Bully Pulpit? Twitter Users’ Engagement With President Trump’s Tweets

Jeffrey Lazarus¹ and Judd R. Thornton¹

Abstract
With nearly all political candidates, officeholders, and organizations using the platform, Twitter has become an important venue for political communication and engagement. In particular, Twitter lowers the cost of entry for political activity, with the result that millions of people follow and interact with political elites online. However, most studies of the political uses of twitter focus on the substance and content of tweets themselves. In contrast, we ask what influences the rates at which users engage with the tweets posted by political elites. To do this, we obtained the number of likes and retweets for each of President Trump’s tweets over a 14-month time span. Using these data, we find first that engagement varies with Trump’s net approval in the broader electorate. Second, we find that engagement varies with the substantive content of the tweet: negatively toned tweets and tweets involving foreign policy receive higher levels of engagement than other tweets. Third, we find that high-salience events—for example, the recusal of Jeff Sessions—lead to more engagement. Fourth, we find some evidence that engagement levels vary with the timing of the electoral cycle. Overall, we argue that the factors influencing Twitter engagement are in some ways similar to the factors influencing political activity more broadly, though it is possible that the fact that Trump’s use of Twitter is unique among politicians drives some of our results.

Keywords
social media, campaigns, political science, participation, elections

Like many other facets of life, political activity is progressively moving online. Political actors of all kinds—voters, candidates, elected officials, interest groups, and others—are increasingly engaging with one another electronically. This online interaction largely supplements rather than replaces other types of political interaction, but online activity itself can take many forms. Social media in particular allows candidates and elected officials to not only communicate with but also interact with voters in numbers that were previously unheard of. By “liking,” sharing, and responding to politicians’ social media posts, social media users become active participants in the political process. As a result, social media has

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partially lowered the barrier to entry for political activity, which in turn has caused the number of people who are at least minimally engaged in politics to soar. In this article, we examine one specific form of online political activity, user engagement with a political elite’s Twitter posts. In particular, we examine the factors that influence the number of people who retweet and “like” tweets posted by Donald Trump.

Using a novel data set of digital trace data, we examine engagement with Trump’s tweets between June 22, 2016, and August 10, 2017. This range captures a portion of the campaign, the period between the election and inauguration, and the first 7 months of Trump’s presidency. In doing so, we first demonstrate that retweets and likes are highly correlated. Next, we test a number of hypotheses based on theories of engagement as expressive behavior. First, we argue that engagement with Trump’s tweets varies over time as the election cycle influences how salient politics is generally with the public. We also argue that Trump’s approval will influence levels of engagement. Third, we argue that highly prominent news events that increase the general salience of politics also influence engagement with Trump’s tweets. Finally, we argue that the character of Trump’s tweets influences levels of engagement more specifically, we argue that tweets that are negative and those that deal with policy will lead to more engagement. Empirical analysis largely supports these predictions.

The primary contribution this article makes to the literature is to show that the factors that drive online political engagement are related to the factors that drive other types of engagement at least in respect with Trump’s tweets. Negative partisanship and presidential approval are well-trod areas of the political engagement literature and strongly influence other modes of political activity (e.g., Abramowitz & Webster, 2017; Caruana et al., 2015; Medeiros & Noël, 2014). The finding that these factors similarly influence levels of online political activity as well seems to indicate that online activity is, in some regards at least, substantively similar to these more traditional types of political engagement. Additionally, this article adds to the literature on the political uses of Twitter, and social media more generally. Most of this literature focuses on the substance and content of politically oriented Twitter posts (see Jungherr, 2016, for a review). Thus, this article adds to the small but growing body of knowledge relating to how users interact with those posts.

**Background**

With the advent of social media, a burgeoning literature has emerged examining its relevance to politics. We ask how Twitter users interact with tweets, and a few themes and trends directly relevant to our research question have emerged in the existing literature. To begin, how do political candidates use social media? They tend to “broadcast” information about campaign activities, including pointing out where individuals can get more information (Adams & McCorkindale, 2013; Enli & Skogerbo, 2013; Evans et al., 2014; Golbeck et al., 2010; Graham et al., 2013, Grant et al., 2010; Kruikemeier, 2014; Shogan, 2010) rather than post calls for mobilization or about policy—although members do engage in positioning themselves relative to other politicians (Hemphill et al., 2013). Only a small percentage of posts tend to be attacks—although this percentage varies by incumbency status (Evans et al., 2014; Rossini et al., 2017), gender (Evans et al., 2014), and by partisanship (Russell, 2018). It seems possible that candidates “use Twitter consciously as a symbol of being in step with the times and being approachable” (Jungherr, 2016, p. 77).

The evidence that Twitter usage by candidates directly impacts election outcomes and attitudes toward candidates is mixed. For example, some evidence indicates that engagement with a candidate on social media leads to actual political participation (Housholder & LaMarre, 2015). LaMarre and Suzuki-Lambrecht (2013) find a correlation between election outcomes and Twitter use as well as the number of followers a candidate has. This finding is consistent with that of Kruikemeier (2014) who finds that Twitter use, especially when the candidate interacts with users, is positively correlated with votes. Using panel data, Bright et al. (2020) find that Twitter use is related to vote share—and while the magnitude is not large, it is comparable to the influence of campaign spending. Ruck
et al. (2019) find a correlation between retweets of pro–Trump tweets and Trump polling numbers during the 2016 election. Finally, there may exist a relationship between twitter sentiment and mentions and party success (DiGrazia et al., 2013; Tumasjan et al., 2011).

