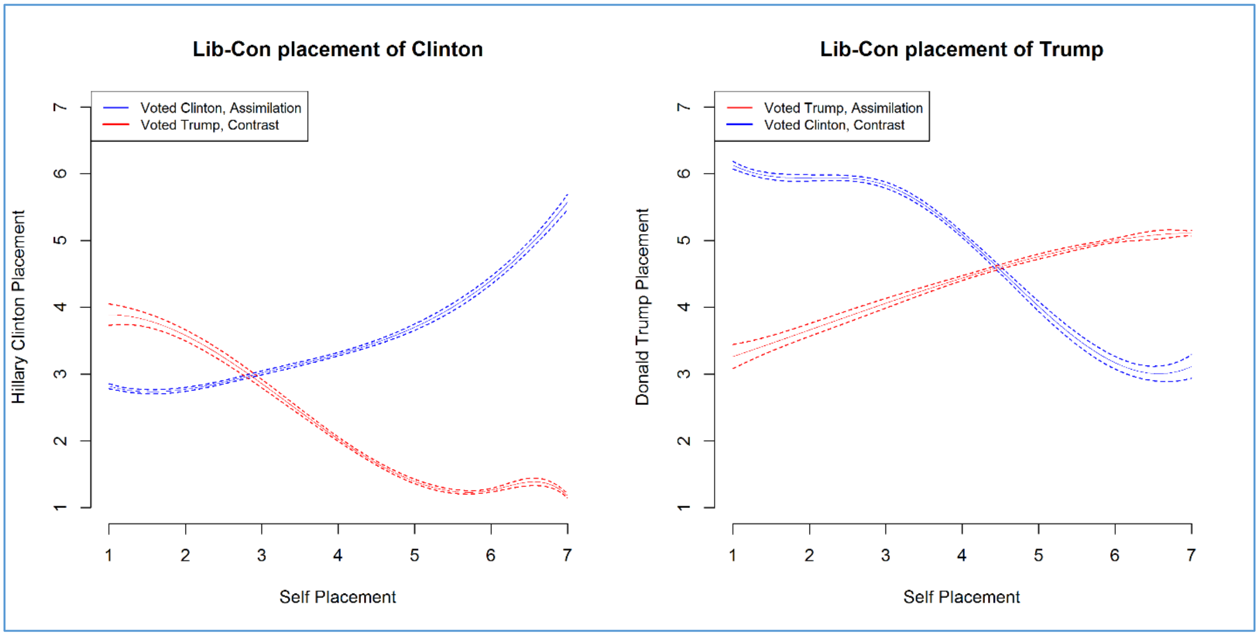
A broad literature shows that respondents view parties they support as ideologically closer to themselves (*assimilation*) and place parties they oppose further away (*contrast*). These changes in the perceived location of parties are not policy related but, instead, reflect a psychological mechanism in which individuals transfer positive or negative valence assessments to the perceived policy positions of parties (Calvo, Chang, & Hellwig, 2014; Merrill, Grofman, & Adams, 2003; Milton, Steenbergen, & Brau, 1995). If social media posts alter the perceived qualities of the candidates (valence) or the emotional frame of the respondent, then the proximity to candidates in general (ideology) or on particular issues (e.g. travel ban), may decrease (assimilation) or increase (contrast).

Consider for example the effects of assimilation and contrast during the 2016 U.S. presidential election, documented in the latest round of the ANES (2016) data. In Figure 1, the horizontal axis describes the left-right self-placement of the respondent and the vertical axis describes the reported ideological location of the candidates. Large and significant assimilation and contrast effects shape respondents' perceived distance from candidates, with positive slopes indicating assimilation (voters on the right see the preferred candidate shifted to the right) and negative slopes indicating contrast (voters on the right perceive the disliked candidates as shifted to the left).

Figure 1 illustrates the relationship between self-placement and the reported ideological location of Hillary Clinton. A very liberal respondent (a 1 in the horizontal scale), perceives Hillary

Clinton as a moderate liberal (3) when voting for her, and as a centrist (4) when voting against her. Meanwhile, a very conservative respondent (a 7 in the horizontal axis), perceives Clinton as conservative when voting for her, and as extremely liberal when not voting for her.

Figure 1: Assimilation and Contrast in the 2016 Presidential Election, ANES (2016)



Note: Positive slopes describe assimilation, where voters report an ideological location that is shifted in the direction of their own ideological preferences. Negative slopes describe contrast effects, where respondents perceive the candidate as further away from their own ideological preference.

As shown in Figure 1, very conservative voters display higher levels of assimilation and contrast than liberal ones. As a result, very conservative voters perceive the ideological distance that separates Clinton and Trump as greater than moderate or liberal voters. As described by Calvo et.al. (2013), different types of policy and non-policy information may affect the extent to which voters perceive liked parties as closer to them than they actually are or disliked parties as further away than they are in reality. There are information spillovers, which alter the frame of reference that voters use to assess the reported ideology (and policies) that candidates prefer. As users process information from social media, valence assessments of the candidates will enter into the policy assessments of voters as assimilation and contrast effects, thereby leading to increased perceived polarization.

Study 1: Exposure to Candidate Tweet

We conducted our first experiment through Nielsen Scarborough from its larger probability-based national panel, which was recruited by mail and telephone using a random sample of households provided by Nielsen Scarborough. The sample of 1,042 adult respondents is matched to the U.S. population on these variables: age, gender, income, education, race, and geographic region using benchmarks from the U.S. Census. The survey was also weighted by partisan identification. It was fielded November 18-23, 2016. The margin of error is 3.04%

Our first experiment was fielded immediately after the 2016 U.S. presidential election. In this experiment, we randomly assigned subjects to three conditions: a negative campaign tweet sent by Donald J. Trump, a negative campaign tweet from Hillary Rodham Clinton, with the remaining third of respondents as a control – receiving no tweet. Figure 2 displays the tweet by Clinton (left panel) criticizing Trump for disrespecting women. On the right panel, is the tweet by Trump that depicted Clinton as corrupt. The purpose of the treatments was for the candidates to attack their opponent's character. Trump attacks Clinton for being corrupt, while Clinton criticizes Trump's insensitive comments on the campaign trail. Respondents in the control group were untreated and not exposed to either tweet.[2]

[2] We implemented an alternative placebo model, with partisan and non-partisan tweets, in the second experiment described in the next section. In our first experiment, our focus was on individuals treated to social media messages compared to those that were not exposed.

