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Analyzing change in network polarization

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Abstract

The growing influence of social media in an era of media fragmentation has amplified concerns of political polarization. Yet relatively few studies have analyzed polarization in user networks over time. This study therefore examines change in network polarization on Twitter during a highly contested general election. Using Twitter's REST API, user networks of 3000 randomly selected followers of well-known partisan and entertainment-oriented accounts were recorded 17 times in the 7 months leading up to the 2016 general election. Results suggest that partisan users form highly partisan networks on Twitter, while moderate, or less engaged, users continue to mostly avoid politics.

Keywords

Change, longitudinal, networks, political polarization, selective exposure, Twitter

The growing influence of social media in an era of media fragmentation has heightened concerns about political polarization. With the potential for algorithms to amplify the homogeneity of user networks, there is a growing concern that social media are contributing to polarization via partisan selective exposure and online echo chambers (Colleoni et al., 2014; Sunstein, 2009; Wojcieszak, 2010). Indeed, if new media platforms exacerbate political divisions to the point where people no longer maintain diverse channels of communication, then self-governance, public deliberation, and respect for pluralism may become unsustainable features of our democracy (Mancini, 2013). However, despite a common perception among scholars and pundits of a more polarized general public in recent years, evidence of political polarization is ambiguous (Prior, 2013). Upon reviewing the literature on political polarization, Prior (2013) concluded that empirical analysis has been "severely hampered by a seemingly simple problem: we do not know how many

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and what kind of people are exposed to which messages" (p. 102). As such, understanding how partisan selective exposure operates on a popular social-networking platform like Twitter could tell us a lot about political polarization in the current media environment.

The purpose of the present study is to better understand change in political follow decisions on Twitter during a high-profile, contentious general election. Toward this end, the current study tracks a random sample of Twitter users during the 2016 general election. The investigation makes three main contributions. First, it provides an empirical account of political polarization on social media during an election using a unique and rich data set from a large, probability sample of 3000 randomly selected Twitter users. The data collection process, which used Twitter's API to record—without measurement error—user networks at 17 different time points throughout the 2016 general election, offers a rare glimpse of change in actual polarization behaviors over the course of an active election. Second, the study sheds light on previously understudied dynamics of user networks *over time* on Twitter. And, third, it provides powerful evidence of why we need to take seriously the influence of social media on civic engagement and the political polarization process. Overall, the study makes a valuable contribution to our understanding of change in user networks and political polarization during an acutely polarizing time in electoral politics (Gramlich, 2016).

Measuring polarization

The consensus in the literature suggesting political polarization is the distance between competing political orientations quickly breaks down when scholars start defining "political orientation" or, especially, "distance." By evoking a metaphor of "polarization," consideration of movement, that is, distance, away from the center and toward the poles naturally follows. What this means in political contexts, however, is not so simple. For the most part, concerns of polarization in the literature focus on the dangers of not communicating with people from the other side (e.g. Arceneaux et al., 2012; Fischer et al., 2005; Garrett, 2009; Kim, 2011; Mutz, 2006; Stroud, 2010). Indeed, concerns undoubtedly reflect contemporary democratic principles of free expression, debate, and public deliberation (Sunstein, 2009), but none of these principles readily translate into physical distance. Rather, most definitions of polarization in political communication research fall into one of five different categories—voting records (e.g. Bartels, 2000; Hetherington, 2001), issue positions and ideologies (e.g. Abramowitz and Saunders, 1998; Baldassarri and Gelman, 2008; Lelkes, 2016), attitudes (e.g. Lau et al., 2016; Lupu, 2015; Westfall et al., 2015), media exposure (e.g. Arceneaux et al., 2012, 2013; Levendusky, 2009), and social networks (e.g. Himelboim et al., 2013b; Huckfeldt et al., 2004; Kim, 2011; Lee et al., 2014; Leighley and Matsubayashi, 2009). Although each category has its own strengths and weaknesses, which will be discussed in more detail in the following section, across all categories, scholars have been limited in their ability to exploit the obvious parallels between polarization and social networks in particular. In other words, although partisanship is formed and maintained via the organization of political social networks, technological limitations and convenience of self-report has produced definitions of partisanship that rarely examine *networks* for evidence of political polarization. This study seeks to address this gap in the research.

Voting records

The clearest evidence of polarization can be found among political elites, specifically elected officials. For the past several decades, considerable evidence suggests political candidates and elected officials have become more polarized (Abramowitz and Saunders, 1998; Hetherington, 2001; Layman and Carsey, 2002; Levendusky, 2009; McCarty et al., 2009). One would assume such an obvious trend of elite-level polarization would contribute to *mass polarization*, or the political polarization of the general public. While several studies have supported this assumption (e.g. Abramowitz and Saunders, 1998; Hetherington, 2001), other studies found evidence of *party sorting*, the proportion of people affiliated with one of the two major parties, but not mass polarization (Fiorina and Abrams, 2008; Hill and Tausanovitch, 2015). But it is also possible that neither explanation is correct. In other words, the polarization of legislators, for example, could be due to gerrymandering (Carson et al., 2007; McCarty et al., 2009; Mann, 2007) or even evolution in political strategy (Ansolabehere et al., 2010; Theriault and Rohde, 2011). Ultimately, voting records of legislators alone do not translate to polarization of the public. Research must instead continue to look at behaviors and communication across the public to understand mass polarization.