But not all research indicates social media use has an impact on elections. Ammann (2010) finds that the amount of tweeting by a candidate is unrelated to electoral outcomes and Jungherr (2013) finds no relationship between hashtag mentions and vote share. And certain kinds of participation such as organizing a protest or boycott, online participation may be unrelated (Ekstroûm & Shehata, 2018) or even negatively related (Schumann & Klein, 2015) to social media use. In terms of attitudes about candidates, it does not appear that merely being more active on Twitter influences opinions about a candidate (Hong & Nadler, 2011) or leads to more followers (Conway et al., 2013).

While there exists disagreement about a generalized influence on election outcomes, social media usage is related to higher levels of at least some kinds of political participation for some members of the public. Some evidence indicates that political participation on social media follows exactly the same process as more traditional participation in terms of individual-level predictors (Carlisle & Patton, 2013)—although many of the same patterns of inequality in involvement in everyday political conversations replicate in Twitter exchanges (Barberâ & Rivero, 2015). And, some of the predictors of online participation are the same as more traditional forms of participation: partisan strength (Bekafigo & McBride, 2013), social capital and self-efficacy (Yang & DeHart, 2016), and trust in traditional media (Bode & Darlymple, 2016) all predict political activity on social media. Xenos et al. (2014) find a general relationship between social media use and political participation; although Yang and DeHart (2016) find that excessive social media use is negatively associated with online political participation. While it is important to note that social media users cannot necessarily be generalized to other members of the public (Mellon & Prosser, 2017), given that social media engagement can lead to participation it seems prudent to examine what factors lead to more or less engagement. Moreover, Twitter may be a proxy for the amount of attention the public pays to politics (Jungherr et al., 2017). In a meta-analysis, Boulianne (2015) finds that social media use is more consistently related to “civic participation” (which Boulianne defines as volunteering, donating, participation in civic group or neighborhood meetings) than voting. Indeed, she concludes that “the meta-data suggest social media has a minimal impact on participation in election campaigns” (p. 534). Although, it may be the case that the relationship between social media use and political behavior is strongest among younger cohort (e.g., Xenos et al., 2014). We also note that there have been relatively few studies on retweet behavior in general, and even fewer that specifically examine what leads to more engagement with tweets from political figures.

**Empirical Expectations**

Here, we develop several hypotheses to explain how Twitter users “engage” with Trump’s tweets. To begin, while some social media activity is undoubtedly instrumental and actively aimed at persuasion, we take the view that the sort of activity we are investigating—liking and retweeting a politician’s tweets—is largely expressive in nature and therefore similar to traditional displays of political attitudes studied in the literature. Expressive political behavior “reflects, wholly or partly, underlying concerns that derive directly from the meaning or symbolic significance of actions or choices themselves” (Hamlin & Jennings, 2011, p. 655). Theocharis (2015, p. 6) conceptualizes social media behavior, and defines “digitally networked participation” as a “personalized action that is carried out by individual citizens with the intent . . . to raise awareness about, or exert social and political pressures.” In other words, liking and retweeting may be designed to draw attention to a cause, or in our case, a candidate or officeholder. And while these sorts of activities are low cost—especially “liking” a post—similar “traditional” acts are also often symbolic, low in costs, and uncertain in their efficacy. Moreover, as Theocharis (p. 8) notes, these criteria are not used to eliminate traditional acts as
participatory. Finally, Hamlin and Jennings (2011, p. 654) argue that for expressive acts, “the actor may form her own audience; i.e. that expression can, at least sometimes, be self-directed.” Thus, even if the only result of the behavior we investigate is a process of self-identification, it is worth understanding. This is especially true given that strong political identities have all sorts of downstream consequences for behavior and attitude formation (e.g., Bolsen et al., 2013).

We also note that it seems reasonable to imagine that different processes govern liking and retweeting. Likes may represent primarily positive reactions while retweeting could represent a mix of positive and negative reactions. Although there has been relatively little research on this relationship—and, as far as we know none in relation to political candidates or elected officials—we build on Meier et al.’s (2014, p. 353) finding that the relationship between retweeting and liking “is very versatile as they are both used for similar motives” and some users prefer one over the other for heterogeneous reasons. In short, although the two behaviors are not identical, we anticipate they will be related. For the data, we consider the empirical relationship between the two is strong: $r = .85$, and for most of the data—for example, for all but a few outliers—it really does appear that there is a linear relationship between likes and retweets. Thus, we term both “engagement.” Our empirical models allow for a further examination of this proposition.

We now turn to our hypotheses. First, we anticipate that the overall “political environment” will influence engagement with Trump’s tweets. We first build on the insight of Gelman et al. (2016) who demonstrate that a portion of the swings observed in polls results from some individuals opting not to participate due to bad news for their preferred candidate. They argue that when individuals are discouraged (or excited), they are less (or more) likely to participate in surveys. We argue a similar pattern exists with engagement on Twitter. In particular, we expect to observe that when times are relatively good for Trump, there should be more engagement with his Twitter account. Likewise, when the overall environment is less positive for Trump, we expect some followers will be less inclined to engage with his tweets. We use approval ratings as a proxy for the environment. Consequently, we hypothesize that engagement with Trump’s tweets will be positively related to his approval ratings.