Figure 2: Tweets of Hillary Clinton and Donald Trump, criticizing their opponents.

Note: Tweet posted by Hillary Clinton (Tweet ID: 790606692547452932, Left) on October 24, 2016 and by Donald J. Trump (Tweet ID: 789594671387447297, Right) on October 21,2016. Dates of the tweets were not included in the experiment.

We decided to use real tweets because we were interested in the effect tweets from the actual campaign had on people's political opinions. This choice caused us to sacrifice some control over our experimental stimuli. However, we think using actual tweets produces results with greater external validity and speak more to how people are influenced by social media in the real world. After assignment to one of the three experimental groups, we asked respondents to indicate the perceived emotional state of the candidate that wrote the tweet (Clinton or Trump) as well as their own emotional response to the tweet.[3] Finally, we asked respondents to place themselves and the two candidates on an ideological scale, from 1 (very liberal) to 7 (very conservative). The latter measures are our primary focus for this paper.

[3] The emotional response questions were asked of users treated to a tweet. We analyze the attitudinal effect of emotion on respondents in a separate manuscript.

In appendix A, we report balance diagnostics for gender, age, partisanship, and income between both the treated and untreated groups. Sample balance in assignments is very good, with small deviations for gender (almost 4% fewer women in the untreated group) and in Clinton voters (3% fewer than average). Given that both Clinton voters and women were found to be less polarized than Trump voters and men in the most recent ANES, these small deviations work against our hypothesis and should make our results more conservative. But when we control for gender in our analysis the results are essentially the same. Consequently, we report our survey results without doing any further post-processing.

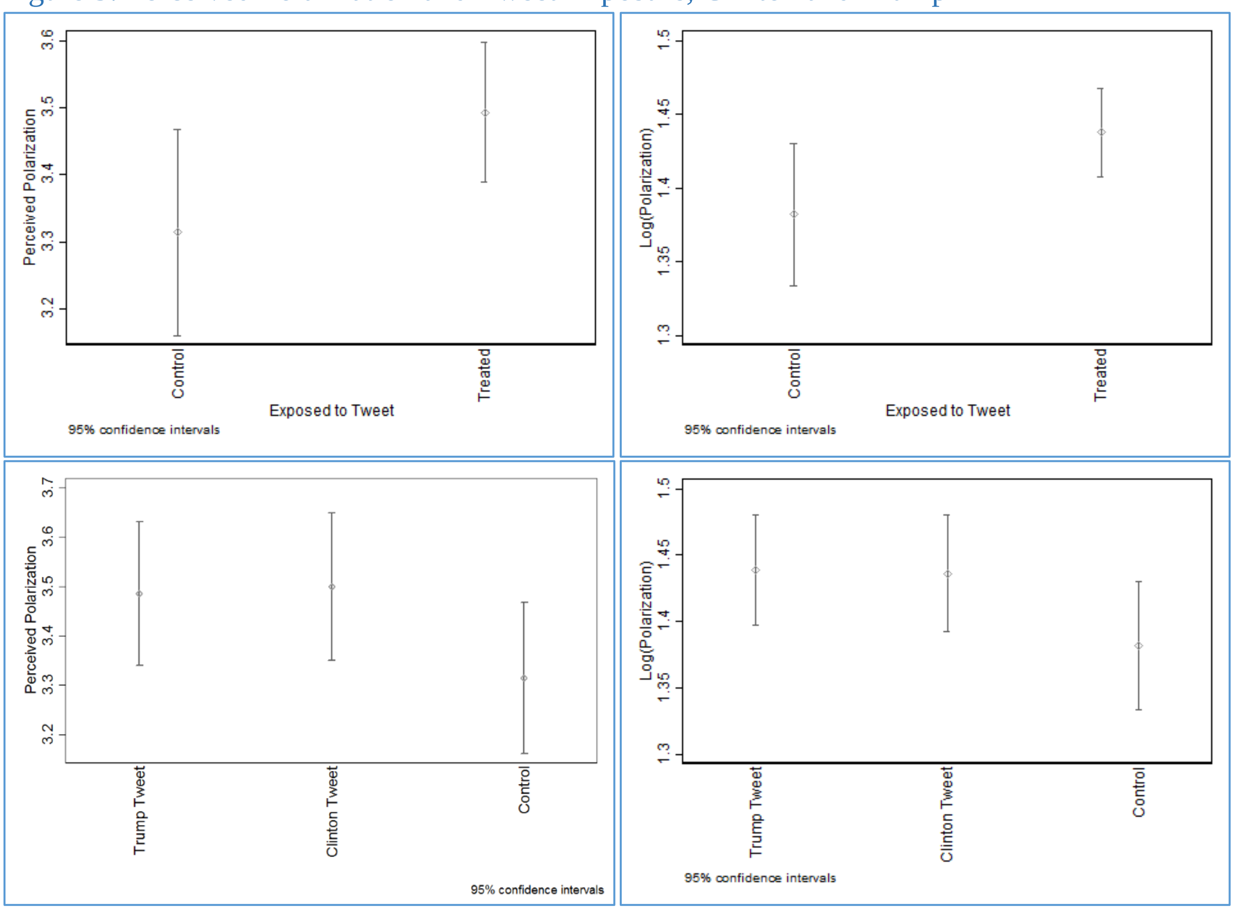
The Dependent Variable

The dependent variable in our analyses is the absolute distance between the reported ideological placement of Donald Trump and that of Hillary Clinton. The average respondent placed Clinton at 2.54 of the seven-point liberal to conservative scale, while the median respondent placed her at 2. The average respondents placed Trump at 5.42, while the median respondent gave him a 6. So, the distributions are skewed to the left (Clinton) and right (Trump). At the individual level, the average distance between the two candidates was 3.44 out of six, with a median distance of 4.