Issue positions, ideologies, and attitudes

The second and third categories of research on political polarization place emphases on issue positions or political ideologies and attitudes. Studies in these categories of research, all of which tend to describe the degree to which people hold competing political perceptions or beliefs, have been instrumental to current understandings of polarization, but they are not without their limitations. For instance, studies often assume issue positions or ideologies reflect some objective reality of political opinions and ignore antagonistic expressions of political competition. Even if it were possible to accurately measure the degree to which political opinions differ, there is little reason to believe perceived differences would correspond with objective differences because political opinions and ideologies do not strictly adhere to some certain set of rules or regulations—for example, research on political cognition makes it clear the role of partisanship should not be understated (Nyhan and Reifler, 2010; Westen, 2008). No doubt insights can be gleaned from studying affective competition between parties (e.g. Lau et al., 2016; Lee et al., 2014; Westfall et al., 2015), but affective, or even emotional, modes of polarization do not directly represent “dangerous,” or closed-off and self-reinforcing, manifestations of polarized societies. In fact, some theorists even claim that passionate and heated debates are cornerstones of democratic deliberation (e.g. Mouffe, 2005).

Furthermore, a significant challenge in the literature finds that when considered in the context of new digital media environments, operationalization of perceptions and attitudes nearly always suffers from a reliance on self-report data (Prior, 2013). Difficulties in the measurement of media exposure have, consequently, highlighted the importance of accuracy and reliability in academic research (e.g. Prior, 2009a, 2009b). And these concerns are magnified for studies that attempt to analyze change in partisan media behaviors over time. The current study remedies this gap in the literature by measuring, directly, polarization behaviors of users during a highly salient time in US politics.

Media exposure

The fourth category of research on political polarization concerns selective exposure and media exposure in an era of unprecedented media choice (e.g. Arceneaux et al., 2012, 2013; Bennett and Iyengar, 2008; Holbert et al., 2010; Prior, 2005, 2013; Stroud, 2008, 2010). Advances in digital media have lowered the cost of entry for providers of media content. As a result, highly specialized and audience-specific news outlets have quickly populated cable networks and online domains. In the political context, the fragmentation of media has led to a considerable increase in partisan media sources (Levendusky, 2013). It is hardly surprising the political consequences of increased media choice brought on by the digital age have been linked by many to perceived increases in political polarization, especially given that the increase in mass polarization seems to coincide with the expansion of media choice and the subsequent rise of partisan media (e.g. Hollander, 2008; Jones, 2002). However, due to limitations in current approaches to the measurement of media exposure, evidence of political polarization via partisan selective exposure in new media environments remains unclear (Prior, 2013).

Social networks

In today's new media environment, understanding the role of media choice is essential to understanding media effects. It is therefore important to examine how emerging media technologies, in particular, shape the flow of information. So far, the most important of these emerging technologies is social media. Use of social media platforms, such as Facebook, Twitter, Snapchat, and Instagram, has become so widespread that American adults are arguably more likely to have used social media—Pew Research Center (2017) estimates 76% of adults use social media—than read a book—YouGov (2013) estimates 72% of all adults read a book in the previous year. Over the past several years, social media has become a fixture of the digital media information environment. Even traditional media outlets are now adapting to a new media environment (Gleason, 2010). Pew research estimates that over 60% of American adults get news from social media (Gottfried and Shearer, 2017), and political communication research has confirmed the importance of social media in political contexts as well. For instance, researchers have linked social media use to voting (Bond et al., 2012), political expression (Warner et al., 2012), civic engagement (Gil de Zúñiga et al., 2012), and even political revolutions (Tufekci and Wilson, 2012).

Partisan selective exposure

In the current political landscape, it is clear that politics is largely dictated by political parties (Gramlich, 2016). Scholars generally agree that partisan sorting, or increases in partisan consistency, has increased in recent years (e.g. Hetherington, 2001), but the extent to which partisanship increasingly shapes behaviors in the general public remains unclear. For example, we know that partisanship can trump political ideology (Glaeser and Sunstein, 2013; Kahan et al., 2013; Kahneman, 2011; Warner and McKinney, 2013) and reinforce selective behaviors (Huckfeldt et al., 2004; Kim, 2011; Leighley and Matsubayashi, 2009; Mutz, 2006; Sunstein, 2009; Tsfati and Nir, 2017), but we still do not know how exactly partisanship affects exposure to diverse viewpoints. Because partisanship is about political affiliations, and not about ideologies or opinions, polarization should therefore be understood at the network level (e.g. Himelboim et al., 2013b; Kim, 2011).

Many selective exposure behaviors on social media such as *follow decisions*, or choosing to follow another account, are influenced by factors other than political ideology—for example, interpersonal relationships or self-presentation goals. Analyzing survey data collected by Pew Research, Bode (2016) found politically motivated *unfriending* occurred among fewer than 10% of respondents. However, it was most common among people who talked more frequently about politics, held strong ideological beliefs, and encountered more information on social media. The Pew survey did not ask about Twitter, specifically, and most of the items borrowed terminology from Facebook and framed the questions to be about the respondents' "friends" on social media. Interpersonal dynamics are especially salient on platforms like Facebook where user networks largely reflect interpersonal relationships that extend offline (Wilson et al., 2012) and where follow decisions must be reciprocal (one user initiates a friend request, and the other user chooses to accept or deny it). Perhaps the biggest problem with the Pew survey data is that it relied solely on users to self-report both their frequency and their motivations for unfriending. Media exposure research makes it clear that participant recall is not entirely reliable. It is also likely not socially desirable to "unfriend" someone or to admit to appear to be "thin skinned." With this in mind, the current study examines a social media platform that should be more vulnerable to partisan motivations as explained in the following section.

