Title:

Framing in Social Media: How the U.S. Congress uses Twitter hashtags to frame political issues

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Abstract

Social media offers politicians an opportunity to bypass traditional media and directly influence their audience's opinions and behavior through *framing*. Using data from Twitter about how members of the U.S. Congress use hashtags, we examine to what extent politicians participate in framing, which issues received the most framing efforts, and which politicians exhibited the highest rates of framing. We find that politicians actively use social media to frame issues by choosing both topics to discuss and specific hashtags within topics, and that recognizably divisive issues receive the most framing efforts. Finally, we find that voting patterns generally align with tweeting patterns; however, several notable exceptions suggest our methodology can provide a more nuanced picture of Congress than voting records alone.

Keywords

- media effects
- framing
- social media
- political communication
- Twitter
- politicians

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Introduction

Social media, and Twitter in particular, are playing increasingly important roles in connecting people to political information (Himelboim, McCreery, & Smith, 2013), and politicians have taken to Twitter to provide information directly to their constituents (Hemphill, Otterbacher, & Shapiro, 2013). Nearly all members of Congress have Twitter accounts, many of which are highly active. This direct connection between a politician and the public disrupts the traditional communication flow of politician → news media → public (McCombs & Shaw, 1972). Without the news media as mediator, politicians have an opportunity to directly influence public perceptions and behavior through *framing*. Frames are communication devices that diagnose, evaluate, and prescribe issues (Entman, 1993), and we rely on them to make sense of what we read (Gamson & Modigliani, 1989; Goffman, 1974)

We examined whether and how politicians use hashtags to frame issues on Twitter. We apply statistical feature selection algorithms to identify hashtags used for framing and were able to classify politicians by party with over 95% accuracy by considering only 100 hashtags. This suggests that the parties are making different choices about which hashtags to use and where to focus their framing efforts. We found that politicians do engage in their own framing efforts, especially around energy policy, women's issues, the economy, and education. Prior research on framing ignores social media and uses a simple presence-absence measure of framing. We contribute to the literatures on framing and media effects by (1) examining framing in new media and under more direct communication conditions and (2) developing a new measure that accounts for relative differences among framing efforts.

Note that not all tweets are actually authored by the politicians themselves. Rather, politicians employ staffers and firms to manage their social media presence. We think of their social media accounts as brands of sorts rather than individual accounts. Regardless of who actually sends tweets, they are posted on a politician's behalf and in line with his team's messaging plan. Like many public statements politicians and their offices make – e.g. press releases, speeches – tweets are probably the work of a team; and like those other public statements, tweets are part of a politician's broader communication strategy. Communication between politicians and their audiences on Twitter are still mediated, just not by traditional media outlets. We provide insight about how politicians (as brands) use Twitter to produce a media effect normally reserved for traditional news media - *framing*.

Background

Overview of Framing

In *Frame Analysis* (1974), Goffman argues that individuals actively work to make sense of our experiences by classifying, labeling, and interpreting them. We use frames to "locate, perceive, identify, and label" information. Building on Goffman, Gamson and Modigliani (1989) offer five distinct framing devices – metaphors, exemplars, catchphrases, depictions, and visual images. For both Goffman and Gamson, frames are devices that help us organize our experiences, tools we use to make meaning of events. Researchers use the term "frame" as both a noun and a verb. In an effort to clarify the term "framing", Entman (1993:52) offered this definition of the verb form: "to frame is to *select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation and/or treatment recommendation* for the item described." (italics in original). Frames, the nouns, then, are the mechanisms we use to accomplish this selection and salience.

Entman argues that frames manifest in texts through the “presence or absence of certain keywords, stock phrases, stereotyped images, sources of information” and statements that reinforce facts or judgments. These frames determine what people notice and how they remember a problem (Kahneman & Tversky, 1984). Frames and framing have received a great deal of attention in studies of political communication, especially in studies of news media. For instance, researchers have examined framing in discourses between news media and audiences in the Student New Left movement (Gitlin, 1980), anti-abortion protests (Pan & Kosicki, 1993), and the Iraq war (Entman & Rojecki, 1993).