The upper-left plot in Figure 3 compares individuals treated with a tweet to those untreated. On average the treated respondents perceived candidates to be 3.48 units away from each other, compared to 3.31 in the control group, a difference of .17(.09) with a p-value of .056. Since the data is skewed towards higher polarization values, we also report the log of perceived polarization, with treated respondents reported a .05(.028), with a p-value of .046. The lower plots compare the untreated group to both tweets separately. They show that individuals treated with either tweet perceived greater ideological distances between the candidates. Increases in perceived ideological distances occur even though the selected tweets provide no policy information to respondents. Instead, tweets framed each candidate based exclusively on valence issues (corruption and sexism for Clinton and Trump, respectively) causing respondents to rate the candidates further apart ideologically.

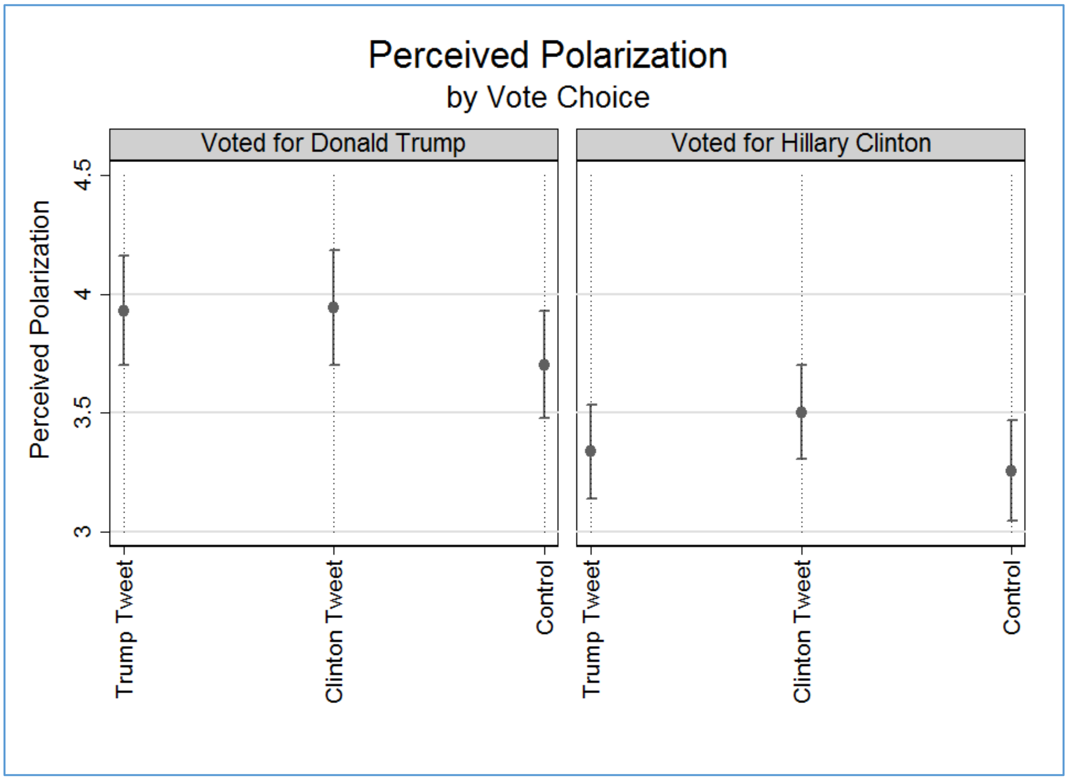
An important question is whether respondents who voted for Clinton or Trump reacted differently to the tweet from their less preferred candidate. As Figure 4 shows, we find that Trump voters' perception of polarization increased almost to the same extent when treated by tweets from either candidate.

Figure 3: Perceived Polarization and Tweet Exposure, Clinton and Trump



Note: Perceived polarization describes the difference between the reported placement of Trump and Hillary for each respondent.

Figure 4: Perceived Polarization, Tweet Exposure, and Vote Choice



Note: Perceived polarization describes the difference between the reported placement of Trump and Hillary for each respondent.

Another important consideration in all analyses, however, is a ceiling effect on exposure, as Trump voters perceive Clinton as being on the extreme left (1.6, only 0.6 unites away from the minimum of 1) while Democrats perceive Trump also extreme but on the right (5.9, only 1.1 unites away from the maximum of 7). In fact, the median untreated Republican voter placed Clinton as a 1, the most liberal score. Meanwhile, the median Democratic voter placed Trump as a 6. Given that Republican voters already perceive Clinton as extremely liberal and that Democratic voters perceive Trump as being very far to the right, the findings we present in our experiment are conservative and, in our view, noteworthy.

Table 1: Perceived polarization with Tweet treatment and controls, First Experiment

VARIABLES	Perceived Polarization (1)	Perceived Polarization (2)	Perceived Polarization (4)	Perceived Polarization (5)	Perceived Polarization (6)	Perceived Polarization (8)
Treated to either Tweet	0.178*	0.195**	0.191**			
	(0.0930)	(0.0954)	(0.0950)			
Treated to Trump Tweet				0.171	0.145	0.151
				(0.107)	(0.109)	(0.108)
Treated to Clinton Tweet				0.185*	0.247**	0.235**
				(0.108)	(0.110)	(0.109)
Voted Clinton		-0.493***	-0.284**		-0.494***	-0.285**
		(0.0904)	(0.135)		(0.0904)	(0.135)
Self-Placement, Lib-Cons			-0.413***			-0.409***
			(0.128)			(0.128)
Self-Placement, Lib-Cons^2			0.0591***			0.0587***
			(0.0156)			(0.0157)
Female			0.00828			0.00343
			(0.0893)			(0.0895)
Age			0.115*			0.114*
			(0.0595)			(0.0595)
White Democrat			0.177			0.177
						(0.141)
Constant	3.315***	3.728***	3.527***	3.315***	3.729***	3.525***
	(0.0759)	(0.0919)	(0.443)	(0.0760)	(0.0919)	(0.444)
Observations	1,011	796	796	1,011	796	796
R-squared	0.004	0.040	0.069	0.004	0.041	0.070
LogLik	-1769	-1313	-1301	-1769	-1312	-1300

Note: Estimates are unstandardized OLS coefficients with standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

While the samples are balanced, a further test of the results that also provides some information about other socio-demographic variables is provided in Table 1, which includes covariates for vote preference, ideological self-placement, age, and white democrats. Results were extremely robust to alternative specifications, with treatment effects remaining substantially unchanged when adding different covariates. Alternative models with logistic distributions and different population weights can be found in the replication files online. All in all, as expected, model results show that perceived polarization is greater for very liberal and very conservative respondents (Table 1, models 4 and 8) as well as for older respondents. Finally, perceived polarization was similar for male and female voters.