Although the current study does not capture user attitudes, there are nevertheless reasons to suspect partisanship will systematically influence decisions of Twitter users. Building on the assumption that all reasoning is motivated (Kunda, 1990), the model of motivated skepticism, for example, explains selective exposure decisions in the context of political information (Lodge and Taber, 2000; Taber and Lodge, 2006). This theory of motivated reasoning suggests media exposure decisions are driven by two competing goals—accuracy and partisanship. Accuracy goals reflect the desire to seek out valid, or correct, information. Partisan goals reflect the desire to defend one's (prior) beliefs. Thus, motivated reasoning suggests that when people encounter new data, they process them along with their prior attitudes. This means people are always updating, and not purely evaluating, information. The degree to which new information influences beliefs relative to prior information depends on the strength and motivation of those priors. Given what we already know about political partisanship, new political information rarely overwhelms prior partisan commitments. Of course, follow decisions may also be influenced by changes in algorithms or other platform features designed to encourage or grow user interactions and networks or by changes stemming from existence of strong ties and/or weak ties. User networks may change, for example, in response to pressures from strong ties or from exposure to diverse or novel information from weak ties (Aral, 2016).

Twitter

When comparing the various social media platforms, there is reason to believe that for users on Twitter, whether they decide to follow political accounts should be relatively unburdened by interpersonal considerations (Colleoni et al., 2014). Unlike Facebook, follow decisions on Twitter are unidirectional. Users can decide to follow any public account (Twitter allows users to opt-in to *protected* accounts, which means their timelines are not publicly available and followers must be granted permission by the original user) whether or not the public account follows in return. A quick examination of political Twitter accounts reveals the vast majority of political elites do not *follow back*. This suggests most users do not personally know the elites they choose to follow. Furthermore, when Twitter users decide to follow political elites, communication tends to be one-directional (from elite to user). For these reasons, it seems unlikely that follow decisions regarding well-known, or elite, accounts are driven by interpersonal factors.

Although users often encounter news on multiple different platforms, research focusing on Twitter, in particular, offers three advantages. First, while more people report using Facebook overall, a higher percentage of people *seek out* news on Twitter (Gottfried and Shearer, 2017). And, Twitter is hardly struggling to attract users. As of 2016, roughly 16% of American adults report using Twitter (Gottfried and Shearer, 2017), which translates to roughly 40 million people in the United States alone. Given the number of users and the salience of trending information, there is reason to believe user behaviors on Twitter will vary as a function of proximity to an election (e.g. Jang and Pasek, 2015).

The second advantage to narrowing the focus of study to Twitter is the unique nature of user connections. Unlike most social media platforms, user connections on Twitter operate asymmetrically. That is, user A can follow user B even if user B chooses not to follow (back) user A. To be consistent with Twitter documentation, the current investigation refers to users who follow an account as *followers* and the users followed by an account as *friends*. So, in the example of users A and B, user A would be considered a follower of user B, while user B would be considered a friend of user A. The asymmetrical nature of follower/friend user networks means users can easily make connections with people, or organizations, they do not personally know, which makes Twitter a natural destination for affiliative expressions (e.g. Hong, 2012). Accordingly, it is not uncommon for Twitter users to follow one or more news organizations or political figures. Even the initial account creation process on Twitter, where users are encouraged to share their email and/or mobile contacts and their interests in order to generate a list of recommended accounts to follow, encourages users to make asymmetrical connections with particularly well-known and popular Twitter accounts. In short, while social media generally facilitates connections with strong ties (i.e. close friends) and, though perhaps to a lesser extent, weak ties (e.g. acquaintances) (Aral, 2016; Gil de Zúñiga et al., 2012; Valenzuela et al., 2018), Twitter makes it particularly easy for users to connect with a wide range of users, for example, close friends, acquaintances, celebrities, public figures, organizations, companies, and so on.

The third advantage to narrowing the focus of study to Twitter is the availability of real-time data generated by millions of users. Other social media platforms offer similar data-sharing services, but few can match the amount of data and the accompanied documentation provided by Twitter. Leveraging such large amounts of Twitter data during especially salient times for politics, like general elections, makes it possible to examine difficult to study concepts—for example, how do political networks change over time? Do politically disinterested people increasingly form new, political connections or do they "tune out" of politics entirely over the course of an election?

In light of the growing influence of social media, the information-seeking nature of asymmetrical certain user networks, and the availability of Twitter data, the current study examines selective exposure in follow decisions on Twitter leading up to the 2016 general election.

Previous research

Numerous studies have examined political information on social media platforms like Twitter (Bakshy et al., 2015; Barberá, 2015; Barberá et al., 2015; Bode, 2016; Boutet et al., 2013; Himelboim et al., 2013a; Larsson and Moe, 2012). And like the research suggesting political orientations shape how people select traditional media (Stroud, 2008, 2010), this research suggests political orientations also shape how Twitter users choose to communicate (Boutet et al., 2013; Shin et al., 2016; Stewart et al., 2018), engage discussion networks (Conover et al., 2011; Himelboim et al., 2013b), share links (Shore et al., 2018), and make follow decisions (Bakshy et al., 2015; Barberá, 2015; Barberá et al., 2015; Conover et al., 2011; Feller et al., 2011). In other words, it is clear the partisan orientation of political elites on social media should, on the whole, match the partisan orientation of their followers.

Change in polarization

Analysis of change

Several studies have examined polarization on Twitter over time (Barberá, 2014; Barberá et al., 2015; Conover et al., 2011; Shore et al., 2018; Trilling et al., 2016), but relatively few studies have focused on the concept of change in this context. For instance, to date, no study has used repeated measures of follow decisions made by ordinary users on Twitter to model between-user *and* within-user change during a major election. Without an understanding of how these behaviors evolve over time and especially during elections, it is impossible to effectively assess the political implications of social media use.