Different political parties typically employ different frames within issue debates. For instance, Republicans frame abortion discussions around the baby or child and specific abortion procedures by using words such as “baby” and “procedure,” while Democrats frame the same issue around women and choice by using words such as “women” and “right” (Monroe, Colaresi, & Quinn, 2009). Through careful word selection, communicators create frames that can influence audience's choices and behaviors (Scheufele & Tewksbury, 2007).

Our study differs from earlier examinations framing and contributes to the literature in a number of ways. First, most of these earlier studies focus on the texts created by the news media rather than on texts created by political officials. The results, then, are analyses of how the *media* frame issues. While politicians may serve as sources in those texts, the news outlets are the actual authors. We are interested, instead, in how officials frame issues when speaking directly to their audiences without relying on news media. To do so, we analyze the texts produced by political officials. Second, earlier studies use content analysis to identify implicit frames created by the attributions and inferences made within news stories (Pan & Kosicki, 1993). We analyze only communicators' explicit attempts to articulate frames through the use of hashtags (analogous to Entman's keywords and stock phrases and Gamson's catchphrases).

Why Framing Matters

Framing matters because frames influence public opinion and behavior. Media frames likely influence our own individual frames, or how we make sense of political news (Entman & Rojecki, 1993). By making only some issues or aspects of an issue salient, framing makes some understandings more easily accessible than others. Repeated exposure to a frame makes it more readily available in memory (Iyengar, 1990), so frames that are used frequently and by many people are likely the most effective at influencing public opinion. Voters are selective about their information exposure (Garrett, 2009b) and are likely to accept the first interpretation of an issue if it is at least marginally acceptable (Lau, Smith, & Fiske, 1991). Therefore, frames used quickly, frequently, and by many people are most effective at influencing the public.

Researchers debate whether framing matters more for prioritizing *issues* or for prioritizing *attributes* of an issue. For instance, McCombs and Shaw (1993) argued that *framing* and *agenda setting* are essentially the same thing - that through framing, the media indicate issues that are important and that demand our attention. In this view, the media accomplish framing by selecting some issues to cover and others to ignore. Media signal the salience of an issue by covering it in detail and repeatedly. Nelson et al. (1997) argued instead that frames influence opinions by highlighting aspects of that issue that we should attend to. For example, Nelson et al. (1997) used news coverage of Ku Klux Klan rallies to study framing effects on tolerance, and argued that frames could highlight either the "public order" aspects of KKK rallies or the "freedom of expression" aspect of the rallies. What mattered was not whether the KKK rallied but what values the media emphasized in covering the rallies.

Each of these arguments about framing claims that media outlets do the framing, and they focus on traditional news media and their abilities to influence the public's political agenda. Social media such as Twitter allow politicians to speak directly through the public, thus circumventing the traditional news media. Because of this new technology, we can now study whether politicians do this kind of framing on their own.

Framing and Political Conversations on Twitter

In order to study whether politicians engage in framing even when their communication is not filtered through the traditional media, we analyze their use of hashtags on Twitter. A Twitter *hashtag* is a string of characters preceded by the # character (e.g., #obamacare). They are entered by the user along with the content of their message to indicate a keyword or topic associated with a tweet. They thus provide useful metadata for searching and browsing tweets. Hashtags are frequently used to organize political discussions, e.g. #iranelection (Gaffney, 2010) and #cdnpoli (Small, 2011). Politicians use hashtags extensively – in our data, roughly 47% of all messages posted by politicians contain at least one hashtag. Tagging generally is an increasingly common activity in which users add keyword metadata to shared content (Golder & Huberman, 2006), and hashtags, much like tags in other systems such as bookmark sharing services (Rader & Wash, 2008), mark individual tweets as relating to a topic or conversation.

