

Title: Doing What I Say: Connecting Congressional Social Media Behavior and Congressional Voting

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Abstract

Public officials' communication has been explored at length in terms of how such their statements are conveyed in the traditional media, but minimal research has been done to examine their communication via social media. This paper explores the kinds of statements U.S. officials are making on Twitter in terms of the actions they are trying to achieve. We then analyze the correlation between these statements, Congressional communication network structures, and voting behavior. Our analysis leverages over 29,000 tweets by members of Congress in conjunction with existing DW-NOMINATE voting behavior data. We find that pro-social and self-promoting statements correlate with Congressional voting records but that position within the Congressional communication network does not correlate with voting behavior.

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Introduction

The polarizing statements that we hear our elected officials make on a seemingly regular basis are intentional and to generate a response from politicians or another key actor within the political sphere (Brady and Han 2006; Saunders and Abramowitz 2004). The subject has been explored in terms of how such statements are conveyed in the traditional media, but minimal research has been done with regard to the role of polarizing language within social media. We engage in a first-ever content analysis of the available Twitter accounts of each elected member of Congress as of August 2011 and provide answers to a number of the most sought-after questions in political communication: What can be gained from making polarizing statements? Do politicians ostracize the most polarizing (in terms of language use) of their cohort? Is there any consistency between the polarizing language used and the polarizing actions taken, and what would this mean for specific sub-groups in Congress?

By identifying Twitter accounts for members of Congress and using the Twitter Database Server (Green 2011) and Twitter-collectors (Hemphill 2011), we gathered 29,694 tweets posted by 411 elected members of Congress between June 14, 2011 and August 23, 2011.¹ Twitter usage generates networks when users establish “follow,” “reply,” and “mention” relationships with one another, and we are able to analyze those networks to reveal insights into a group’s dynamics via NodeXL (Smith et al. 2010). For instance, we can compare the networks of elected officials to determine whether they reach the public through Twitter or whether they establish a virtual “echo chamber” in which they only reach themselves. If the latter is true, “tweeting” would fall under a special category of political communication not unlike discussions in the halls of Congress.

¹ We also collected tweets in which officials were explicitly mentioned by other users who were not in our pool of public officials, and those included another 550,000+ tweets.

In order to identify these qualities and, as mentioned above, make clear their relationship to polarizing statements, we first outline the existing literature across three strata: a linguistic framework for understanding and coding Twitter based statements or “tweets”, political communication and social network analysis, and theories of ideological division and polarization in Congress. In each stratum, we find significant deficiencies in terms of what we know about the link between social media behavior and voting behavior, but this is to be expected given the nature of Twitter, its phenomenal surge over the last few years, and the inherent complexity of interpreting a political statement comprised of 140 characters or less. We then propose four hypotheses and outline the methods in which they are tested, especially the details of our iterative process of coding tweets. Our results, in line with the multifaceted theory development and literature review, are presented in terms of social network analysis and determinants of polarizing behavior. A final, concluding section then highlights our broad findings and proposes avenues for future research.

Literature & Hypotheses

Studies of political communication often focus on the language officials use in traditional media (Cook et al. 1983; Edwards III and Wood 1999; Entman 2007; Kedrowski 2000; Lee 2009), but minimal research has examined language use within social media. Rarer still are studies that examine relationships between politicians’ communication networks in social media and political outcomes.² This vacuum in the political science literature is no longer acceptable: elected officials are capitalizing on the inexpensive and personalizing qualities of social media to stay in contact with constituents and relay information. Properly categorizing and thus understanding such communication is a major challenge.

² Still rarer are attempts to examine these relationships leading up to elections, and we have this planned for the elections in November 2012.

The following examples, collected on October 26, 2011 and tweeted by Senator Robert Menendez and Congresswoman Ileana Ros-Lehtinen, respectively, are illustrative of officials' use of Twitter:

SenatorMenendez: "Pres @BarackObama is right, #WeCantWait to lower education costs + make college more affordable for #NJ families <http://t.co/r7yuPKMK>"

RosLehtinen: "Thanks to Dean Acosta and Director Stack for hosting a great event! <http://t.co/877KqXNq>"

We treat posts like these as individual speech acts and recognize that they accomplish a number of tasks beyond simply describing the world. We use a Process Coding (Saldana 2009) approach to code tweets according the actions they are trying to accomplish – e.g., positioning the author in relation to a political issue, narrating an individual's day, or establishing a social connection with someone else. The examples above illustrate two of the actions for which we coded tweets: Senator Menendez positions himself in relation to President Obama and with regard to education costs, while Representative Ros-Lehtinen's tweet is pro-social, thanking others for their actions. Both tweets also direct their audiences to more information by providing URLs.

These examples illustrate that what officials say and to whom are just two aspects of their communication behavior. What those speech acts accomplish, or try to accomplish, is also important. We have found that voting patterns and positions within Twitter-based networks are correlated with the actions indicated in Twitter posts, and our efforts provide a much-needed link between officials' language behaviors within a specific medium (i.e., Twitter), their social affiliations (i.e., networks), and their political behaviors (e.g., voting).

Our project builds on earlier research by expanding both the scale and scope of inquiry. Our dataset (29,000+ tweets) is far larger than earlier datasets of either Congressional Twitter posts (Golbeck, Grimes, & Rogers, 2010) or politicians' web pages (Xenos and Foot 2005),

enabling us to address questions of the consistency and generalizability of results raised earlier. Analysis of elected officials in the context of social media has also been limited to how they address redistributive goals or how traditional media affects them (Golbeck, et al., 2010; Xenos and Foot, 2005). In sum, ours is the first examination of this scale and scope of the relationships between social media use and political behavior among elected officials, although preliminary analysis has been done of broad network structures (e.g., (Hsu and Park 2012) for the Korean case). Given the relational nature of politics (Lazer, 2011) and ongoing studies of political communication which fail to address the strategies of policy makers (Auer 2011), Twitter-based networks and the interactions that occur within them provide an interesting and valuable natural experiment.