Political salience and the election

In its simplest form, the hypothesis forwarded here suggests that change in network polarization, or the number of partisan-consistent follow decisions compared to the number of partisan-discrepant follow decisions made by a user, should occur as a function of proximity to the election and whether or not the users were sampled from a partisan rather than entertainment-centered account. Studying the trajectories of selective-exposure decisions on a popular social media platform like Twitter should shed light on the role of change in the polarization of user networks in new media environments.

Within users, one would expect to find that network polarization increases as the election approaches. Proximity to the election should also raise the salience of political orientations, driving users to increasingly add more homogeneous follow decisions to their user networks. Not only should politics become more salient as coverage of the election intensifies, but the value placed on homogeneous political connections should increase as well. This would explain why, using ANES data collected during the 2004 election, Stroud (2008) found that people increasingly selected attitude consistent cable news programs leading up to the election. So, if the salience of partisanship positively correlates with proximity to the election, and if political stakes grow as the election approaches, then the effect of partisan selective exposure on follow decisions should increase within-users leading up to the election as well. Therefore, this study tests the following hypothesis:

> *H1*. Follow decisions on Twitter during the 2016 election will vary as a function of user partisanship and proximity to the election.

Method

Data collection

To test the theorized relationship between partisan preferences of users and proximity to the election, a sample (N=3000) of partisan and non-partisan users were randomly selected and then tracked at frequent time intervals (N waves=17) in the months leading up to the 2016 election. Data were collected via Twitter's public REST API using the R package *rtweet* (Kearney, 2016). Data collection started on 13 June 2016, shortly after the second of the two major party candidates for US president—Hillary Clinton of the Democrats and Donald Trump of the Republicans—became their party's presumptive nominee, and concluded on 11 November 2016, 3 days after the general election.

User population and sampling

The population of users consisted of followers of 12 well-known partisan and non-partisan *source accounts*. Four source accounts were selected to represent each of three groups. The selection of source accounts was based primarily on use or estimates of partisanship in previous research but also with an effort to select relatively equivalent (in terms of popularity, activity, whether the account represents a person or organization, etc.) accounts. The republican group consisted of followers (N=4,551,488) of Drudge Report (@DRUDGE_REPORT), Fox News Politics (@foxnewspolitics), Sarah Palin (@SarahPalinUSA), and Sean Hannity (@seanhannity). The democratic group consisted of followers (N=8,566,150) of *Huffington Post Politics* (@HuffPostPol), Rachel Maddow (@maddow), Paul Krugman (@paulkrugman), and Salon.com (@Salon). Finally, because research suggests politically moderate users tend to tune out of politics,

Table 1. Source account descriptive statistics.

Screen name	Sample users	Followers	Friends	Statuses
AmericanIdol	1	2,090,180	5773	75,539
survivorcbs	317	495,992	131	9435
AMC_TV	471	622,058	223	11,574
SInow	211	1,577,758	662	183,918
foxnewspolitics	212	784,015	247	40,268
SarahPalinUSA	301	1,313,279	137	3272
seanhannity	192	1,842,831	6791	33,169
DRUDGE_ REPORT	295	1,080,190	2	180,211
maddow	48	5,527,141	2411	4526
HuffPostPol	271	980,521	9048	261,936
paulkrugman	327	2,108,324	8	7996
Salon	354	870,115	6060	137,760

the moderate group consisted of followers (N=4,715,390) of entertainment-focused AMC TV (@AMC_TV), American Idol (@AmericanIdol), Sports Illustrated (@SInow), or CBS's Survivor (@survivorcbs). The number of followers, friends, and statuses of the source accounts at the time of sampling can be seen in Table 1.

Due to Twitter API rate limits, a three-stage sampling strategy was devised to leverage probability-based sampling methods while also allowing the filtering out of private (it is not possible to gather network information for users who opt-in to private account status), likely elite (exceptionally popular accounts), inactive, or automated (bot) accounts. First, user-level data were looked up for a large sample of randomly selected followers from each source account group (N=20,000).[1] Second, filters based on firsthand experience and previous research (e.g. Barberá, 2015; Haustein et al., 2016; Yardi et al., 2009) were applied to the randomly sampled users data to remove elite, inactive, and automated accounts.[2] Users were removed if they had fewer than 50 or greater than 1500 followers (number of accounts followed by a sampled user) or friends (number of accounts a randomly sampled user followed), or if they posted fewer than 200 statuses in total or failed to post at least one status on average every 10 days. Because follow/unfollow decisions occur relatively infrequently, the final filter (one status on average every 10 days) was used to ensure a minimum level of user activity. Other filters were similar[3] to those used by Barberá (2015). Third, using the filtered data, an equal number of users (n=1000) were sampled from each group, yielding a final sample size of 3000 users (N=3000). For a summary of user statistics and estimates of non-missing observations[4] for each group, see Table 2.

Follow decisions

The dependent variable of interest is network polarization, the degree to which partisanship of a user's network is homogeneous. Network polarization was measured by

Table 2. Summary statistics of sample and group.

Group	Waves	*N* per wave	Followers	Friends	Statuses
Dem.	16.52	971.88	396.12	736.38	4029.10
Ent.	15.84	931.88	335.88	694.26	4108.36
GOP	16.24	955.42	364.19	705.42	3690.30
Mean	16.20	2859.18	365.81	712.30	3941.72
SD	2.84	67.93	268.84	423.89	5332.66

collapsing all observations across time and calculating a weighted estimate of partisanship for each follow decision made by sample users in each group. To classify the partisanship of follow decisions, target accounts, or *elites*, were identified as republican, democrat, or moderate. Given the sampling method used—random samples of users taken from multiple source accounts selected to represent republican, democrat, and moderate groups—whether the target [account] of a follow decision was republican or democrat was approached as an empirical question. Thus, targets of follow decisions were considered elites and included in the analysis if they were followed by at least one sampled user from at least two different source accounts—regardless of whether the source accounts came from the same or different partisan groups. For example, an account was included as an elite if it was followed by a user sampled from Sean Hannity's followers and a user sampled from Sarah Palin's followers.