Similarly, we expect that the political cycle will influence levels of engagement. In particular, we argue that engagement with Trump’s tweets will decline over time from his inauguration for two reasons. First, Trump’s behavior on Twitter—both in its tone and amount—is quite novel for a president. The novelty might initially lead to more engagement, especially given the surprising nature of his victory. However, as the electorate becomes accustomed to his behavior, the novelty might wear off. Therefore, we expect that as time from inauguration increases, we should see a decline in engagement. Second, partisan engagement more generally waxes and wanes with the electoral cycle (e.g., Michelitch & Utych, 2018; Singh & Thornton, 2019) meaning that as politics recedes into the background, we should expect engagement to similarly decline. Consequently, our second hypothesis is that engagement will decline over time.

Another way to consider context is to investigate if specific events in the public discourse influence engagement. This is consistent with existing evidence that exposure to news can foster participation and interest (Boulianne, 2011; de Vreese & Boomgaarden, 2006). Along these lines, we identified three high-salience events likely to have stimulated political public engagement: Attorney General Jeff Sessions’s recusal from overseeing the Russia investigations, the appointment of Robert Mueller as Special Counsel, and the Senate vote to repeal the Affordable Care Act (which narrowly—and dramatically—was defeated). These events might make feelings about Trump more salient or cause his supporters to rally. Accordingly, we hypothesize that engagement will increase immediately following these events.

We next delineate two hypotheses about how the content of the tweet will impact engagement. To do so, we first draw on the extensive literature on negative partisanship. The increase in individuals’ negative reaction toward the other party and its implications has been well-documented (e.g., Bafumi & Shapiro, 2009; Enders & Armaly, 2018; Huddy et al., 2015; Iyengar et al., 2012; Mason,
Webster and Abramowitz (2017), p. 22 conclude that ongoing confrontational politics leads voters to have negative views of the other party and that these negative views “encourage political elites to adopt a confrontational approach to governing.” In other words, in an era of highly contentious politics, members of the public—perhaps especially those who interact with candidates and elected officials online—will be more apt to interact with negative posts. We also note that in a study of Trump (using a different time period than our own) as well as three other candidates with similar styles, Gonawela et al. (2018) find that “insults” lead to more engagement. Thus, our fourth hypothesis is that tweets that are negative in character will receive more engagement.

Finally, we examine posts that reference specific policies or policy areas. Here, our expectations are guided by Gerodimos and Justinussen (2015) who examined engagement with President Obama’s Facebook page during the 2012 campaign. They found that substantive posts—and in particular posts that directly dealt with policy—tended to receive more engagement as compared to promotional posts or personal appeals. As a result, our fifth hypothesis is that posts that are about policy will receive more engagement.

Data

To examine the hypotheses identified above, we obtained information about every tweet posted by the @realdonaldtrump account between June 22, 2016, and August 10, 2017. We wanted a time span that covered the campaign, the transition period between the campaign and inauguration, as well as a portion of Trump’s presidency. Thus, our data range include the final 4.5 months of the 2016 presidential campaign, approximately 2 months during which Trump was president elect, and approximately 7 months during which Trump was president. In total, our data comprise 3,225 tweets posted over 415 days. For each tweet, we obtained the text included in the tweet as well as the total number of twitter users who liked the tweet and the total number of users who retweeted the tweet as of the day we obtained the data. We do not analyze Trump’s tweets which were retweets.

Figure 1 plots the average number of tweets Trump posted per day over the span of our data set. We are not the first to point this out, but one noticeable feature of our data is that Trump tweets a lot. He tweeted at least once on all but two of the 415 days we cover, and in no month that our data cover
do Trump’s average fall below four tweets per day. Thus, even in his least prolific months, Trump posted well over 100 tweets. His most prolific months occurred during the 2016 election. From June through September, Trump tweeted 9–11 times per day, and in October that number jumped to 17 times per day. However, following the election, his rate fell precipitously and remained relatively low through the end of our data set. Trump tweeted between four and seven times per day between November 2016 and May 2017. In June of that year, the rate jumped slightly but did not reach the levels at which he tweeted during the campaign.

Next, we coded the tweets for subject matter content. Along with two graduate student assistants, we read the text of all 3,225 tweets and assigned each one a preliminary code which reflected the substantive topic of the tweet. There were 102 preliminary codes. The topics reflected in these codes include other political personalities (codes included Hillary Clinton, Sally Yates, or Barak Obama), political or policy issues (immigration, veterans, gun rights, drugs), media entities (The New York Times, Buzzfeed), events (meetings with other politicians, campaign events), foreign countries (Syria, Russia, and North Korea), or demographic groups (African Americans, women). At the conclusion of that process, we consolidated these preliminary codes into 10 broader codes in an attempt to describe the data more parsimoniously. These broader codes are not mutually exclusive—many of the tweets fit well into several categories, so we elected to not restrict their inclusion in that way.