Our project also provides a much-needed revision to existing measures of polarization in politics. Discussions of polarizing behavior of members of Congress are typically based on congressional voting records (Carroll et al. 2011; K. T. Poole and Howard Rosenthal 1984). On a more fundamental level, though, these data fail to capture the underlying signals and heresthetics which now inform us of political ideology. Below, we account for such signals by developing a coding scheme of Twitter content and constructing measures which are useful for analyzing political communication at a deeper level.

Political Communication

Using social media as a means of communicating to the larger public effectively supplements communication that was previously only possible through traditional media outlets (Cook et al. 1983; Edwards III and Wood 1999; Entman 2007; Kedrowski 2000; Lee 2009) or, more recently, websites and blogs that reported statements and speeches of public officials (Gentzkow and Jesse M Shapiro 2010). Because Twitter allows public officials to avoid the

filters of traditional media and communicate directly to their followers, the negative effects of incomplete information held by voters can be exacerbated.³ Such effects are already produced via traditional media outlets (Gentzkow and Jesse M Shapiro 2010), but there is no evidence of how a direct line from members of Congress to constituents might predict problems from incomplete information. Our research, thus, opens the door for making predictions about how public officials' frequent use of polarizing statements may promote misconceptions about specific political or policy-related issues. Consider, for example, the following statements made with regard to health care reform:

RepPaulRyan: "A1: Thx! Our plan: no more empty promises; saves Medicare w no changes 4 those 54+ & real reform 4 next generation #ryanttv"

YvetteClarke: "I will continue to defend Social Security and Medicare from attacks by Republicans in Congress."

Each statement approaches the issue from opposite directions, and they both contain language which attempts to strengthen the speakers' positions while weakening countering viewpoints.

The most significant implication for the voting public relying on incomplete information is that polarized voters are more active (Abramowitz and Saunders 2008). Polarized voters can also be made more consistent (Gentzkow and Jesse M Shapiro 2010) and are even more "correct" in how they vote (Levendusky 2009). Our analysis of political communication via Twitter, thus, helps advance a political communication theory which accounts for the effects of micro-blogging efforts on party and social group formation. Existing studies attempting to predict political candidate success in elections (Lau, Andersen, and Redlawsk 2008) or portraying public sentiment about candidates (Baum and Groeling 2008) focus primarily on

³ For example, traditional media must adhere to standards of accountability including but not limited to fact-checking and source verification. When these standards are not met or if violations occur, traditional media issue a retraction. In the case of Twitter, public officials issue retractions and engage in fact-checking at their own discretion.

network size and strength of ties (Baum and Groeling 2008). We do, too, and apply them for the first time ever to public officials' statements.

Speech Acts

In putting forward the concept of a *speech act*, Austin (1962) proposed that communication between humans is often much more than a means to transfer information from a speaker (sender) to a hearer (recipient). We are often trying to achieve a particular goal when we speak, and these underlying actions are referred to as being speech acts (Bach 1998). Similarly, a question of particular interest in our work is what an official achieves (or is trying to achieve) when he or she posts a given tweet. In other words, we can approach the analysis of officials' tweets using the concept of the speech act.

Extending Austin's concept, Searle (1969) proposed a taxonomy of speech acts, in which there are five key categories. Table 1 provides a brief explanation of Searle's categories, as well as an example of a tweet from our data set that would fall into each category. One challenge in using Searle's speech acts to analyze tweets, is that in his scheme, speech act categories are mutually exclusive; he assumes that any new speech act uttered by a speaker will fall into only one of the above categories.

[Insert Table 1]

Two previous studies shared goals similar to those of our current work. In particular, Baron and colleagues (Baron et al. 2005) and Natri and colleagues (Natri, Pena, and Hancock 2006) analyzed away messages used in instance messaging. Like tweets, away messages are relatively short texts and often serve multiple communicative purposes. For instance Baron et al. (2005) found that most away messages are designed in order to inform recipients of the sender's whereabouts or thoughts, at the same time entertaining them. While Natri and colleagues (2006)

point out that the mutually exclusive nature of Searle's speech acts is problematic in the context of their analysis of away messages, since the messages typically serve multiple purposes. Their approach in analyzing messages is to allow for multiple speech acts within an individual message, with each speech act coded for exactly one of Searle's categories.

In contrast to previous work, we do not attempt to classify tweets into one of five of Searle's speech acts. Instead, we developed our own coding scheme for tweet "action," as will be explained. While inspired by the concept of speech act, the codes in our scheme are not mutually exclusive, and allow us to better capture what officials are trying to accomplish when they post a tweet.

Social Media and Networks

Where available, research on Twitter use in Congress is primarily descriptive, looking at length of Twitter adoption rates by followers of members of Congress (Boutyline and Willer 2011; Himelboim, McCreery, and Smith 2011) or determining that tweeting is often concentrated in the hands of only a few politicians (Kim and Park 2012). Twitter followers have also been found to aggregate into politically homogeneous or homophilous groups (Siegel 2011). With the U.S. government being clearly divided along party lines, we entertain this possibility and predict that public officials will create homophilous communication networks via Twitter and produce echo chambers in which they speak primarily to one another.

Our approach provides a methodological innovation: existing Twitter-based research relies extensively on adoption rates and followers, but such measures have been superseded by more appropriate measures (e.g., "mentions," "replies," and TwitterRank) to measure network characteristics (Siegel 2011). We incorporate these newer measures as an example of what is

now both methodologically feasible and also theoretically salient: the more active a member of Congress is, the more central his/her role within the Congressional tweeting network.

Positioning statements also function as drivers for prompting responses from other actors in the political sphere (Kim and Park 2012). At an exploratory level, we intend to show the pattern of such statements in Twitter and how they predict polarizing voting behavior in Congress. We are particularly interested in the combined effects of positioning speech acts and conventional political variables on polarizing behavior.

Acknowledging the propensity for the public to have preconceived views about the source of information (McClain 2009; Ng and Detenber 2006; Papacharissi 2004), we also consider whether officials' networks grow in size and/or in strength of support with the action of their statements. We focus specifically on statements that do positioning work or pro-social work. For instance, YvetteClark's tweet above is an example of a positioning statement. She positions herself in relation to an issue, Social Security and Medicare, and in relation to a group, Republicans. RosLehtinen's tweet, on the other hand, does pro-social work by thanking others. We expect that pro-social speech behavior will reliably predict political centrism and that positioning behavior correlates with extremism.