Study 2: Effect of attention on Perceived Polarization

In this section, we present results from a second experiment that measures the effect of time of exposure to Twitter on perceived polarization. Here, we randomly exposed respondents to three different tweets by the New York Times, Fox News, and Associated Press, which report on the dismissal of Acting Attorney General Sally Yates for her decision not to enforce President Trump's executive order known as the Muslim Ban. Specifically, we treated respondents alternatively with a liberal media tweet (NYT), a conservative media tweet (FOX News), or an ideologically neutral media tweet (Associated Press) on the Yates dismissal. Figure 6 shows the selection of tweets. In all three conditions, we measured the length of time subjects spent reading their assigned tweet and their responses (*i.e. like, retweet*, *reply,* or *ignore*). The objective of this second experiment was to test whether respondents who spent a longer amount of time reading a tweet perceived larger ideological distances between Democrats and Republicans. We define the time spent reading the tweet as *attention,* which is analyzed in detail in this section.

Figure 6: Perceived Polarization, Twit Exposure, and Vote Choice

Note: Selection of tweets was done based on networks analyses of approximately 10 million tweets collected between January 31st and February 2.

There are a few noteworthy differences from our first experiment, given that this survey was fielded three months after the 2016 election. First, we test for differences in the perceived polarization of parties rather than the perceived polarization of candidates. Second, in contrast to the first experiment, we measure perceived polarization on both a policy issue and in general. That is, one question concerns the distance between Democrats and Republicans in general while the second one is about policy locations regarding the executive order with travel restrictions to citizens from seven majority Muslim countries. A final difference from the original experiment is that the control group was a placebo, an ideologically neutral tweet from the Associated Press.

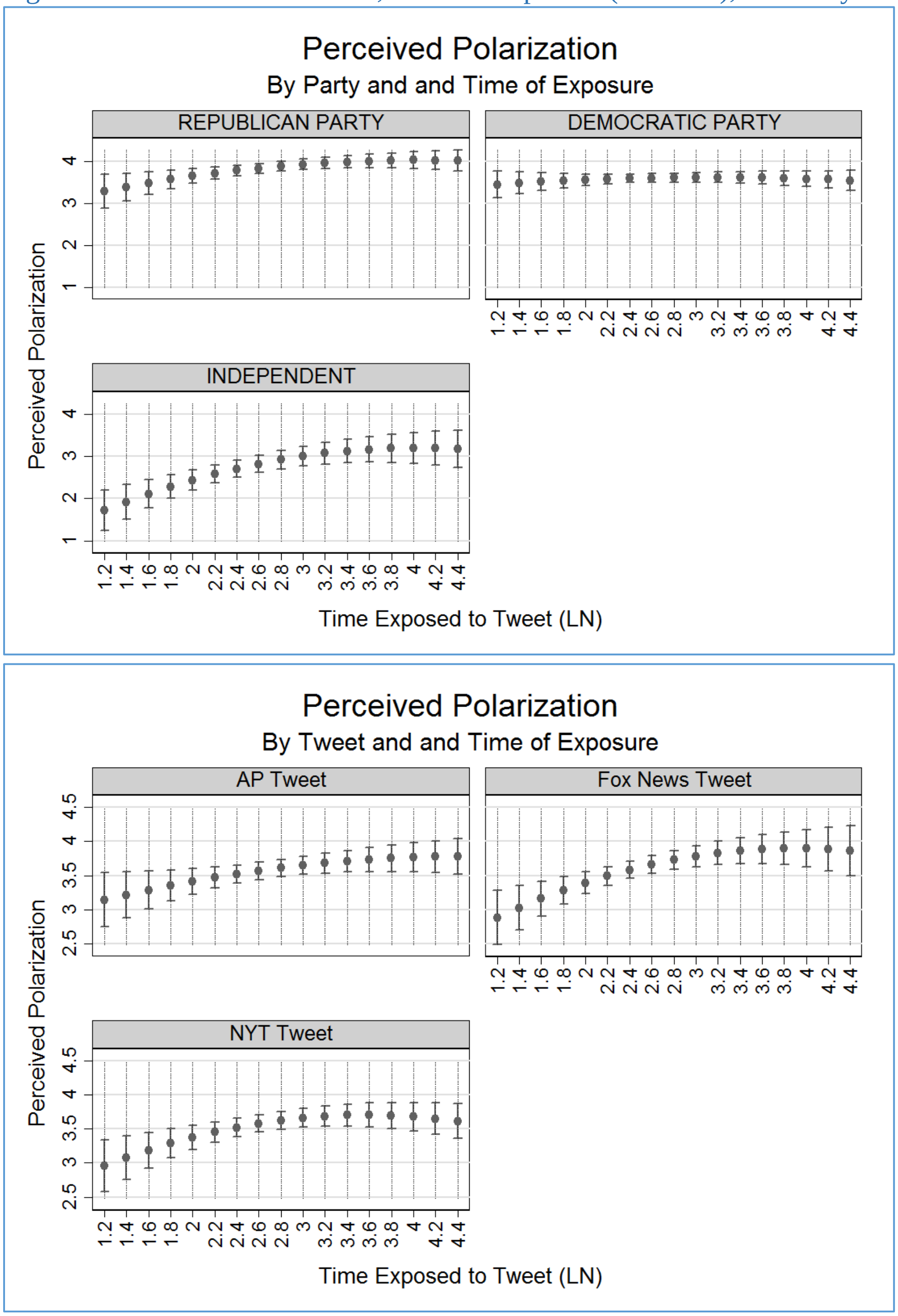
Data for the second experiment was collected between April 12 and 17 of 2017, three months after President Trump was inaugurated. As in the first experiment, this one was also conducted through Nielsen Scarborough from its larger probability-based national panel, which was recruited by mail and telephone using a random sample of households provided by Nielsen Scarborough. The sample included 2138 adult respondents, almost twice the size of the previous survey. It was matched to the U.S. population on these variables: age, gender, income, education, race, and geographic region using benchmarks from the U.S. Census. The survey was also weighted by partisan identification. The margin of error is 2.12%.