The categories reflected in these broader codes, and summary statistics about the tweets within these categories, are in Table 1. The largest categories (in terms of encompassing the most tweets) are “election campaign,” which includes all tweets referring directly or indirectly to the 2016 election, and “negative”, which includes all tweets in which Trump attacks a political opponent or other person or entity. On average, tweets about Russia (which include—but are not limited to—tweets about Trump’s relationship with Russia) received the most likes; following are tweets about the government, which include tweets about other elected officials and branches of government. On the other hand, tweets about the 2016 election received the highest mean number of retweets, while tweets about Russia received the highest median number of retweets. This could be because a relatively few tweets about Trump’s victory in November of 2016 were retweeted an exceptionally high number of times.

### Analysis

We begin by examining variation in engagement over time. Figure 2 presents smoothed averages of the number of likes (top) and retweets (bottom) received by Trump’s tweets over time, counting by
days since the start of our data set. Each figure denotes Election Day (November 8, 2016) and Inauguration Day (January 20, 2017). Both likes and retweets display the same broad patterns, though overtime variation is more pronounced for likes than for retweets. In both cases, the series starts off with a brief rise in the first 10 days, which is likely the tail end of a longer term rise in engagement with Trump via twitter over the course of the 2016 Republican primary. After that, engagement is relatively flat through approximately the 100th day of our data set, September 29. At that point engagement begins to rise; the increase continues through Election Day until just prior to Inauguration Day. Shortly after Inauguration Day, engagement begins to drop, and the downward trend continues through the end of the data set, consistent with our prediction.

Although this decline does not appear substantively large Figure 2, this is partially because it is overshadowed by the relatively larger increase following the election. For both likes and retweets, peak engagement occurs slightly after Inauguration Day, and the drop which occurs from that point onward is significant. Looking at likes first, the 87 tweets posted during the 2 weeks following Trump’s inauguration received a mean of 128,242 likes and a median of 124,803 likes; in comparison, the 181 tweets posted in the final 2 weeks of our series received a mean of 66,770 likes and a
median of 70,916 likes. Thus, mean likes dropped by 48% from the postinauguration peak to the end of our data set, and median likes dropped 43%. The drop-off is smaller for retweets but still substantial. Tweets posted in the 2 weeks after inauguration received a mean of 26,344 retweets and a median of 23,707 retweets. Tweets in the final 2 weeks of our series received a mean of 17,960 and a median of 17,124. Thus, mean retweets dropped 32% and median retweets dropped 28% in the 7 months between inauguration period and the end of our data set. Using difference of means tests, the drops in both modes of engagement are statistically significant (p < .001 in both cases). In summary, while the increase in engagement during the period between the election and inauguration was quite large, engagement drops over the remainder of the series, but still substantial. Tweets posted in the 2 weeks after inauguration received a mean of 26,344 retweets and a median of 23,707 retweets. Tweets in the final 2 weeks of our series received a mean of 17,960 and a median of 17,124. Thus, mean retweets dropped 32% and median retweets dropped 28% in the 7 months between inauguration period and the end of our data set. Using difference of means tests, the drops in both modes of engagement are statistically significant (p < .001 in both cases). In summary, while the increase in engagement during the period between the election and inauguration was quite large, engagement drops over the remainder of the series.

Next, we turn to the relationship between engagement and Trump approval, while also formally testing the drop-off hypothesis. We hypothesize that engagement should be positively related to Trump’s overall approval levels. We test this by obtaining day-to-day measures of Trump approval via the poll aggregator site www.realclearpolitics.com. Aggregators create a measure of presidential approval for each day during a president’s term by averaging the polls made public that day as well as the several days prior. Thus, for each tweet posted after Inauguration Day, we observe president Trump’s aggregated net approval, which is the percentage of the population approving of his performance as president minus the percentage of the population disapproving, for that day.

For the time period of Trump’s presidency for which we collected data (immediately after Inauguration Day through August 2017), Trump’s net approval ranges from −19.5 through 0.39 points. His highest net approval ratings occur in the earliest days of his presidency and fall with relative consistency throughout the remainder of our data set. As a result, the drop in engagement described above may be due to disengagement over time, but it may also be due to Trump’s drop in popularity; to some extent, these hypotheses are competing with one another. To disentangle the effects of these variables, we estimate negative binomial models of the number of likes and retweets each tweet gets, with net approval and a variable counting the number of days since inauguration. We expect the coefficients associated with net approval to be positive (as more people should engage with Trump when he is more popular) and the coefficients associated with the day counter to be negative (as engagement drops consistently after Trump is inaugurated). We employ negative binomial regression because both measures of engagement are count models with significant overdispersion. (We test the robustness of our results by estimating a linear regression and find substantively similar results to those presented in the main text. These models are presented in the Supplemental Material.)

Another methodological concern is multicollinearity—net approval and the day counter variable correlate at \( r = −.94 \) (and the variance inflation factor is 8.90 indicating substantial collinearity). To account for this, for both dependent variables (likes and retweets), we report three models: one with just net approval, one with the day counter, and one with both independent variables. These models include only the tweets Trump posted after his inauguration. Results are reported in Table 2.