Hypotheses

Based on the related literature, our apparent interest in social network analysis, and the required attempt to understand and explain at a highly sophisticated level how members of Congress use social media for political communication, we propose the following hypotheses:

- H1. Twitter is a virtual echo chamber in which officials interact mainly with themselves and create homophilous networks.
- H2. A member of Congress's location in the network is significantly predicted by both Twitter-based and non-Twitter-based characteristics.

H3. The degree to which members of Congress are followed and befriended is a positive function of positioning and pro-social statements via Twitter and polarizing voting records.

H4. Polarizing voting records are particularly reflected by positioning and pro-social statements via Twitter.

Method

This section presents details of the methods used to collect and code the Twitter-based data and to test each of the hypotheses mentioned above. Our first task was to identify Twitter accounts for members of Congress, based on listings at Congress.org.⁴ We then hired workers through Mechanical Turk (MTurk) to collect and recheck Twitter screen names for all members of Congress. Mturk, increasingly leveraged by researchers to collect and evaluate the quality of social science data (e.g., (Bakshy, et al., 2011; Cha, et al., 2010; Weng, et al., 2010), is a marketplace in which requesters hire workers to complete small, self-contained tasks that require human intelligence. We paid workers on MTurk a set fee (\$0.06) for each Twitter screen name they could find, hired two or more workers to look up each official, and then compared their responses. In cases where the workers disagreed about the screen name, we checked the official by hand on their websites and on Twitter. 411 accounts were verified.

Using the Twitter Database Server (Green 2011) and Twitter-collectors (Hemphill 2011), we gathered 29,694 tweets posted by 411 elected members of Congress between June 14, 2011 and August 23, 2011. Twitter usage generates networks when users establish “follow,” “reply,” and “mention” relationships with one another. Network analysis via UCINet (Borgatti, et al., 2002) and NodeXL (Smith, et al. 2010) enables us to analyze those networks to reveal insights into a group’s dynamics. For instance, we can compare the networks of elected officials to

⁴ <http://www.congress.org/congressorg/directory/congdir.tt>

determine whether they reach the public through Twitter or whether they establish a virtual “echo chamber” in which they reach only themselves, which is precisely outlined by H1. Additionally, following someone on Twitter allows a user to be updated every time the followed user tweets and thus enables a passive, peripheral awareness of another user’s contributions. Mentioning, on the other hand, is an active, deliberate communicative act in which one user directs a comment to another or explicitly references another user in his own tweet.

We construct below both “follows” and “mentions” networks for the officials we studied in order to compare at an exploratory level how members of Congress interact within social media. This is but the first step in what we expect will be a continuing analysis of networks both offline (e.g., legislative committee-based or campaign finance-based) and online. There are several methods for measuring influence or centrality within a network (Borgatti and Martin G Everett 2006),⁵ but we are partial towards betweenness, which is determined by first calculating the shortest path between all the pairs of vertices and then by summing the fraction of shortest paths between all pairs that go through the vertex in question. We normalize this betweenness measure in order to make comparisons between two networks and identify uniquely situated individuals.⁶ For example, nodes that fall between different clusters of individuals provide a unique understanding of political communication and behavior: they lie on the shortest path between the less-connected nodes of the less-connected individuals of the established clusters and by virtue of their position at the intersection of social groups are generally members of more social groups than those with low betweenness. Such individuals are said to be weakly connected (Granovetter 1983), but there is still something inherently valuable in the way such ties

⁵ The most common are degree, betweenness, plainness, and eigenvector. Betweenness is often used as a measure of influence within a network (Davis, Yoo, and Baker 2003; Newman 2005).

⁶ The normalization process is determined by the following equation: $(n-1)/\text{centrality} * 100$, where n is the number of individuals.

contribute to the inflow of political information (Granovetter 1983) and how they occupy structural holes or places in the graph where if that person were removed, the graph would no longer be connected. Finally, high betweenness individuals often have a lot of influence because of the diversity of their connections: they have access to all the social groups of which they are a member, and their messages/connections experience less decay because they do not have to travel as far to reach audiences.

To test H1, we use network analysis to determine the direction and audience of tweets. If H1 holds, we will detect more links among members of the same political party than between members of different parties.

Our test of H2 is based principally on how betweenness is predicted. We collect each Congressman's number of friends, followers, and tweets for the period under analysis, which we have established above as being the most salient explanatory variables from Twitter. We also predict that betweenness is also impacted by conventional political demographics: legislative branch membership, gender, and party affiliation. Together, these two sets show whether or not a Congressman is a good conduit for information, opinion, or other content flowing over the network. When a network is relatively dense, we suspect that these conduits represent key voting positions. They are, after all, the people who can be targeted if one's intention is to have a message passed along to a group that could not otherwise be reached.

With regard to H3 and H4, our method of identifying positioning and pro-social statements is the result of an iterative process of establishing inter-coder reliability across a spectrum of action-based categories. As well, to see how the speaker of such statements correlates with his/her peripheral location in the network, we must first establish that the network exhibits core-periphery qualities and then look at correlation patterns. We used three rounds of

coding to develop a robust coding scheme for the action taken in tweets. The resulting scheme used six codes – narrating, positioning, directing to information, requesting action, giving thanks, and other – to categorize the kind of action taken in a tweet. Codes were not mutually exclusive meaning a tweet could be coded as exhibiting more than one action. For example, “Today is Medicare's 45th Anniversary. House GOP have a plan to preserve it, others just criticize & let it go bankrupt <http://t.co/tQnsRGu>,” a tweet from RepDaveCamp, was coded as both positioning and directing to information. We calculated Cohen’s kappa scores for each code and found very strong agreement between coders. The code definitions, examples, and kappas are reported in Table 1. Positioning and directing to information were by far the most common actions exhibited on Twitter.