A principal components analysis (PCA) with oblique rotation was conducted to validate group assignments for the 12 source accounts. PCA was chosen over the ideal point estimation method used in Barberá (2015) due to its flexibility and ease of use for generating estimates across multiple dimensions (Potthoff, 2018). The results of the PCA revealed that the observed clustering of follow decisions by users sampled from each of the source accounts was consistent with the assumed group associations described earlier. The rotated loading matrix can be seen in Appendix 1. Regression scores for each of the three components (columns)—identified as democrat, republican, and moderate—generated by the PCA were then used as weighted estimates of the elite accounts (rows). The regression scores were then converted into weighted estimates by dividing the dimension values by the row sum for each elite account—in effect creating a proportional likelihood, which, importantly, sums to 1.0, for each elite along all three dimensions. The benefit of the weighted estimate is that the values translate into the actual number of follow decisions rather than simply the statistical loading on a rotated component. At each time point, the sum of weighted estimates for each component (partisan-republican, partisan-democrat, and non-partisan/moderate) was calculated based on the follow decisions made by each user. Network polarization was then calculated at each time point by taking the absolute value of the difference between the sum of republican follow decisions and the sum of democrat follow decisions.

Results

By randomly sampling from well-known partisan-republican, partisan-democrat, and non-partisan entertainment accounts, and by collecting repeated measures ($n_{waves} = 17$)

of each user's follow decisions in the months leading up to the election, the current study has compiled a unique data set that makes it possible to not only examine partisanship of networks *between* users but also to examine change in networks *within users*.

It was hypothesized that follow decisions during the 2016 election would vary as a function of user partisanship and proximity to the election. To account for other user-related differences, models also included several time-invariant covariates, including years since joining Twitter (account age), the number—in thousands—of tweets posted by a user (statuses), the number of accounts—in hundreds—a user follows (friends), as well as the number—in hundreds—of accounts that follow a user (followers).

Multilevel modeling

Models were estimated using multilevel modeling, which provides a framework for making inferences for both constant (fixed) and varying (random) effects (Gelman, 2005). The decision to use multilevel modeling was supported by empirical and theoretical reasons. The empirical support comes in the form of considerable observed variance in follow decisions between users in both their starting points (intercepts) and their change over time (slopes), intraclass correlation coefficient (ICC) = .75—95% confidence intervals = .74–.76. And the theoretical support comes from the theorized effect of proximity to the election on follow decisions depending on whether users were partisan or non-partisan. Thus, a random intercept and random slope was included in all models.

Models

Coefficients for the three estimated models predicting the weighted number of homogeneous (partisan-matching) follow decisions are included in Table 3. Model 1 included several level 2 predictors, including account age, statuses, followers, friends, and the number of weeks from the start of data collection. Model 2 added the partisan grouping variable—that is, whether a user belonged to a partisan group (democrat or republican) or the non-partisan group. Model 3 added the interaction of the number of weeks from the start of data collection with the partisan grouping variable (Partisan × Weeks).

Models were compared using the change in chi-square ($\Delta\chi^2$) test. The test revealed Model 2 fit the data significantly better than Model 1, $\Delta\chi^2(1) = 474.88, p < .001$, which suggests that partisan user groups contributed significantly to explaining change in partisan follow decisions. To determine if the follow decisions of partisan-democrat/republican users differed from those of non-partisan/entertainment users as a function of proximity to the election, Model 2 was then compared with the final mode. The chi-square test revealed that Model 3 fit the data significantly better than Model 2, $\chi^2(1) = 69.90, p < .01$. This finding suggests the relationship between proximity to the election and homogeneous follow decisions was conditional on the partisanship of the user, which is consistent to the proposed hypothesis.

Interpreting the interaction

A visual depiction of the interaction is provided in Figure 1. The second facet (on the right) in Figure 1 shows the average number of weighted follow decisions for partisan

Table 3. Varying intercept/slope estimates predicting change in homogeneous follow decisions.

	Model 1	Model 2	Model 3
Fixed effects			
(Intercept)	18.96***	−12.70***	−16.06***
	(3.42)	(3.45)	(3.47)
Account age	−1.62**	−1.90***	−1.90***
	(.55)	(.51)	(.51)
Statuses	−.49*	−.22	−.22
	(.23)	(.22)	(.22)
Followers	.00	−.84*	−.83
	(.46)	(.43)	(.43)
Friends	7.97***	7.98***	7.98***
	(.06)	(.06)	(.06)
Weeks	.21***	.21***	−.09*
	(.03)	(.03)	(.04)
Partisan		52.62***	57.69***
		(2.29)	(2.37)
Partisan × Weeks			.45***
			(.05)
Random effects			
Var: User (Intercept)	4438.60	3709.90	3704.21
Var: User weeks	1.84	1.84	1.79
Cov: User (Intercept) weeks	27.98	22.71	22.21
Var: Residual	38.98	38.98	38.98
AIC	251,288.99	250,816.11	250,748.21
BIC	251,373.30	250,908.84	250,849.37
Log likelihood	−125,634.50	−125,397.05	−125,362.10
No. observations	33,878	33,878	33,878
No. groups: User	3000	3000	3000

AIC: Akaike information criterion; BIC: Bayesian information criterion.
***$p < .001$; **$p < .01$; *$p < .05$.

users over time with the red line representing the average of the republican group and the blue line representing the average of the democrat group. As expected, the number of weighted homogeneous follow decisions of partisan users increased as the election got closer. In contrast to partisan users, the first column (left side) of Figure 1 shows that follow decisions of non-partisan/entertainment users increased only slightly as the election approached. Taken together, these results support the hypothesis that homogeneous follow decisions would vary as a function of user partisanship and proximity to the election.