Looking first at the likes models, Models 1 and 2 report the results for bivariate regressions with day counter and net approval, respectively. In both models, the coefficient for the two independent variables is significant and in the expected direction: There is a positive correlation between net approval and the number of likes each tweet gets, and there is a negative correlation between day counter and the number of likes each tweet gets. Model 3 reports the multivariate model including both dependent variables; in this model, net approval is significant and positive, while day counter is
not significant. Given that net approval and day counter correlate so highly, there are concerns multicollinearity has the effect of inflating standard errors and making it difficult to identify the coefficients. Thus, we interpret this result as strong support for the public approval hypothesis. However, for the same reason, we do not feel as if we can conclusively reject the time-based hypothesis: It is possible that day counter is insignificant due to multicollinearity, rather net approval acting as a cofound. Turning to retweets, once again both independent variables are significant and in the expected direction in the bivariate models. However, in the multivariate model, neither variable is significant. As before, we believe this may be due to multicollinearity inflating standard errors. Thus, at this point, the interrelationship between popularity, time, and engagement is somewhat inconclusive. However, note that the coefficients for day counter drop in size quite a bit as well for both dependent variables when including net approval. Ultimately, it is our sense that we are unable to adjudicate between these possibilities with this data.

The substantive relationships between the number of likes and retweets received by President Trump’s and net approval are presented in Figure 3A and B, respectively. These figures are taken from Models 2 and 5 of Table 2, respectively. Trump’s mean level of net approval over the course of our data set is −11.2% (i.e., the percentage of people approving of Trump is 11.2 percentage points lower than the percentage of people disapproving). The models predict that tweets posted when Trump has −11.2% net approval receive approximately 86,500 likes and 19,850 retweets. Moving up one standard deviation in net approval (4.96 points) results in a tweet getting approximately 11,000 more likes and 1,000 more retweets. Over the entire range of net approval, the number of likes varies by approximately 30,000 and the number of retweets by approximately 3,200.

Next, we test the prediction that twitter engagement responds to highly salient political events. To do this, we chose three newsworthy events that occurred during the time period we collected data for and during which Trump was president. We limited our search to this time period because we want to control for Trump’s popularity when testing the hypothesis, and we only have daily approval data for his presidency. The three events we examine are Attorney General Jeff Sessions’s recusal from overseeing the Russia investigations (March 2, 2017), the appointment of Robert Mueller as Special Counsel (May 17, 2017), and the Senate vote in which the Republican plan to repeal the Affordable Care Act was defeated (July 27, 2017). For each of these three events, we created a dummy variable coded 1 for tweets posted on the day of the event or the subsequent 2 days. We replicated Models 3 and 6 from Table 2, but this time included the three additional variables. If political events spur engagement, the coefficients on

Table 2. Twitter Engagement and Presidential Approval, Postinauguration.

<table>
<thead>
<tr>
<th>Tweet Topic</th>
<th>Likes</th>
<th>Likes</th>
<th>Likes</th>
<th>Retweets</th>
<th>Retweets</th>
<th>Retweets</th>
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<tbody>
<tr>
<td>Net approval</td>
<td>—</td>
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<td>0.025***</td>
<td>—</td>
<td>0.010***</td>
<td>0.0089</td>
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<td></td>
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<td>(0.007)</td>
<td></td>
<td>(0.003)</td>
<td>(0.009)</td>
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<tr>
<td>Days since inauguration</td>
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<td>—</td>
<td>0.0004</td>
<td>−0.0008***</td>
<td>—</td>
<td>−0.0007</td>
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<tr>
<td></td>
<td></td>
<td>(0.0002)</td>
<td>(0.0005)</td>
<td>(0.0002)</td>
<td></td>
<td>(0.0007)</td>
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<tr>
<td>Constant</td>
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<td>11.60***</td>
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<td>10.01***</td>
<td>10.02***</td>
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<tr>
<td></td>
<td>(0.058)</td>
<td>(0.027)</td>
<td>(0.118)</td>
<td>(0.073)</td>
<td>(0.034)</td>
<td>(0.151)</td>
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<tr>
<td>N</td>
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<td>1,059</td>
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<tr>
<td>Overdispersion</td>
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<td>0.145***</td>
<td>0.145***</td>
<td>0.237***</td>
<td>0.232***</td>
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<td></td>
<td>(0.003)</td>
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Note. ***$p < .001$. 

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the additional dummy variables should be positive and significant in both models. Results are presented in Table 3. Once again, these models only include tweets from Trump’s presidency.

Results indicate partial support for the hypothesis. Of the six coefficients testing the political events hypothesis, three are significant. However, all three significant coefficients are in the predicted direction, positive. The Sessions’s recusal dummy variable is positive and significant in both the likes and retweets models, and the Mueller appointment dummy variable is positive and significant in the retweets model. Thus, it appears that two of the three events tested spurred additional twitter engagement of at least some kind. According to the model’s predicted values, the jump in engagement following the two events is of substantial size. The predicted number of likes on each tweet is in the period following Sessions’s recusal is 46.3% higher, and the predicted number of likes following the Mueller appointment is 59.6% higher than the baseline predicted number of likes (i.e., the model’s predicted number of likes for all tweets not in the three time periods being tested). The predicted number of retweets following Sessions’s recusal is 17.7% higher than the baseline predicted number of retweets.