[Insert Table 2]

The sample of tweets on which we test H3 and H4 is both stratified and selective. This was necessary because, first, we wanted to focus on the most revealing groups within those members of Congress using Twitter. We look specifically at those whose tweeting patterns are either at the highest or lowest ends of the spectrum of Congressional Twitter use. Second, the labor-intensive nature of hand-coding each tweet using the action coding scheme described above makes it difficult if not impossible to automate the coding process.⁷ We take a stratified sample of the population using three criteria. First, to fall into the qualifying category, members of Congress must, during the June, July, and August 2011 period, be among the ten most and the ten least tweeting, followed, and friended among all Congressional tweeters. There is some

⁷ Using MALLETT (<http://mallet.cs.umass.edu/>) and related software, we are now attempting to generate an algorithm that automatically codes tweets by exploiting their linguistic characteristics. It is still unclear whether that will be possible without losing some of the richness of the data produced via manual methods such as those applied here.

overlap between members falling into the three top-ten and bottom-ten groups, respectively, but only one stratified sample per qualifying individual is taken.

The dependent variable for H3 and H4 – political voting in Congress – is the existing and widely used DW-Nominate measure (Carroll et al. 2011; K. T. Poole and Howard Rosenthal 1984) and we use the available data for the 111th Congress. Because the DW-Nominate measure can only be calculated after a Congress has completed, there are a number of senators and representatives who are newly elected and, thus, have no DW-Nominate scores. From the aforementioned stratified sample, members of Congress without DW-Nominate scores include Representatives Walsh, Landry, Gardner, and Amash and Senators Blunt and Ayotte.

Results

Our results are divided into two sections. First, we test H1 and H2 using network analysis. Following, we engage in an analysis of the complex relationships between positioning and pro-social statements and political variables. This second stage integrates the language-specific variables for the H3 and H4 tests but makes very explicit predictions about the relationships between these variables and betweenness. We then make a formal test of H5 to see whether Twitter statements predict the polarizing voting of members of Congress. That is, do members of Congress do what they say?

Social Network Analysis

We make two exploratory observations about the Congressional tweeting network. First, the transitivity of the Congress mention network is low. Transitivity is a measure of the triad consensus in the graph, i.e., how often two of an individual's connections are connected to each other. In small worlds, we would expect transitivity to be higher than normal. The Congress mention network does indeed has higher transitivity (0.229) than a random network of the same

size and density (0.012); yet, transitivity between 0.3 and 0.6 is “normal” for graphs though, so this one can still be considered low (Faust 2006; Newman, D J Watts, and Strogatz 2002). Second, the degree of separation between members of Congress is six, which is surprising in such a closed network. On the basis of these two point, we might conclude that members of Congress are not using Twitter to explicitly position themselves in terms of others. This provides additional evidence in support of existing research which shows that politicians, albeit campaigning ones, are more likely to provide only the most basic issue-related information online while avoiding most other forms of issue dialogue (Huckfeldt et al. 1995). Without formal analysis of the positioning efforts of members of Congress, these findings are still premature.

Figures 1 and 2 show, respectively, the networks resulting from officials mentioning and officials following one another. In both figures, blue solid squares represent Democrats, and red hollow circles represent Republicans. The lone Independent Senator is a yellow solid disc and is visible only in the mentions network (Figure 1), but there is no real role of third parties, confirming Xenos and Foot (2005). The darkness of the lines connecting each node depends on a measure of the strength of that relationship. In the mentions network, the darkness of a line is determined by the number of times two individuals mention one another, and darker lines indicate more frequent mentioning. In the follows network (Figure 2), gray lines indicate one-way connections (i.e., one official follows another who does not follow him) while black lines represent reciprocal relationships (i.e., both officials follow each other). Edge opacity here indicates the number of mentions, and the dark self-loops on some nodes indicate that officials frequently mention themselves.

[Insert Figure 1 here]

[Insert Figure 2 here]

A division between parties is visible in both graphs. In the mentions graph (Figure 1), we can see that lines connecting Republicans to each other are darker, indicating that Republicans mention one another more often than Democrats do. Earlier research that explored similar mentioning behaviors among political bloggers (using links between blogs to indicate connections) found a similar pattern – conservative bloggers also linked to each other more often (Adamic and Glance 2005). The division between parties in the follows graph (Figure 2) is starker. There, we see clear clusters of Democrats and Republicans with fewer links between them. We also see isolates (nodes that do not connect to any others) and two large, disconnected components (subgraphs that are connected to each other but not to the rest of the graph). The smaller component on the left of Figure 2 shows a less clear division between parties.

Differences in the strength of relationships are visible in both graphs as well. In the mentions graph, the lines connecting Republicans are darker, indicating that they mention each other more often. In the follows network, the large component has more black lines, indicating reciprocal relationships, than does the smaller component. Taken in tandem with our earlier evidence, a lack of transitivity suggests a lack of hierarchy in this network. With no evidence of hierarchy and no evidence of a core-periphery structure, the network does not display any immediately apparent structure.

The follows network is nearly ten times as dense as the mentions network (0.134 vs 0.014, respectively), indicating that officials are passively connected to far more people than the number of people they are actively connected to. This pattern is not surprising – it makes sense that we can only engage with some subset of the people we know or are aware of. What is interesting is that in both cases, the density of the graph is surprisingly low. In a network of actors who are so similar and who, in theory, work together, we would expect to see a much

higher density. Instead, we see that, at a maximum, only thirteen percent of the possible connections are made, indicating that even though officials clearly use Twitter, they underutilize the ability to passively monitor one another's behaviors.

These graphs cannot tell us why officials choose to follow or mention such a small subset of their peers, although other research on Twitter during Congressional campaigns suggests that the density of the network correlates to the cohesion of the network's message (Livne et al. 2011). In other words, we would expect more cohesion among those who are part of a network with a united front.

Twitter Statements & Political Determinants

As was stated above, people with high betweenness are generally members of more social groups than those with low betweenness, occupying structural holes and playing potential key roles in the political process. In an attempt to further understand the impact of a member of Congress having higher numbers of followers and friends as well as tweeting with greater frequency, we statistically analyze the relationship between betweenness and the characteristics of members of Congress. Specifically, we are interested in the relationship between networks measured by normalized betweenness and each Congress member's number of followers, number of friends, and number of tweets in the data collection period.