In our survey experiment, we randomly assigned participants to groups treated with one of the three tweets in Figure 6. These are actual tweets posted on January 31, after President Trump signed the first executive order restricting foreign travel. The signing of the executive order led to the firing of Acting Attorney General Sally Yates, who publicly refused to enforce it. From January 31st to February 2, we collected close to 10 million tweets related to the crisis, measuring user behavior in twitter data such as *likes*, *retweets*, *replies*, together with the associated metadata. Through network analysis, we identified the NYT and FOX tweets as circulating predominantly within Democratic and Republican online communities respectively. The AP tweet, on the other hand, was centrally located in the network and was retweeted by both pro- and anti-ban users. Again, we use actual tweets on the Yates firing because we are interested in the effect of real tweets on people's political opinions. Although we sacrifice some control over our experimental stimuli, as in the first experiment, we believe focusing on actual tweets strengthen the external validity of our results.

The median time that respondents spent reading either of the tweets was 14 seconds and the mean was 27 seconds. The data was skewed right, with 90% of respondents taking less than 40 seconds before moving to the next screen. This second screen asked respondents whether they would "like," "retweet," or "reply" to the tweet. A third set of questions were focused on the emotional response to the tweet by the user. Finally, we asked respondents to place themselves, the political parties, and the parties' positions on immigration on the liberal to conservative scale.

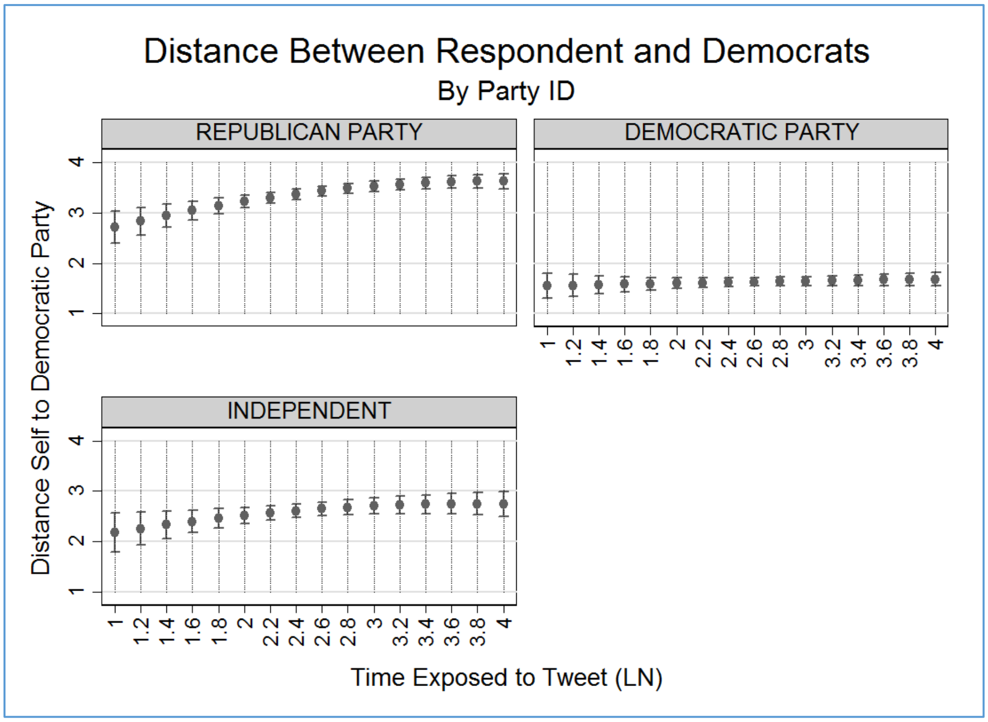
As in the first experiment, we measure perceived polarization as the reported distance between Democrats and Republicans, both in general and on immigration specifically. Respondents perceived parties as slightly more polarized on general policy (3.70 points) than on immigration (3.57). The correlation between the two dimensions was 0.672, indicating that they are highly related. The level of overall polarization was slightly higher than for candidates at the time of the election (3.70 compared to 3.43). This difference in polarization seems to be driven to a large extent by enhanced perceptions of polarization among Democrats, with reported distances increasing from 3.3 to 3.7 in those few months. However, as noted earlier in this article, Republicans respondents' perceptions of polarization (3.95) remain significantly greater than those of Democrats (3.71) and Independents (2.98).

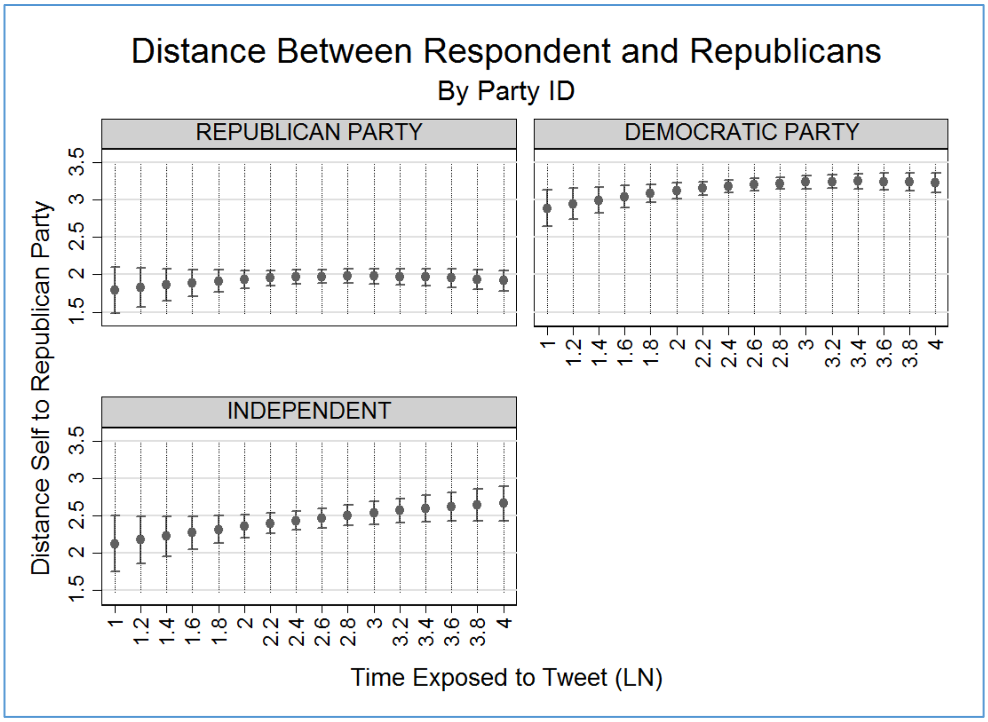
Figure 7: Perceived Polarization, Time of Exposure (attention), and Party ID