Finally, we turn to hypotheses regarding how tweets’ substantive content influences engagement. As discussed above, we make two predictions. First, we predict that negative tweets

![Figure 3. (A) Predicted number of likes by net trump approval. (B) Predicted number of retweets by trump disapproval.](image)
receive higher levels of engagement than positive or neutrally toned tweets. Second, we predict that tweets discussing policy see higher engagement than other tweets. To test these hypotheses, we turn to three of our broader codes of tweet content. Negative is coded 1 if the tweet includes a personal attack on a person or a negative statement directly referring to specific entity. Over 37\% of tweets in the data set (1,218 of 3,225) are negative in tone. Regarding policy, we created two codes to separately identify tweets dealing with Foreign Policy and those dealing with Domestic Policy. Overall, 29\% of the tweets in the data set relate to domestic policy, and 17\% deal with foreign policy. Once again, the codes are not mutually exclusive so there is some overlap between the categories. (There are 165 tweets dealing with foreign and domestic policy, 282 domestic policy tweets that are negative in tone, and 162 foreign policy tweets that are negative in tone.)

As before, we employ negative binomial regression to estimate two dependent variables, the number of likes and retweets received by each tweet. For each DV, we estimate four models: one includes our full sample, and the other three divide the sample into the pre-election period, the time when Trump is president, and the postinauguration period. Each model includes the dummy variables domestic policy, foreign policy, and negative. Additionally, each also includes the day counter variable which indicates how many days since the beginning of that period the tweet was posted. Finally, the postinauguration period also includes net approval, the same variable used in our Table 2 models. Results are presented in Tables 4 (likes) and 5 (retweets.)

Across both sets of results, we find no support for the hypothesis that tweets about domestic policy lead to more engagement. Domestic policy is significant in only one of the eight models reported (the postinauguration period model reported in Table 4); however, it has a negatively signed coefficient. Foreign policy is significant and correctly signed in seven of the eight models. Thus, there is strong evidence that tweets about foreign policy receive significantly higher levels of engagement than other tweets. This result is perhaps consistent with evidence that nontraditional news outlets can bring attention to foreign policy (Baum, 2002).

Our results are largely as predicted for negative. This variable is significantly related to the dependent variable in six of the eight models and positively signed in all six. The two models in which negative is not significant are the two estimating engagement when Trump was president

<table>
<thead>
<tr>
<th>Tweet Topic</th>
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<th>Retweets</th>
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<tbody>
<tr>
<td>Net approval</td>
<td>0.030***</td>
<td>0.022*</td>
</tr>
<tr>
<td>Day counter</td>
<td>0.0008</td>
<td>0.001</td>
</tr>
<tr>
<td>Mueller appointment</td>
<td>0.62</td>
<td>0.455***</td>
</tr>
<tr>
<td>Sessions recusal</td>
<td>0.163*</td>
<td>0.372***</td>
</tr>
<tr>
<td>Obamacare repeal vote</td>
<td>-0.011</td>
<td>-0.036</td>
</tr>
<tr>
<td>Constant</td>
<td>11.4***</td>
<td>9.75***</td>
</tr>
<tr>
<td>N</td>
<td>1.061</td>
<td>1.061</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>12.532</td>
<td>11.207</td>
</tr>
<tr>
<td>Overdispersion</td>
<td>0.154***</td>
<td>0.256***</td>
</tr>
<tr>
<td>Pseudo R^2</td>
<td>0.006</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .01, ***p < .001.
Table 4. Number of Likes and Tweet Subject Matter.

<table>
<thead>
<tr>
<th>Tweet Topic</th>
<th>Full Sample</th>
<th>Preelection</th>
<th>President Elect</th>
<th>Postinauguration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic policy</td>
<td>0.033</td>
<td>-0.014</td>
<td>-0.057</td>
<td>-0.020</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.031)</td>
<td>(0.062)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>Foreign policy</td>
<td>0.137***</td>
<td>0.135***</td>
<td>-0.045</td>
<td>0.086***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.043)</td>
<td>(0.101)</td>
<td>(0.028)</td>
</tr>
<tr>
<td>Negative tweet</td>
<td>0.059*</td>
<td>0.202***</td>
<td>-0.006</td>
<td>0.083***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.024)</td>
<td>(0.063)</td>
<td>(0.255)</td>
</tr>
<tr>
<td>Day counter</td>
<td>0.004***</td>
<td>0.002***</td>
<td>0.0005</td>
<td>0.0003</td>
</tr>
<tr>
<td></td>
<td>(0.0009)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>Net approval</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>-0.023***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>Constant</td>
<td>10.0***</td>
<td>9.96***</td>
<td>11.2***</td>
<td>11.5***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.0287)</td>
<td>(0.202)</td>
<td>(0.118)</td>
</tr>
<tr>
<td>N</td>
<td>2,968</td>
<td>1,532</td>
<td>380</td>
<td>1,056</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-34.168</td>
<td>-16.497</td>
<td>-4,538</td>
<td>-12,411</td>
</tr>
<tr>
<td>Overdispersion</td>
<td>0.300***</td>
<td>0.219***</td>
<td>0.263***</td>
<td>0.142***</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.024</td>
<td>.003</td>
<td>.0001</td>
<td>.004</td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .01, ***p < .001.