Regardless of the model, when examined at the group level, there is no missing the clear preference of politically homogeneous follow decisions among Twitter users. This is perhaps best illustrated in Figure 2, which depicts change in partisan follow decisions—relative to the baseline partisanship of user networks at time 1—in each of the

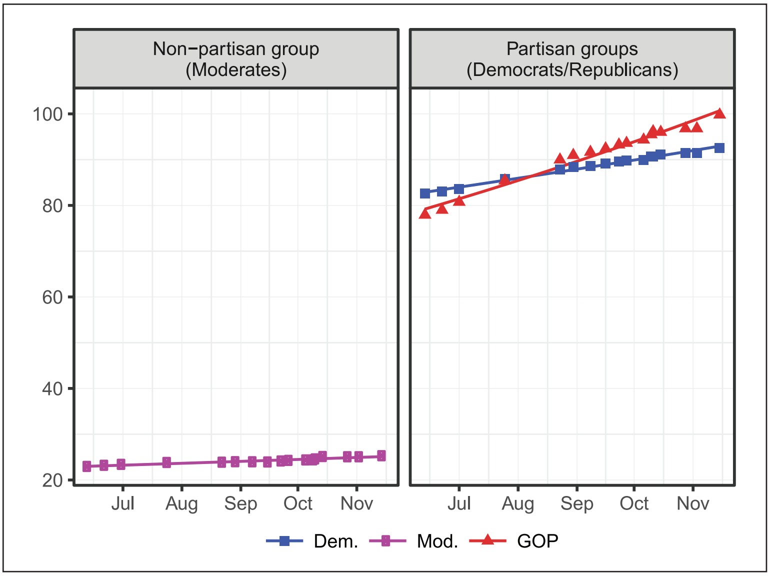

Figure 1. Change in number of weighted partisan follow decisions by partisan versus non-partisan group.

groups of sampled users during the 6–7 months leading up to the 2016 election. As expected during a highly polarizing election contest, partisan-democrat, partisan-republican, and non-partisan/entertainment follow decisions made by users in each group, which are represented in the three columns in Figure 3 and Figure 2, appeared to increase as the election got closer. The rate of partisan follow decisions, represented by the red (republican) and blue (democrat) lines in Figure 2, appear to vary according to the partisanship of the user group. In other words, homogeneous follow decisions—when users from a partisan group follow elites who scored highest in the *matching* partisan component—were made more often than heterogeneous follow decisions—when users from a partisan group follow elites who scored highest in the *competing* partisan component. In contrast to the variations observed in partisan follow decisions, the rate of non-partisan follow decisions, represented with the purple line in Figure 3, increased only slightly over time for all groups. This suggests that while all users tend to follow more elite accounts over time, the rate at which partisan users make partisan-matching follow decisions demonstrates a clear preference for partisan homogeneity in user networks.

Discussion

The present investigation is the first study of its kind to examine change in real-time behaviors of political polarization via network follow decisions during a politically charged general election. The purpose of this study was to better understand change in network polarization on Twitter during a highly contested general election. Toward this end, social networks on Twitter were analyzed during the 2016 general election to

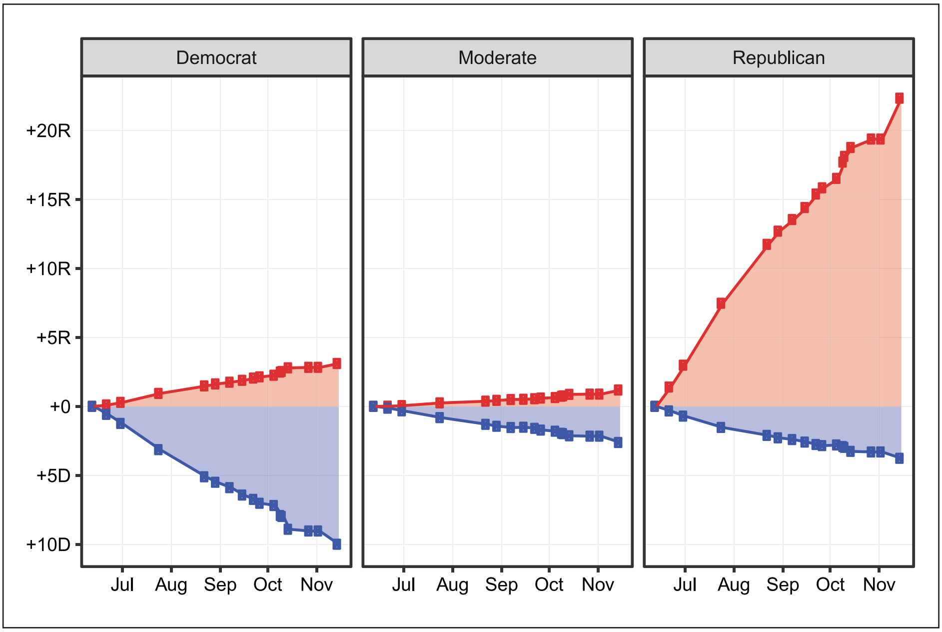

Figure 2. Change in number of weighted partisan follow decisions by partisan groups.