In this way, we are able to test H2 with the understanding that betweenness is a function of followers, friends, and number of tweets. If any of these positively predict betweenness in the network, there is some semblance of a core-periphery structure, albeit not in the conventional network analytical sense. These relationships are also predicted by party affiliation, branch of Congress, and gender, the latter two of which can be considered exploratory.

Based on the results of least squares regression for all members of Congress for which data is available ($N = 374$), without controlling for differences in gender, party, or branch, Table 3, column 1 shows via ordered probit analysis that there are no statistically significant effects from a member of Congress having additional numbers of followers, friends, or tweets. The same is true when we account for differences in gender, party, and branch, shown in Table 2, column 3, although there are indications in columns 2 and 3 that branch significantly predicts betweenness. We code gender “1” for males and “0” for females, party “1” for Republicans and “0” for Democrats, and branch “1” for the Senate and “0” for the House.

To understand such differences further and in the context of the number of a Congressman’s followers, friends, and tweets, interactions between each with gender, branch, and party are introduced in an attempt to eliminate confounding variables. In Table 3, column 4, where all possible interactions are included, it is shown that a large number of followers increase betweenness for females relative to males, but that a large number of friends increase betweenness for males relative to females. In terms of interactions between party and Twitter-based network measure, the only significant difference between parties occurs with regard to the number of followers: as the number of followers increase, betweenness for Republicans increases relative to Democrats. This could be an indication of the tighter network effects and exclusivity among Republicans, possibly countering our earlier network analysis-based results of a strongly non-homophilous network. Finally, with regard to branch of Congress, a large number of followers increase betweenness for House members, while a large number of followers decreases betweenness for Senate members.

In sum, these results present an image of specialized effects from each of the three Twitter-based measures (number of followers, friends, and tweets) based on gender, party, and

Congressional branch. In terms of the ability to convey messages across what has been determined to be a particularly unstructured network, communication is most likely through the most networked members of Congress: males with large numbers of Twitter friends; Republicans with large numbers of Twitter followers; House members with large numbers of Twitter followers.

[Insert Table 3]

We include now our content analysis in order to test H3 and H4, and Table 3 presents the ordered probit regression output for predicting the same three qualities of Twitter users: followers ranking, friends ranking, and ranking based on the number of tweets made during the summer of 2011. We have established that the core-periphery structure is not in effect, but the results from Table 4 show that, even if it were present, positioning statements would not be correlated with peripheral locations in a network. This conclusion is based on the fact that positioning tweets positively predict a higher rank in terms of a member of Congress's followers (Table 4, columns 1 and 2) and friends (Table 4, columns 4 and 5). Indeed, our results in Table 4 show that follower and friend rankings are most consistently and positively affected by positioning: narrative tweets reduce one's ranking while providing information increase one's ranking in followers but reduces one's ranking in friends. On this basis, we induce and update our earlier theory with the statement that followers and friends are much more likely indicators of having a solid social media base in terms of the Congressional Twitter network.

Further, where the results from our ordered probit regressions are statistically significant, the followers and friends rankings seem to be closely related. The exception is content that provides information. In this case, members of Congress who provide information will have a higher ranking on the follower scale but a lower ranking on the friends scale. We can infer, thus,

that the this Congressmen is more focused on releasing information than in receiving it since a Twitter accounts “friends” are the accounts it follows, the people from whom a user receives information. Content which is positioning, however, does have an impact on both followers and friends ranking, indicating that, for those members of Congress who are interested in establishing a solid following in social media, they should make positioning statements.

In Table 3, we observed that the number of tweets does not predict at a significant level normalized betweenness among members of Congress. These results are further strengthened in Table 4, columns 7-9, which show that the amount of tweeting is not positively predicted across the bulk of our explanatory variables. We conclude, thus, that the frequency of tweeting has little to do with garnering a political following based on statements and behavior, and that very little predicts tweeting rank beyond members of Congress who are male and Republican.

Providing explicit confirmation of H3, Table 4 also shows that polarizing behavior in the form of Congressional voting records has a positive effect on the strength of members of Congress’ social media base. In Table 4, columns 2 and 4, DW-Nominate positively and significantly predicts the rank of followers and friends for members of Congress.⁸ To fully test H3, we also showed the combined effects of polarized voting and Twitter statements, presented in columns 3 and 6 for the rank of followers and friends, which have been established now as our dependent variables of interest. Positioning tweets, as described above, have consistent effects for both the followers and friends ranking. For the effects on both the followers and friends rankings, the interaction between polarizing behavior and statements is positive and statistically significant and marginally larger for the followers ranking.

⁸ Of less importance but nonetheless statistically significant, polarizing behavior decreases one's tweeting rank, implying that the most polarized members of Congress (in terms of voting records as well as in terms of statements) do not tweet with great frequency.

[Insert Table 4]

Having established the significance of polarizing voting in Congress for our three qualities Twitter-based ranking measures, we can now make a devoted test of H4. Using the log-transformed measure of DW-Nominate as the dependent variable and proxy for polarizing voting, we see in Table 5, column 1, that positioning increases polarizing voting by 9 percent (after back-transforming the coefficient). Providing information increases polarizing voting by 7.1 percent while thanks decreases polarizing voting by over 27.4 percent. These findings are statistically significant and robust to the inclusion of White's standard errors, but the fit of this model ($R^2 = 0.04$) is less than desirable. This is somewhat alleviated after controlling for variance across three key characteristics of members of Congress: gender, party, and chamber (of Congress).

We now see in Table 5, column 2, that positioning continues to remain statistically significant and that male Republican House members are most likely to vote in a polarizing manner. Our exploratory analysis of the combined effects of positioning speech acts and political or demographic variables is also informative. For this, we include interactions between gender, party, and chamber of Congress and positioning tweets. Table 5, column 6, for example, presents all three of these interactions simultaneously and shows that polarized voting increases with position tweets for females by 42.5 percent (relative to males); for Republicans by 17.8 percent (relative to Democrats); and for members of the Senate by 18.7 percent (relative to members of the House).