Note: Exposure to Tweet by Party ID and by Treatment.

Figure 8: Distance to Democrats and Republicans by Party ID and Tweet Exposure





Note: Exposure to Tweet by Party ID and by Treatment.

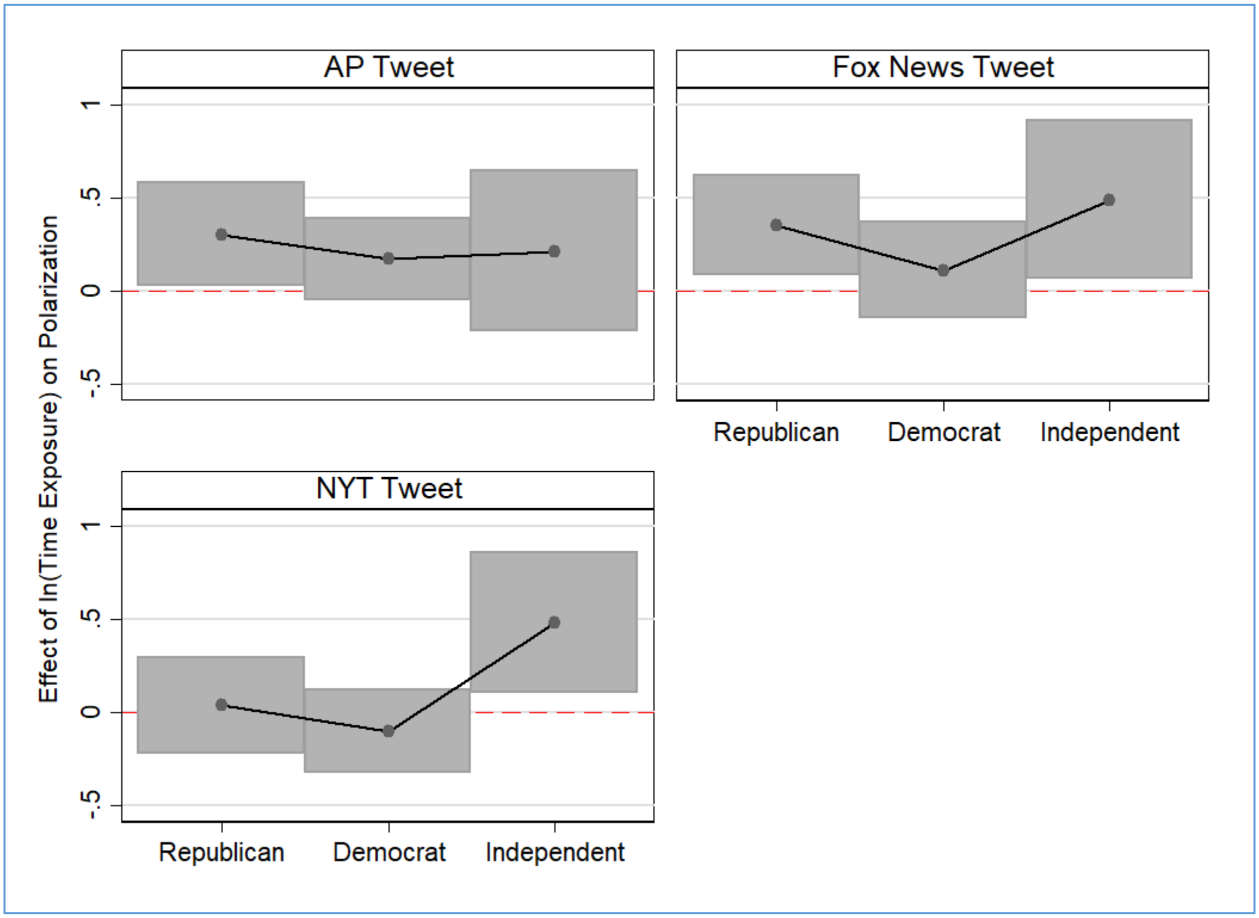
Figure 7 shows the effect of exposure time on perceived polarization on the travel ban, distinguishing by partisanship, first, and by type of treatment, second. The effect of exposure on perceived polarization is positive and statistically significant for all treatments, but it is larger for Fox News. The effect of exposure is larger for independents and Republicans. Meanwhile, results are not statistically significant when considering Democrats only.

As shown in Figure 8, higher levels of polarization are primarily driven by larger contrast effects for the less preferred party. Figure 8 presents estimates of distance between the self-reported position of respondents and their reported position of Democrats and Republicans. The horizontal axes indicate the length of time that respondents spent reading the original tweets. The vertical axes show the absolute distance between respondents and the Democratic and Republican Parties respectively. Separate plots by party ID show that Republican respondents perceived greater distances between themselves and the Democratic Party when exposed to tweets. Similarly, Democratic respondents perceived larger distances between themselves and the Republican Party when exposed to tweets.

The larger effect for Fox News is primarily driven by increased psychological *contrast* among Republicans, who increase distance between themselves and the Democrats to a greater extent than Democrats did when exposed to the NYT tweet. Meanwhile, among Independents, treatment with any tweet let to larger *contrast* and greater perceived distance from both parties. As a result, perceived polarization increased the most among independent voters.