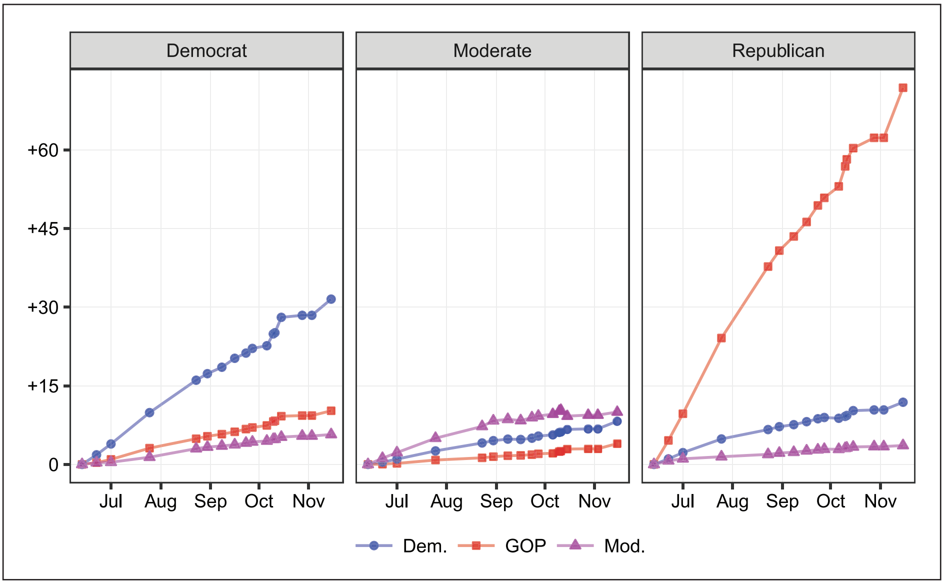

Figure 3. Change in number of partisan follow decisions by all groups.

provide a much needed perspective on political polarization in the new media environment. The sample consisted of followers randomly selected from well-known partisan and entertainment accounts. The data were collected by recording the entire friend network (all accounts followed by a user) of sampled users across 17 time points—spanning from June, shortly after both major party candidates had become presumptive nominees, until November, shortly after election day. Data collection occurred during the final 7 months leading up to the highly contentious 2016 general election.

Network polarization

Partisan users were hypothesized to engage in more politically homogeneous follow decisions than non-partisan users. Analyses therefore proceeded by examining the relationship between proximity to the election (coded as the number of weeks from the start of data collection) and within-subject change in network polarization. Overall, findings made good on a key assumption of the study—that the election would be noticed on Twitter. Results suggested that partisan users form highly partisan networks on Twitter, while moderate, or the less engaged, users mostly avoid politics. Over the full range of the data, findings suggest these patterns—partisan users with politically homogeneous networks and non-partisan users with mostly entertainment-focused follow decisions—held and, in the case of partisan users, intensified as the election got closer.

On the whole, these results present strong support for the hypothesis that change in network homogeneity, or network polarization, increases with proximity to the election, especially among partisan users. The clearest evidence of this can be seen in Figure 2, which depicts the moving average of partisan follow decisions (or partisan composition of networks leading up to the election) from start to finish of data collection. As the figure plainly shows, partisan follow decisions of both partisan-democrats and partisan-republican users resulted in a clear pattern of network polarization as the election got closer, while the follow decisions of users in the entertainment/moderate group experienced only a minor up-tick in the number of partisan and non-partisan accounts that were added to networks.

Partisan users demonstrated a clear preference for homogeneous follow decisions, but it should also be noted that the number of heterogeneous follow decisions also increased over the course of the election for all groups. Thus, while the net result of follow decisions was a larger total number of homogeneous compared to heterogeneous follow decisions, this does not necessarily translate to an increase in the overall partisan homogeneity of user networks. For instance, if at the start of the study, a user had followed 200 democrat elites and 50 republican elites, then adding two democrat elites for every one new republican elite during every week leading up to the election would actually result in a more politically heterogeneous user network. This result can be explained by the relative proportion of democrat follow decisions at the start of the study (200 of 250 or .80) is greater than the proportion of democrat follow decisions during the course of the study (2 of 3 or .67). One major limitation with this kind of proportional representation of homogeneity is that the values can only range between 0 and 1, which makes it especially difficult to detect increases in network homogeneity for users who already have a high proportion of homogeneous follow decisions. And because the goal of the present study was to understand change in *follow decisions* leading up to an election, the current study does not include analysis of change in the proportion of homogeneity.

One benefit to modeling the weighted number of follow decisions as opposed to the proportion of homogeneous follow decisions is that they can reveal patterns found in the total number of follow decisions. For instance, in the current study, the relative lack of partisan follow decisions for users in the entertainment group provides additional evidence in support of the theory that proximity to an election has a greater influence on partisan users because non-partisan users simply continue to *tune out* of politics. In other words, the current study adds to the research suggesting that media choice reinforces existing gaps between the politically engaged/informed and disengaged/uninformed (e.g. Arceneaux et al., 2013; Bode et al., 2017; Prior, 2005). Evidence of this specifically comes from comparing the rate at which the non-partisan (entertainment) users added political accounts compared to the rate at which they added partisan (political) accounts. Post hoc regression analysis of the group-level means over time found change in non-partisan/entertainment follow decisions was not significantly different from change in partisan-democrat or partisan-republican follow decisions. In other words, the current study found users who tend to avoid politics do not suddenly become more interested in politics or politically active as a result of a highly covered general election. Rather, users who prefer to "tune out" of politics continue to do so during contentious elections even if one of the leading candidates for president regularly made headlines for posts made on the same platform.