We can study framing at both the issue and attribute level. We can tell whether parties give attention to issues by analyzing whether they discuss the issue at all. We can also analyze whether Democrats and Republicans highlight different attributes of the same issue by examining the hashtags they choose when they do discuss an issue.

Because frames influence how audiences understand and act on information (Entman, 1993; Lau et al., 1991; Pan & Kosicki, 1993), we should understand how politicians attempt to create frames and thereby influence their audiences. We address four research questions around framing political communication in social media:

- **RQ1**: How frequently do politicians use hashtags on Twitter?
- **RQ2**: Which hashtags are used for framing?
- **RQ3**: Which topics exhibit the highest rate of framing?
- **RQ4**: Which politicians exhibit the highest rate of framing?

Our results indicate that politicians do accomplish framing on Twitter and that the two parties use different frames to discuss the same issues. Among topics, healthcare, the economy, and education exhibit the highest rates of framing. Among politicians, Rep. Ken Marchant (R-TX) and Sen. Kirsten Gillibrand (D-NY) exhibit the highest rates of framing. A signed chi-squared algorithm provided the most useful algorithmic approach to identifying framing hashtags and politicians' framing efforts.

Methods

Data Collection

We collected tweets using Twitter's Streaming API. We identified verifiable accounts associated with individual Members of Congress (MoCs) and collected all tweets posted by those accounts from April 1, 2012 through September 30, 2012. We identified 10,546 different hashtags used by 474 users in 119,277 tweets[1].

Detecting Frames

Analyses of media framing efforts have used a combination of manual and computer-assisted approaches to analyze both content and structure (Matthes and Korhing, 2008). For instance, Shah et al. (2002) used InfoTrend to help detect framing in the news coverage of the

[1] Lists of the tweet ids, Twitter screennames, and hashtags in our dataset are available at [removed for blind review].

scandal involving President Bill Clinton and Monica Lewinsky. In their approach, human analysts provide InfoTrend with idea categories, words from those categories, and rules about idea pairings, and the software automatically analyzes the content. Pan and Kosicki (1993) used a manual qualitative approach to identifying frames: they had human coders analyze the syntactic, script, thematic, and rhetorical aspects of news stories about anti-abortion rally in Wichita, Kansas. We leverage feature selection techniques from the machine learning and statistics literature (Guyon & Elisseeff, 2003) to quantify and measure differences in hashtag selection and use among individuals and between parties. Details about the algorithms we used are presented in the Results section.

Results

First, we provide descriptive statistics of the dataset, analyzing hashtag frequency and highlighting party differences. We then describe an algorithmic approach for identifying hashtags that are most likely to be used for framing purposes. Finally, we apply this approach to rank topics and MoCs by their level of framing.

RQ1: How frequently do politicians use hashtags on Twitter?

General Hashtag Use

We first looked to see whether politicians use hashtags at all and provide an overview of their hashtag use. **Table 1** presents two different measures of use:

- users/hashtag: how many users ever tweeted the hashtag
- total uses: a raw score of how many times a given hashtag was tweeted by any user.

Table 2 displays the most used tags along and the most popular hashtags for each major party. Distributions of users/hashtag and total uses are all heavily skewed. Most hashtags are used by only one user, used only once by any user, or used only once by anyone. Among the most used hashtags, those used by many users (high users/hashtag) and used in the most tweets (total uses) are general topic tags such as #JOBS and #SCOTUS that likely matter to broad constituencies.

Comparing Hashtag Use Between Groups

As seen in Table 2, the issues Democrats and Republicans discuss overlap, but the hashtags they use to mark their conversations differ. The top of the Democrats' list includes healthcare (#ACA, for the Affordable Care Act), student loans (#DontDoubleMyRate), and employment (#JOBS). The Republicans' top issues are similar: employment (#4jobs), themselves (#tcot), and healthcare (#Obamacare).