Figure 4. Predicted number of likes (Top) and retweets (Bottom) by tweet tone and presidential status. Note. All predicted values taken from corresponding models in 4.
But both when Trump was a candidate for president and during his presidency, negatively toned tweets received significantly higher levels of engagement both in the form of likes and retweets than tweets that are positive and neutral in tone.

We generate predicted values of the number of likes and retweets for each category of tweet. Figure 4 presents the predicted number of likes and retweets of negative tweets compared to all other tweets, and Figure 5 presents the predicted numbers for foreign policy tweets compared to all other tweets. Figure 4 indicates that across the entire data set, negative tweets receive approximately 2,000 (5%) more likes and 2,200 (20%) more likes than positive or neutrally toned tweets. The differences were greatest during the pre-election period, when negative tweets received 40% more retweets and 22% more likes than other tweets. Also interesting to note is that, percentage wise, negative tweets received a much greater “boost” in the number of retweets than they did in the number of likes they received. The same is true for tweets dealing with foreign policy (Figure 5). Across all three time periods, foreign policy tweets were retweeted between 20% and 25% more than other tweets, but in no time period does do these tweets receive anything above 14% more likes than other tweets. This may indicate a difference in the way Twitter uses approach liking and retweeting.
Finally, we emphasize that the results are similar but not identical across the models for retweets and likes. The coefficients across models share the significance in 80% of the cases. And, we do not observe a pattern in any discrepancies that we would expect a priori. Nevertheless, the results do suggest that while the two behaviors are similar, they are not identical.

**Conclusion**

Given the surprising nature of Trump’s victory and his aggressive use of social media, scholars and commentators have both been interested in his use of Twitter. In this article, we endeavored to contribute to our understanding how Twitter users engaged with his tweets. In particular, we find that engagement with Trump’s twitter account correlates strongly with his level of approval as well as with the substantive content of his tweets. In particular, negative tweets and tweets related to foreign policy receive significantly higher levels of engagement than other tweets. Engagement also seems to be influenced by major events in the news cycle. Finally, the engagement appears to be influenced by the electoral cycle: Trump saw a significant increase in engagement in the run-up to his election in 2016, and a significant drop-off after he was inaugurated in January 2017. Although the jury is still out to some degree owing to collinearity with Trump’s approval rating, the evidence we present here at least suggests that the timing of the political cycle influences Twitter engagement.

It is worth keeping in mind that Trump’s use of Twitter appears to be unique. For example, while Barack Obama has more followers than Trump and Hillary Clinton tweeted more often during the campaign—and, indeed, more frequently attacked her opponent (Evans et al., 2018)—Trump appears to be able to use his Twitter activity to draw attention from journalists in ways other politicians cannot. And, while in-depth interviews with reporters and editors suggest that tweets from politicians and interest groups are able to influence the agenda of traditional media outlets (Parmelee, 2014), Trump received more “free media” (Francia, 2018) and engagement with his tweets, in the form of the number of retweets, which correlated with future press coverage (Wells et al., 2016). Trump’s pattern of tweeting was also distinct from other Republicans in the 2016 primary in terms of negative tweets sent and received and in his tendency toward “attacking down” against candidates who were trailing in the

<table>
<thead>
<tr>
<th>Tweet Topic</th>
<th>Full Sample</th>
<th>Preelection</th>
<th>President Elect</th>
<th>Postinauguration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic policy</td>
<td>-0.003</td>
<td>0.017</td>
<td>-0.056</td>
<td>-0.059*</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.033)</td>
<td>(0.067)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Foreign policy</td>
<td>0.188***</td>
<td>0.198***</td>
<td>0.226*</td>
<td>0.178***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.045)</td>
<td>(1.09)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Negative tweet</td>
<td>0.191***</td>
<td>0.341***</td>
<td>0.056</td>
<td>0.179***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.026)</td>
<td>(0.068)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Day counter</td>
<td>0.003***</td>
<td>0.004***</td>
<td>-0.002*</td>
<td>-0.00004</td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0003)</td>
<td>(0.001)</td>
<td>(0.0007)</td>
</tr>
<tr>
<td>Net approval</td>
<td>—</td>
<td>—</td>
<td>—</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.009)</td>
</tr>
<tr>
<td>Constant</td>
<td>9.00***</td>
<td>8.72***</td>
<td>10.3***</td>
<td>9.92***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.031)</td>
<td>(0.219)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>N</td>
<td>2,968</td>
<td>1,532</td>
<td>380</td>
<td>1,056</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-30,405</td>
<td>-15,044</td>
<td>-4,026</td>
<td>-11,066</td>
</tr>
<tr>
<td>Overdispersion</td>
<td>0.289***</td>
<td>0.248***</td>
<td>0.300***</td>
<td>0.222***</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.014</td>
<td>.010</td>
<td>.001</td>
<td>.003</td>
</tr>
</tbody>
</table>

Note. *p < .05, **p < .001.
All predicted values taken from corresponding models in Table 5.
polls (Gross & Johnson, 2016), and in the general election he displayed a willingness to directly attack the media (Evans et al., 2018). In other words, it remains to be seen if this other candidates and elected officials will show a similar ability to set the agenda and drive the narrative using social media. We do know that presidents adapt to new media environments (Baum & Kernell, 1999). And down ballot candidates copy strategies they view as successful—new members of Congress are certainly attempting to make Twitter part of their tool box.