The greater sensitivity of Republicans to the messages from Fox and AP is displayed in Figure 9, which shows the marginal effect of exposure time on polarization, conditional on the media source and the party. As one can see, the longer the exposure time to the Fox News and to the AP tweets, the greater the perceived polarization. That is, alignment with the source of the message increased contrast with the opposing party, leading to more polarization. Among independents, the tweets by both Fox News and the New York Times increased contrast with both parties as well as increased perceived polarization. Meanwhile, as noted before, there was no statistically significant effect on Democrats.

Figure 9: Marginal effect $\left(\frac{dy}{dx}\right)$ of Time of Tweet Exposure on Perceived Ideological Polarization, by Treatment and Party



Note: Results describe the marginal effect (slope) of time of exposure on polarization, conditional on the party of the respondent and the news organization of the tweet.

Table 2: Perceived polarization and Attention, Second Experiment

	(1) Polarization (Policy)	(2) Polarization (Policy)	(3) Polarization (Policy)	(4) Polarization (Ban)	(5) Polarization (Ban)	(6) Polarization (Ban)
Self-Ideological Placement	-0.0976*** (0.0264)	-0.0985*** (0.0264)	-0.0867*** (0.0268)	-0.0810*** (0.0283)	-0.0826*** (0.0283)	-0.0679** (0.0287)
Party ID: Democratic	-0.515*** (0.101)	-0.456*** (0.140)	-0.377*** (0.142)	-0.454*** (0.108)	-0.404*** (0.150)	-0.323** (0.152)
Party ID: Independent	-1.028*** (0.110)	-1.171*** (0.185)	-1.007*** (0.187)	-1.081*** (0.118)	-1.427*** (0.198)	-1.277*** (0.200)
Time Exposure in Seconds (LN)	0.0899** (0.0418)	0.637*** (0.155)	0.610*** (0.155)	0.110** (0.0449)	0.625*** (0.166)	0.602*** (0.166)
Time Exposure in Seconds^2		-0.0822*** (0.0226)	-0.0803*** (0.0226)		-0.0778*** (0.0243)	-0.0745*** (0.0243)
Treatment: Fox News	-0.110 (0.0772)	-0.0966 (0.122)	-0.104 (0.123)	0.0808 (0.0829)	0.0873 (0.131)	0.0738 (0.132)
Treatment: NYT	0.0127 (0.0758)	0.0380 (0.122)	0.00932 (0.123)	-0.00772 (0.0814)	-0.0519 (0.131)	-0.0668 (0.132)
Democrat*Fox News		-0.106 (0.163)	-0.0831 (0.164)		-0.184 (0.175)	-0.139 (0.177)
Independent*Fox News		-0.0643 (0.162)	-0.0237 (0.163)		0.0231 (0.174)	0.0538 (0.175)
Democrat*NYT		0.377 (0.248)	0.262 (0.249)		0.722*** (0.265)	0.705*** (0.267)
Independent*NYT		0.0913 (0.252)	0.0175 (0.252)		0.322 (0.270)	0.247 (0.271)
Native American			-0.148 (0.294)			-0.0684 (0.316)
Caucasian			0.392*** (0.135)			0.405*** (0.145)
Asian or PI			-0.117 (0.227)			0.150 (0.245)
Multiracial			0.0450 (0.199)			0.136 (0.215)
Other			-0.0913 (0.186)			-0.138 (0.200)
Internet Usage: X-Times a Week			0.228 (0.143)			0.155 (0.154)
Internet Usage: Weekly			0.294** (0.135)			0.285** (0.145)
Internet Usage: Not Often			0.196* (0.112)			0.179 (0.121)
Internet Usage: Never			0.273** (0.117)			0.183 (0.126)
Like			0.0695			0.110

			(0.0901)			(0.0971)
Retweet			0.187			0.204
			(0.144)			(0.155)
Reply			-0.0537			0.0246
			(0.116)			(0.126)
2.age_cat	-0.197	-0.197	-0.165	-0.303**	-0.293*	-0.296*
	(0.143)	(0.143)	(0.143)	(0.154)	(0.153)	(0.154)
3.age_cat	-0.370**	-0.394***	-0.374**	-0.432***	-0.453***	-0.468***
	(0.151)	(0.151)	(0.151)	(0.161)	(0.161)	(0.162)
4.age_cat	-0.123	-0.158	-0.174	-0.314**	-0.342**	-0.376**
	(0.141)	(0.141)	(0.142)	(0.151)	(0.151)	(0.152)
5.age_cat	-0.0814	-0.125	-0.178	-0.101	-0.140	-0.204
	(0.135)	(0.135)	(0.137)	(0.145)	(0.145)	(0.148)
6.age_cat	0.0985	0.0406	-0.0358	-0.0161	-0.0719	-0.161
	(0.137)	(0.138)	(0.141)	(0.147)	(0.148)	(0.152)
2.educat_wt	0.186	0.184	0.219	0.237	0.220	0.245
	(0.231)	(0.230)	(0.232)	(0.247)	(0.247)	(0.249)
3.educat_wt	0.384*	0.383*	0.441*	0.420*	0.409*	0.448*
	(0.232)	(0.232)	(0.234)	(0.249)	(0.248)	(0.251)
4.educat_wt	0.505**	0.508**	0.544**	0.548**	0.537**	0.555**
	(0.229)	(0.228)	(0.230)	(0.245)	(0.244)	(0.247)
2.income_wt	0.334***	0.323***	0.297***	0.195*	0.179	0.128
	(0.107)	(0.107)	(0.108)	(0.116)	(0.115)	(0.116)
3.income_wt	0.439***	0.435***	0.387***	0.399***	0.381***	0.309***
	(0.110)	(0.110)	(0.111)	(0.119)	(0.118)	(0.119)
4.income_wt	0.564***	0.548***	0.524***	0.449***	0.421***	0.372***
	(0.112)	(0.112)	(0.112)	(0.121)	(0.121)	(0.121)
5.income_wt	0.523***	0.514***	0.488***	0.440***	0.417***	0.358***
	(0.119)	(0.119)	(0.119)	(0.129)	(0.128)	(0.129)
6.income_wt	0.650***	0.629***	0.606***	0.606***	0.579***	0.518***
	(0.132)	(0.132)	(0.132)	(0.143)	(0.142)	(0.143)
Female	-0.0255	-0.0306	-0.0151	-0.155**	-0.160**	-0.148**
	(0.0644)	(0.0643)	(0.0645)	(0.0693)	(0.0690)	(0.0696)
Constant	3.578***	2.781***	2.187***	3.565***	2.867***	2.307***
	(0.328)	(0.400)	(0.438)	(0.352)	(0.427)	(0.469)
Observations	2,073	2,073	2,051	2,065	2,065	2,043
R-squared	0.097	0.105	0.124	0.093	0.103	0.117
LogLik	-3637	-3628	-3570	-3768	-3757	-3702