As Table 2 shows, among the top 15 most frequently used hashtags in each party, only five appear on both lists, but overall tag frequency values for Republicans and Democrats were strongly correlated ($r(10{,}545)=0.23$, $p<0.001$). These analyses suggest that Congress has converged on a set of hashtags, and those same hashtags are used by both parties. However, given the skew of the distributions for tag use, these raw counts of hashtag frequency may overestimate a tag's popularity. In the next section, we present results from our algorithmic approaches to analyzing framing through hashtags. These approaches provide more robust means for comparing between groups than correlation allows.

RQ2: Which hashtags are used for framing?

Hashtags, like keywords, are evidence of intent to frame an issue. Since not all hashtags are necessarily used to frame (e.g., #ff for “follow Friday”), we need a way to identify *framing hashtags* (e.g., #obamacare, #aca). To do this, we assume that different political parties use different framing strategies. It follows that hashtags whose usage differs significantly between parties are likely to be framing hashtags. To quantify this, we turn to the *feature selection* literature of machine learning and statistics (Guyon & Elisseeff, 2003).

In machine learning, a *feature* is a measurable property of a phenomenon, and a *class* is the category to which a given observation belongs. *Classification* is the problem of estimating a function that accurately maps an observation to its proper class. In our case, hashtags are features, political parties are classes, and MoCs are observations. We represent each MoC as a binary vector indicating which hashtags he has used. For example, if only two hashtags #tcot and #aca are considered, then each MoC will be represented by a vector of length two, where the first element represents the presence of #tcot, and the second element represents the presence of #aca. Thus, a MoC who mentions only #tcot is represented by the vector {1,0}, while a MoC who mentions both hashtags is represented by {1,1}. One could also represent each MoC by a count vector, which considers the number of times a MoC has used a hashtag instead of just its presence or absence. However, doing so would allow one prolific user to bias the results. For example, Rep. Tim Griffin (R-AR) used the tag #ar2 in 967 different tweets. If a count vector were used, the feature selection algorithm would rank the #ar2 highly, since it is so predictive of the Republican party.

Generically, feature selection algorithms determine which features (hashtags) are most useful for determining class (party). Feature selection algorithms typically proceed by analyzing a set of observations for which the classes are known and assigning a real-valued score to each feature, where a larger score means the feature is more predictive of class. We use the score assigned to each hashtag to quantify the likelihood that the hashtag was used with framing intent. We compare three algorithms (see [Guyon & Elisseeff, 2003] for mathematical details):

- **Information gain**: Computes the decrease in entropy of the class label distribution when a feature is included compared with when it is not.

- **Chi-squared**: Computes the chi-squared test statistic for the null hypothesis that the class label and feature value are independent.
- **Log odds ratio**: Computes the log of the odds of a feature appearing in one class divided by the odds of it appearing in the other class.

Evaluating hashtag selection algorithms

To determine which algorithm is most appropriate for our data, we follow the standard approach of evaluating each method by the party classification accuracy it produces, across a range of feature sizes. Here, the classification task is to predict the party of a MoC based on the set of hashtags that he or she has used. Average accuracies on held-out data are computed using *k*-fold cross-validation (k=10). That is, given a labeled set of observations *D*, a feature selection algorithm *F*, and a maximum feature size *m*, we do the following:

- Split D into k equal-sized sets $D_1 \ldots D_k$
- For each set
    - Construct $D_{\text{train}} = D \setminus D_k$; $D_{\text{test}} = D_k$
    - Rank features in D_{train} according to F
    - Retain the top m features
    - Fit a classifier on D_{train} using only the selected m features
    - Predict the class assignments for the held-out observations in D_{test}

We compute the average accuracy over the k sets D_{test} for each feature size m. Good feature selection algorithms should produce higher accuracies than bad algorithms across a range of values for *m*. Figure 1 displays the average accuracy (and standard error) for each algorithm using many feature sizes. For all results, we use a Naive Bayes classifier[2] (Hastie, Tibshirani, & Friedman, 2009).