[Insert Table 5]

Conclusion

Communication via social media is an increasingly common way for elected officials to convey their views. Our observations above, particularly the lack of closeness in Congressional networks and the absence of a core-periphery structure are surprising. It certainly indicates that we must be innovative in our attempts to understand and properly identify the function of social media in political communication. As of yet, though, there does not seem to be an overly coordinated effort among members of Congress to establish themselves within the Congressional Twitter network. Such findings have been identified only in partial form here, and we acknowledge that future study is needed to fully address differences in party affiliation.

We also acknowledge that future study must deal with the disconnected components in both Figures 1 and 2. Exactly who is not connecting, and why? What is preventing Democrats and Republicans from talking? And is there a pattern to the reciprocal relationships; e.g., are Democrats following Republicans but not getting followed in return? The answers to these questions are expected to be answered with a much more comprehensive look at the statements used by tweeters. Coding for such tweets is crucial in assessing the degree to which compromise and statements are correlated. In many ways, thus, this is a preliminary analysis lacking in its ability to properly compare uncompromising behavior, e.g., Congressional voting patterns, with uncompromising statements. This will also help set up what are expected to be networks of polarizing language which have heretofore been identified only through inference or anecdote.

Though our results provide many avenues for future work, it is important to recognize our findings thus far. When testing H1, we found mixed results. While Congress showed a slight degree of homophily, other features of the network such as density were more telling. With regard to H2, we found no statistically significant effects from a member of Congress having additional numbers of followers, friends, or tweets on his or her betweenness centrality in the

network. When testing H3, we found polarizing behavior in the form of Congressional voting records has a positive effect on the strength of members of Congress' social media base. Finally, the results of our test of H4 confirm that positioning speech acts increase polarizing voting. Overall, we found interesting correlations between Congress' social media behavior and their voting behavior, demonstrating that social media is ripe for political communication studies.