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Taken together, Figures 7, 8, and 9 provide evidence that exposure to tweets increases polarization through heightened ideological contrast rather than through assimilation. In the case of Independents, Twitter messages have the largest effect, as they increase contrast with both parties. In the case of Republicans, polarization is driven by increased contrast with the Democratic Party, which is perceived as being further to the left. While the effect is positive and significant among Democratic voters when taken together, results fail to achieve statistical significance when considering the smaller samples of the three treatments.

Table 2 includes results with an extended set of controls, including socio-economic variables such as age, income, education, gender, race, as well as controls for the frequency of use of social media in internet and the behavioral response to the treatments (like, retweet, and reply). Consistent with prior survey findings, polarization increases with age, income, and education. Controlling for those factors, both experimentally and through covariates, our findings provide evidence of a direct effect of social media exposure on perceived polarization. This increase in perceived polarization, we show, is primarily driven by contrast effect, where the opposing party is viewed as more extreme when respondents were shown Tweets. These effects where more pronounced when the source of the message was aligned with the preferences of the respondent.

5. Discussion

We live in polarized times, both in our daily lives as well as in our media feeds. We are affectively polarized, ideologically polarized, and more partisan than ever. Social media reflects this heightened polarization, providing an outlet to commune with fellow believers and to excoriate ever more disliked opponents. This is an important area of research, politically consequential and theoretically salient.

While we recognize that users in social media are polarized, there is little research showing that social media polarizes users. Results of the two experiments presented in this article provide conclusive evidence that exposure to tweets increases perceptions of polarization and that greater attention to tweets increases perceptions of polarization. The effect is statistically significant when exposing respondents to tweets by candidates, as well as when we exposed them to partisan media. We also observe a slightly stronger reaction to the tweets among Trump voters than Clinton voters. It is possible that Republican voters are more motivated to defend their partisan identity than Democrats (Theodoridis 2017). As a result, they are more likely to see a greater distance between the parties.

We explain our findings as the result of increased contrast effects in the placement of parties and candidates. Further, we show that exposure to tweets increases contrast both for the candidate people support as well as for the one they oppose. That is, rather than fostering an *us vs. them* state of mind, we find that the users exposed to tweets saw all candidates and parties as more extreme. Our experimental findings also show that increasing the time spent reading a tweet (attention) has a significant effect on our perceptions of polarization. The effect of attention increased rapidly in the early seconds, holding steady as time progressed.

Observers differ over how respond to the growth in polarization in American politics. Some seek to change attitudes, while others advocating modifying political institutions. In either case, an improved understanding of the sources of polarization and the mechanisms that exacerbate it is indispensable. The findings we report suggest that social media is a contributing factor. While leading social media companies have recently begun efforts to deal with fake news, the effect we find is a more basic one. Social media are not going anywhere and, for the foreseeable future, neither is polarization.

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Appendix A: Balance between Treatments, both experiments

Experiment 1	Trump Tweet			Clinton Tweet			Control Group		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Polarization	338	3.485	1.361	336	3.500	1.393	337	3.315	1.430
Hillary Vote	315	0.517	0.500	316	0.509	0.501	311	0.463	0.499
Ideology	346	3.934	1.716	346	3.951	1.738	347	4.138	1.705
Woman	347	0.473	0.500	348	0.537	0.499	347	0.447	0.498
Age	347	2.262	0.781	348	2.293	0.771	347	2.219	0.789
White Democrat	347	1.870	0.336	348	1.876	0.330	347	1.873	0.333

Experiment 2	AP Tweet			Fox Tweet			NYT Tweet		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Polarization	690	3.583	1.541	686	3.599	1.590	700	3.534	1.603
Ideology	699	3.950	1.812	697	4.024	1.716	714	4.003	1.800
PartyID	703	1.750	0.660	712	1.751	0.686	723	1.743	0.660
Race: Native American	700	0.013	0.113	706	0.016	0.124	715	0.011	0.105
Race: Caucasian	700	0.803	0.398	706	0.800	0.400	715	0.803	0.398
Race: Asian	700	0.036	0.186	706	0.025	0.158	715	0.022	0.148
Race: Multi-racial	700	0.043	0.203	706	0.031	0.174	715	0.048	0.213
Race: Other	700	0.046	0.209	706	0.064	0.244	715	0.055	0.227
Internet: Several Times aWeek	700	0.103	0.304	706	0.085	0.279	715	0.083	0.275
Internet: Weekly	700	0.107	0.310	706	0.125	0.331	715	0.113	0.317
Internet: Not often	700	0.409	0.492	706	0.377	0.485	715	0.378	0.485
Internet: Never	700	0.283	0.451	706	0.331	0.471	715	0.312	0.464
TimeExposed (LN)	702	2.853	0.802	711	2.600	0.670	723	2.812	0.821
Action: Like	703	0.174	0.379	712	0.167	0.373	723	0.152	0.359
Action: Retweet	703	0.060	0.237	712	0.024	0.153	723	0.068	0.252
Action: Reply	703	0.085	0.280	712	0.073	0.260	723	0.089	0.284
Age	703	4.114	1.624	712	4.097	1.550	723	4.050	1.601
Education	703	3.275	0.884	712	3.206	0.875	723	3.201	0.907
Income	703	3.349	1.586	712	3.279	1.518	723	3.245	1.570
Woman	703	1.506	0.500	712	1.494	0.500	723	1.484	0.500

Note: Summary values for treatments and variables in Table 1 and Table 2.