Whether or not the precise patterns we identified here generalize to other candidates remains an open question. Trump’s use of Twitter may be unusual for a major party candidate given his lack of political experience (Evans et al., 2018). It is worth noting, however, that our results regarding policy are consistent with Gerodimos and Justinussen’s (2015) study of Obama’s use of Facebook. Although, in our data set, we found that foreign policy but not domestic policy generated more engagement. Gonawela et al. (2018) examine the tweets of Narendra Modi, Nigel Farage, and Geert Wilders alongside Trump and found that insults led to more engagement. So, while this is clearly not an exclusively Trump phenomenon, it remains to be seen if the relationship between tweet tone and engagement is similar among a different sort of candidate—one who is less populist and endeavors to build a more traditional coalition. Indeed, it may be the case that future studies will identify a relationship between use of Twitter—tone, tactics, and so on—and a candidate’s ideology. We also note that as candidate and president, Trump made use of a personal (as opposed to official) account for his twitter activity. It could well be the case that this sort of behavior leads to more personalized relationship and thus different patterns of engagement. This remains an area for future research.

One final issue to consider is the extent to which engagement with Trump’s tweets is not driven by human users of Twitter but by bots. This is a serious concern: One recent study estimates that between 9% and 15% of Twitter’s active users are bots (Varol et al., 2017), and Fishkin (2018) used the online tool SparkToro to estimate that up to 61% of Trump’s followers are bots or some other form of inactive/nonhuman accounts. This suggests that a substantial share of the engagement we are measuring may indeed come from bots. This raises the questions, which tweets are bots most likely to engage with, and do their engagement patterns vary systematically over tweets? To answer these questions, we would need to know how bots “choose” which tweets to interact with. To our mind, there are three possibilities. First, bots might like and/or retweet everything Trump posts. Second, they might like and retweet a certain percentage of his tweets at random. Third, bots might use an algorithm to select certain tweets to engage with based on parameters such as the date or time it was posted, who else has engaged with the tweet, and—most critically for our purposes—the content of the tweet.

At first glance, the first two possibilities would seem to mitigate against our hypotheses. If human engagement with Trump’s tweets is dwarfed by generalized or at random bot activity, that would make it more difficult to uncover any type of systematic political patterns in engagement. The fact that we do find such patterns at all despite (probably) high levels of bot activity is, itself, evidence that a substantial amount of the interaction with Trump’s tweets is human-driven. The third possibility may be more problematic, though only if the content of the tweet is one of the parameters used by these algorithms. Short of that possibility, bot activity is likely orthogonal to our analysis because it would represent a constant (or monotonically increasing over time, as more bots follow Trump) share of engagement over all tweets. Under these conditions, bots would likely introduce no bias into the analysis of user engagement with Trump’s tweets. The extent to which bots drive user engagement with Trump’s tweets—and how those bots influence broad patterns of engagement—is itself a fruitful area for further research.
Acknowledgments
We would like to thank Jeanine Kraybill for helpful comments on an earlier draft; Reagan Griggs, Richard Gardiner, Mohammad Hamza Iftikhar, and Morgan Smith for research assistance; and Jason Morey for help with the data collection.

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Supplemental Material
The supplemental material is available in the online version of the article.

Notes
1. More specifically, Meierr et al. (2014), in a study examining self-reported favoriting behavior, find that users indicated a range of reasons they engaged in liking and retweeting. Users report favoriting to support and engage with the poster. While this is a general behavior, some users explicitly stated they do so in relation to celebrities which is relevant for political actors (especially one who was, previously, a celebrity). A similar conclusion is reported by Hayes et al. (2016), who use a focus group and find users indicated interpreting “liking” literally.
2. Some portion of these “users” are bots, which may impact our analysis depending on how bots choose which tweets to engage with. We discuss this issue in the Conclusion section.
3. To examine the reliability of our coding, a second set of coders independently coded the data. There is 88.8% agreement between coders. More details are provided in the Supplemental Material.
4. We note that the decline in engagement after inauguration primarily occurs in the first 75 days. This is consistent with the evidence presented in Singh and Thornton (2019) who find that the decline in the salience of partisanship flattens after an initial drop. We present figures for both likes and retweets in the period following Trump’s inauguration in the Supplemental Material.
5. We note that the decline in engagement after inauguration primarily occurs in the first 75 days. This is consistent with the evidence presented in Singh and Thornton (2019) who find that the decline in the salience of partisanship flattens after an initial drop. We present figures for both likes and retweets in the period following Trump’s inauguration in the Supplemental Material.
6. We performed a series of further empirical tests using time-series models. For these models, the unit of analysis was the day, and for each day, we took the average number of likes and retweets for every tweet posted that day. We replicated the models in Table 2 using standard autoregressive time series, autoregressive moving average (ARMA) models, and autoregressive integrated moving average (ARIMA) models. We also employed Prais–Winston estimation and an autoregressive poisson model. None of them significantly altered the results.
7. We display the relationship between net approval and day counter in the Supplemental Material.

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