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Figures and Tables

Figure 1 Congressional mentions network

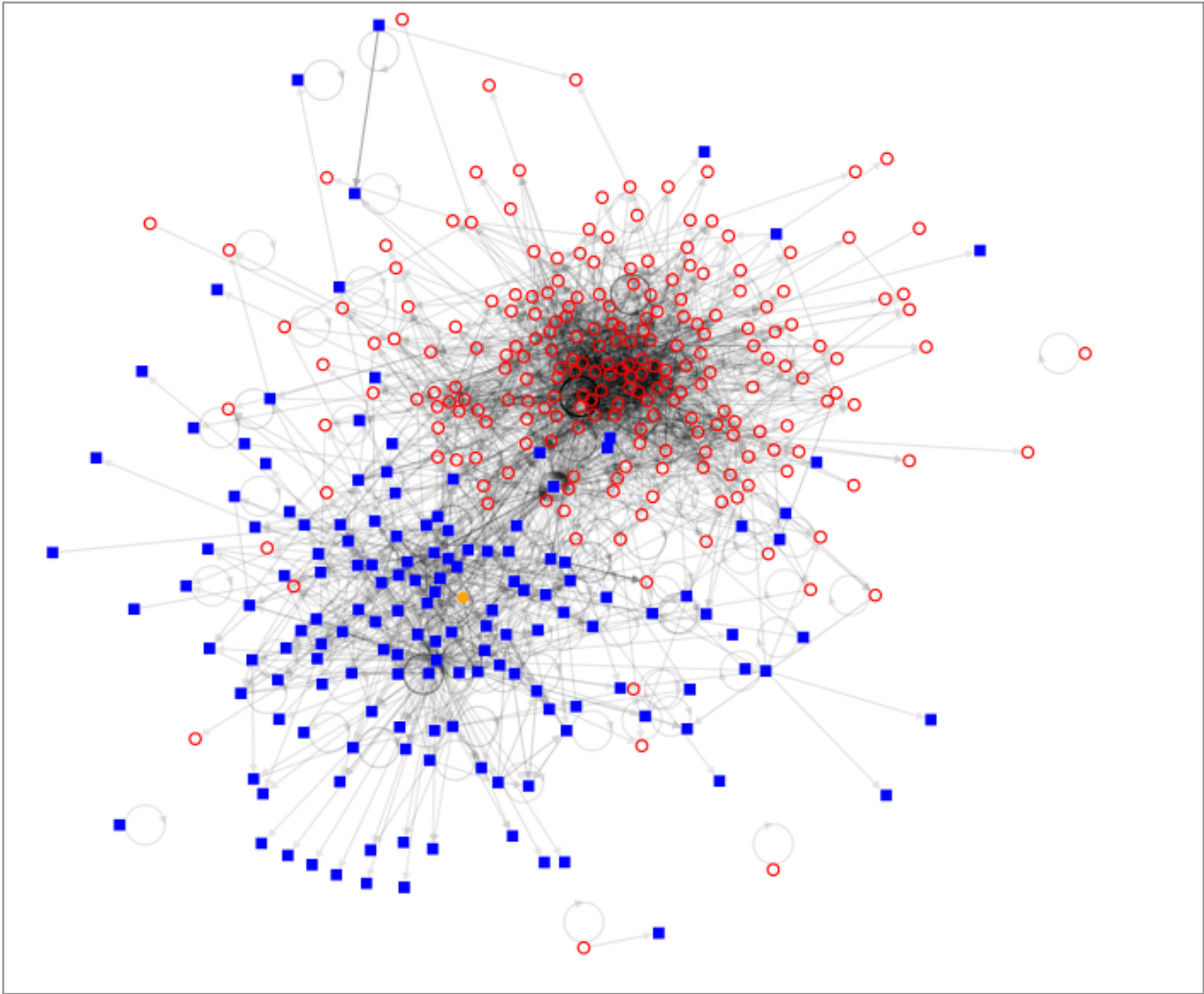


Figure 2 Congressional follows network

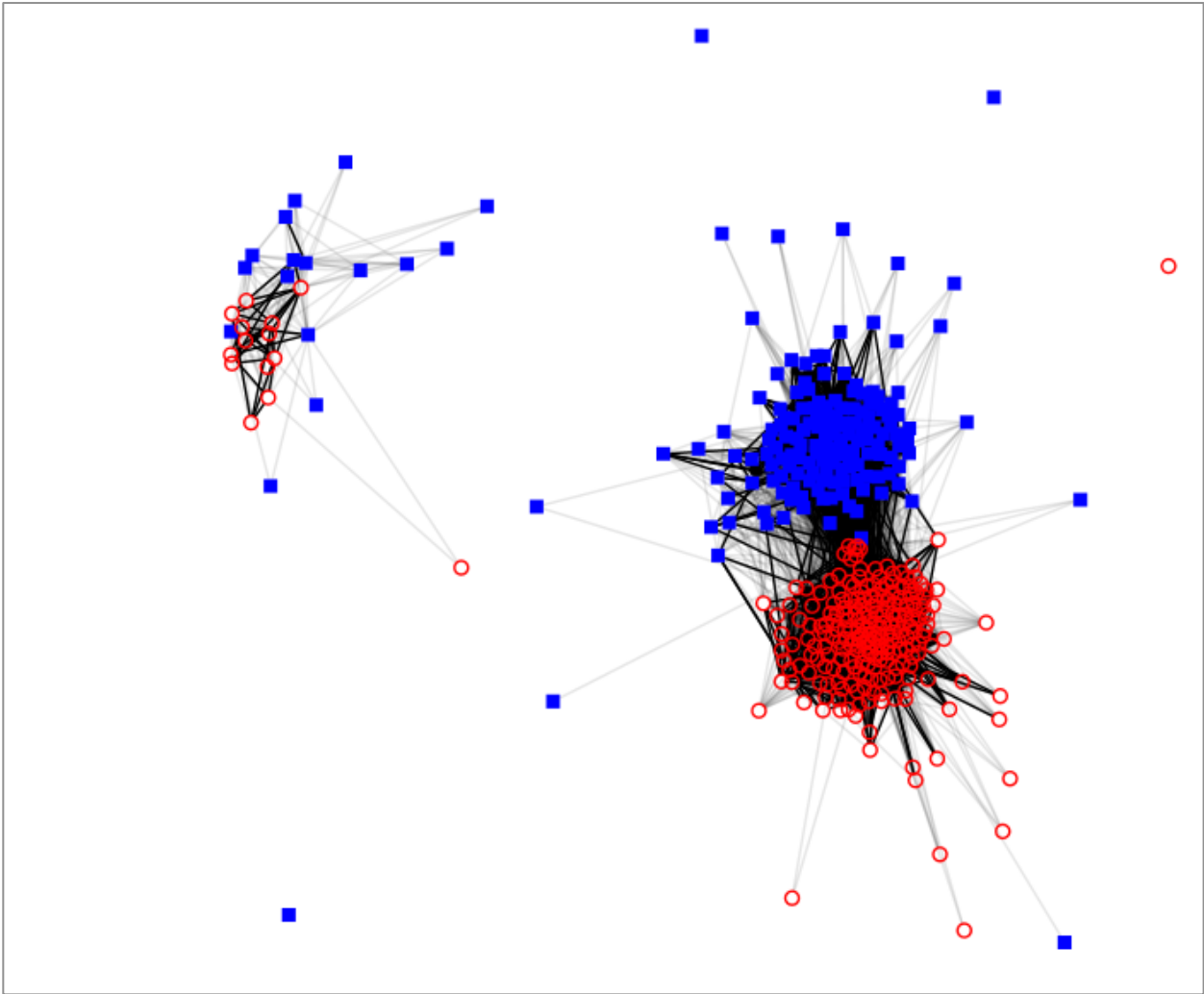


Table 1. Searle's (1969) five categories of speech acts

Category	Explanation	Tweet example
Assertives	Speaker makes a statement; asserts that it is true.	Joining Dr. Bill Bennett's Morning in America radio show in a few moments.
Directives	Speaker calls hearer to action, without committing self to action.	Repeal your unconstitutional appointments. #SOTU
Commissives	Speaker commits self to doing some action.	I will be holding 3 town halls this Feb. 24 in #Kansas http://t.co/8rB2TuSd
Expressives	Speaker expresses feelings or emotion to hearer.	@owaizdadabhoy, love you all in Yorba Linda. Back home in my beloved freezy Minnesota.
Declaratives	Speaker changes or determines a state of affairs within an institution in which s/he holds some power.	I will not only vote against moving [PIPA] forward next week but also remove my cosponsorship of the bill.

Table 2. Definitions and examples of qualitative action codes

Code	Definition	N	Cohen's kappa
Narrating	Telling a story about their day, describing activities	173	0.83
Positioning	Situating one's self in relation to another politician or political issue, may be implied rather than explicit	405	0.87
Directing to information	Pointing to a resource URL, telling you where you can get more info	465	0.70
Requesting action	Explicitly telling followers to go do something online or in person (not just visiting a link but asking them to do something like sign a petition, apply, vote) - look for action verbs	15	0.70
Thanking	Says nice things about or thanks someone else, e.g. congratulations, compliments	57	0.90
Other	Doesn't fit in any other Action category, or one can't tell what they're doing	20	-

Table 3. Predicting betweenness

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
	Normalized betweenness	Normalized betweenness	Normalized betweenness	Normalized betweenness
Followers	-7.53e-10 (9.39e-09)		1.41e-09 (9.70e-09)	2.74e-07*** (7.88e-08)
Friends	1.28e-08 (2.63e-07)		1.88e-08 (2.69e-07)	-2.68e-06*** (7.47e-07)
Tweets	5.94e-06 (3.89e-06)		5.92e-06 (3.91e-06)	7.80e-07 (5.03e-06)
Male		-0.0004 (0.0019)	-0.0007 (0.0019)	-0.0014 (0.0017)
Repub.		0.0019 (0.0013)	0.0003 (0.0013)	-0.0021 (0.0016)
Senate		-0.0027*** (0.0009)	-0.0039** (0.0016)	0.0025 (0.0020)
Follow* Male				-1.23e-07 (1.61e-07)
Friends* Male				1.94e-06** (7.78e-07)
Tweets* Male				-4.72e-07 (5.35e-06)
Follow* Repub				3.86e-07** (1.94e-07)
Friends* Repub				-2.83e-07 (7.03e-07)
Tweets* Repub				3.90e-06 (2.49e-06)
Follow* Senate				-5.42e-07*** (2.06e-07)
Friends* Senate				7.57e-07 (6.67e-07)
Tweets* Senate				-2.22e-06 (3.71e-06)
N	374	374	374	374
F-stat	0.85	3.16**	1.09	4.86***
R2	0.1007	0.0075	0.1059	0.3105

Note: ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. For ease of identification, statistically significant coefficients and standard errors are in bold font. Robust standard errors are in parentheses.