The gap in the effect of proximity to the election on partisan follow decisions between partisan and non-partisan users may also explain seemingly contradictory findings from previous research on partisan selective exposure in social media. Although some research suggesting users cluster together according to partisanship (e.g. Barberá, 2015; Colleoni et al., 2014; Himelboim et al., 2013a), other research suggests social media use positively associates with exposure to cross-cutting perspectives (Kim, 2011; Lee et al., 2014). Implications from the current study offer one possible explanation for these conflicting findings. Results presented here suggest that whether social media use leads to partisan homogeneity may ultimately depend on the degree to which politics is salient. This would explain why partisan homogeneity is more pronounced on social media when users discuss political compared to non-political topics (Barberá et al., 2015). In other words, social media does not inherently increase exposure to diverse viewpoints nor does it inherently shelter users by creating self-reinforcing filter-bubbles. Rather, social media amplifies and reflects trends found in broader media environments.

The current study also demonstrates the importance and influence of social media on the US political landscape. Between talk of "fake news" and a leading presidential candidate who frequently used his own social media account to express hostility toward "the media," it is clear Twitter played a profound role during the 2016 presidential election (e.g. Enli, 2017), and the current study provides some of the first empirical evidence of it. Across all three groups—partisan republican, partisan, and non-partisan (entertainment) users—partisan follow decisions increased over the course of the election. Partisan users not only followed more politically oriented accounts in total, but they continued adding political accounts at higher rates than they did non-partisan (entertainment) accounts. And to the extent users in the sample demonstrated clear evidence of network polarization, the results presented here also suggests that decentralized (or fragmented) media environments like Twitter may even reinforce polarization behaviors among users in the mass public.

Finally, this study contributes to the definition and measurement of political polarization. To date, our understanding of polarization has been limited by technological difficulties and the convenience of self-report. As a consequence, research has largely failed to extend the concept of networks as an apt and powerful heuristic for understanding how polarization occurs in political contexts. As demonstrated here, however, today's technological tools now make it relatively easy to directly measure political networks and even track how political networks change over time. The current study therefore provides a novel demonstration of measuring political networks in addition to its contribution of additional network-level evidence of political polarization.

Limitations

The study presented here has several limitations. Due to lack of controls and reliable measurement of exposure to politics on Twitter, it is impossible to make any definitive causal claims. Although unlikely, it is possible that follow decisions were driven by something other than the election or politics more generally that happened to line up with the partisan associations attributed to users in the sample. In addition, even if politics was a likely influence of follow decisions made during the study, evidence of polarization resulting from those decisions could still be more a function of Twitter's internal algorithms—for example, algorithms responsible for making "people you may know" recommendations and other promotional features likely exploiting an assumed preference for network homogeneity—than a function of considerate decisions made by users. Similarly, the prevalence of weak ties via features unique to Twitter—asymmetrical user connections and algorithmic emphases on chronological displays of information—may also dampen the influence of strong ties and contribute to the observed composition user networks. Regardless of the mechanism, however, the implications for network diversity and exposure to cross-cutting and democratic deliberation remain the same.

Although the current study examined a highly captivating election, its focus was still limited to a single country. Understandings of communication, political parties, and Twitter use are limited to their context, which is to say the findings presented here are not representative of global and international norms, nor do they necessarily translate into understanding for other politically or digitally similar contexts. Furthermore, research continues to reveal, for example, the extent to which automated or troll accounts influenced trends and activities on Twitter during the 2016 election (Howard et al., 2017, 2018). Future research should continue to examine selective exposure and political polarization on a variety of social media platforms and across multiple different national and international contexts.

Another limitation of the current study is that it only describes a trend in follow decisions among three groups of users. There was no direct attempt to explain why individual follow decisions were made or why they varied between individual users. Future research should investigate the specific motivations of both follow decisions and unfollow decisions. For instance, are follow decisions motivated by activity in the target account, such as an account posting statuses too frequently, or are they influenced by social endorsements and algorithm-based recommendation systems built-in to Twitter's platform?

In summary, the current study aimed to provide the first in-depth explanation of change in network polarization during a highly charged political election. Results confirmed the effect of partisan preferences on user behaviors on Twitter and provided evidence that those partisan preferences become amplified during political elections. Overall, the results provide strong evidence that partisan preferences play a major role in the organization of user networks and in the behaviors of social media users.

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Notes

1. Due to an overlooked rate limit error, the number of accounts with complete user-level data was much lower for two source accounts—American Idol and Rachel Maddow. As a result, the final sample included only one user sampled from the followers of American Idol and only 48 users sampled from the followers of Rachel Maddow. At the group level, however, a chi-square test revealed no significant differences in user statistics.
2. Users who appeared two or more times were not filtered out of the data, and no single user appeared more than once in the final round of random sampling.
3. Barberá (2015) applied similar filters such that users were only selected if they posted more than 100 statuses, sent at least one status in the previous 6 months, and had at least 25 followers. One notable difference is that Barberá (2015) also limited users to those who followed at least three political accounts. By expanding the range of potential elites, as is done in the current study, it is also possible to examine whether users who follow entertainment accounts tend not to follow political elites.
4. Likely factors contributing to missingness include rate limit errors, modification of account privacy settings, account deletion, and account suspension. The overall effect of missingness, however, was likely small as fewer than 5% of all observations were missing and user networks were relatively stable (any missed variation in one wave would have very likely been captured in the following wave).

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Author biography

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Appendix 1

Table 4. Standardized rotated loading matrix of 12 source accounts.

Source Account	1	2	3
SarahPalinUSA	.999	−.083	.015
seanhannity	.942	−.114	.037
foxnewspolitics	.832	.135	−.021
DRUDGE_REPORT	.896	.174	−.031
Salon	−.003	.976	−.064
paulkrugman	−.027	.984	−.051
HuffPostPol	.091	.907	.049
maddow	.001	.746	.294
AMC_TV	−.042	−.006	.815
survivorcbs	.025	.019	.845
SInow	.107	.026	.563
AmericanIdol	−.048	.168	.206