Table 4. Understanding the determinants of Twitter-based characteristics

	(1) Ordered probit	(2) Ordered probit	(3) Ordered probit	(4) Ordered probit	(5) Ordered probit	(6) Ordered probit	(7) Ordered probit	(8) Ordered probit	(9) Ordered probit
	Followers rank	Followers rank	Followers rank	Friends rank	Friends rank	Friends rank	Tweeting rank	Tweeting rank	Tweeting rank
Narrative	-0.1450 (0.1011)	-0.1054 (0.1065)	-0.0856 (0.1068)	-0.2210** (0.0966)	-0.1753* (0.1032)	-0.1598 (0.1035)	-0.3399*** (0.1142)	-0.3355*** (0.1193)	-0.3359*** (0.1196)
Positioning	0.1859** (0.0858)	0.1476* (0.0904)	-0.3517 (0.2264)	0.1399* (0.0818)	0.0771 (0.0875)	-0.4011* (0.2284)	-0.1376 (0.0952)	-0.1122 (0.1002)	-0.1005 (0.2725)
Providing info	0.2284*** (0.0826)	0.2926*** (0.0867)	0.2843*** (0.0868)	-0.4409*** (0.0806)	-0.4399*** (0.0856)	-0.4500*** (0.0857)	-0.3475*** (0.0924)	-0.3363*** (0.0968)	-0.3362*** (0.0969)
Requesting action	0.2275 (0.2843)	0.14769 (0.2936)	0.1490 (0.2936)	0.5020* (0.2860)	0.4140 (0.3002)	0.4142 (0.3003)	0.3201 (0.3178)	0.4061 (0.3255)	0.4060 (0.3255)
Thanks	0.0835 (0.1613)	0.2281 (0.1743)	0.1906 (0.1752)	-0.0567 (0.1546)	0.0150 (0.1693)	-0.0179 (0.1698)	-0.2547 (0.1798)	-0.3428* (0.1962)	-0.3420* (0.1969)
Other	-0.0771 (0.2712)	0.0149 (0.2783)	0.0309 (0.2788)	0.0535 (0.2499)	0.0881 (0.2588)	0.1062 (0.2590)	-0.2906 (0.2812)	-0.3369 (0.2927)	-0.3370 (0.2927)
Male	-0.7484*** (0.1074)	-1.5310*** (0.1318)	-1.5284*** (0.1320)	-0.2264** (0.1044)	-0.8505*** (0.1276)	-0.8416*** (0.1276)	1.0943*** (0.1563)	1.1565*** (0.1744)	1.1562*** (0.1745)
Republican	1.2018*** (0.0969)	1.4472*** (0.1155)	1.4117*** (0.1165)	0.8278*** (0.0914)	1.2013*** (0.1142)	1.1686*** (0.1150)	0.2225** (0.1044)	0.3755*** (0.1187)	0.3762*** (0.1197)
Senate	1.0222*** (0.0934)	1.4420*** (0.1054)	1.4203*** (0.1058)	0.2382*** (0.0883)	0.6176*** (0.1004)	0.6008*** (0.1008)	0.1441 (0.1033)	0.0881 (0.1100)	0.0887 (0.1107)
DW Nominate		1.3480*** (0.2182)	1.0324*** (0.2547)		0.8990*** (0.2153)	0.5815** (0.2570)		-0.7140*** (0.2494)	-0.7058** (0.3065)
Positioning* DW Nominate			0.8574** (0.3563)			0.8190** (0.3614)			-0.0200 (0.4319)
N	791	711	711	791	711	711	791	711	711
Chi2	221.33***	346.09***	351.88***	122.57***	211.27***	216.41***	94.69***	93.86***	93.87***
Pseudo R2	0.0739	0.1202	0.1222	0.0360	0.0708	0.0726	0.0436	0.0485	0.0485

Note: ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. For ease of identification, statistically significant coefficients and standard errors are in bold font.

Table 5. Predicting polarizing action in Congress with speech actions

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
	log of polarizing votes (DW Nominate)	log of polarizing votes (DW Nominate)	log of polarizing votes (DW Nominate)	log of polarizing votes (DW Nominate)	log of polarizing votes (DW Nominate)	log of polarizing votes (DW Nominate)
Narrative	-0.0504 (0.0442)					
Positioning	0.0870** (0.0399)	0.1016*** (0.0296)	0.3066*** (0.1035)	0.0966** (0.0461)	0.0745* (0.0423)	0.2420** (0.1124)
Providing info	0.0695* (0.0391)					
Requesting action	-0.1252 (0.1747)					
Thanks	-0.2426*** (0.0901)					
Other	0.0858 (0.1124)					
Male		0.3648*** (0.0492)	0.4978*** (0.0851)	0.3651*** (0.0490)	0.3627*** (0.0498)	0.5576*** (0.0833)
Republican		0.3464*** (0.0288)	0.3403*** (0.0285)	0.3417*** (0.0444)	0.3472*** (0.0286)	0.2540*** (0.0430)
Senate		-0.0626** (0.0282)	-0.0626** (0.0284)	-0.0627** (0.0282)	-0.0989** (0.0420)	-0.1495*** (0.0397)
Positioning *Male			-0.2459** (0.1071)			-0.3544*** (0.1011)
Positioning * Repub.				0.0090 (0.0594)		0.1638*** (0.0561)
Positioning * Senate					0.0728 (0.0557)	0.1716*** (0.0554)
N	711	711	711	711	711	711
F-stat	4.42***	68.20***	56.01***	55.93***	56.71***	48.27***
R2	0.0421	0.3218	0.3312	0.3218	0.3232	0.3391

Note: ***, **, and * represent statistical significance at the 1, 5, and 10 percent levels, respectively. For ease of identification, statistically significant coefficients and standard errors are in bold font. Robust standard errors are in parentheses.