The results indicate that we can classify MoCs by party with over 95% accuracy by examining the presence or absence of only 100 hashtags. The best result is 97.67% accuracy using 1,000 hashtags selected by chi-squared. Information gain and chi-squared feature selection strategies perform comparably, and both are superior to log odds. Averaged across all feature sizes, both chi-squared and information gain have an average accuracy of 95.44%, compared with 91.77% for log odds. Given chi-squared's performance and simplicity, we use it in subsequent experiments. Table 3 lists the top 15 hashtags sorted by chi-squared value. Note that 5 of the top 15 do not appear on the list of most frequent hashtags in Table 2. This is because the chi-squared measure accounts for the relative frequency across classes, giving a clearer picture of framing relevance. It is interesting to note that #obamacare is the third most frequent hashtag used by Republicans, but is only the 15th ranked hashtag according to chi-squared. This is an interesting hashtag in that it started as a Republican frame, but then was in part co-opted by Democrats, thereby diluting its score.

Assigning frame scores to hashtags

To determine which hashtags politicians used to frame topics, we computed a signed version of chi-squared, in which positive values are predictive of Republican MoCs and negative values are predictive of Democratic MoCs. We use positive values for Republicans and negative for Democrats because the first dimension of DW-NOMINATE, the most common measure of political polarization, uses the same scale (Lewis and Poole, 2004). We determine this sign by selecting the party for which the hashtag probability is larger. Thus, in Table 3 #4jobs has signed

[2] We also used tested logistic regression and support vector machine classifiers, but neither resulted in higher accuracy, so we omit them from further discussion.

value of +125.3 because relatively more Republicans use it, while #aca has a signed value of -110.6 because relatively more Democrats use it.

Overall, we see that many tags have small signed chi-squared values, even those such as #jobs that are used by many MoCs. #jobs has a small chi-squared value because members of both parties frequently use it. Republicans appear to prefer the tag #4jobs over the more ambiguous #jobs. Other tags such as #scotus, #veterans, and #medicare that do not take clear policy positions also appear near the midline. Tags used in discussions about contentious issues such as the Affordable Care Act and the Lily Ledbetter Fair Pay Act do show measurable signed chi-squared values. In discussing the Affordable Care Act, #aca is more likely used by Democrats while #obamacare and #fullrepeal are more likely used by Republicans. The Lily Ledbetter Fair Pay Act provides an interesting case because Democrats are likely to talk about it – as evidenced by the #equalpay and #equalpayday tags – but Republicans don't seem to talk about it at all. There is no clear counter tag with positive chi-squared value. Thus, this appears to be a case of framing as agenda setting, as discussed above.

RQ3: Which topics exhibit the highest rate of framing?

We used a similar approach to determine which topics exhibited the highest rates of framing. We manually coded each tag into one of 40 categories[3]. We used several sources, including public opinion polls and lists of U.S. congressional committees and Cabinet departments while developing a typology of political issues. The majority of these categories correspond to political issues. Hashtags may be used to join a discussion about a broad issue (#immigration) or to comment on specific legislation (#sb1070). To provide a higher-level summary than the hashtag analysis, our coding scheme use broad topics when possible. So, for

[3] A complete list of hashtags and their topic categories is available at [removed for blind review].

example, both of the previously mentioned hashtags fall into the "Latino Issues" category, along with hashtags #dreamact and #racialprofiling. Hashtags that were not related to any specific political issue were coded according to their function. For example, "Promotion" hashtags are those used to promote a TV appearance by a legislator (#TheWarRoom).

To determine the signed chi-squared score for each topic, we sum together the signed chi-squared scores for each hashtag it contains. Figure 3 plots topics by this aggregated signed chi-squared value and by the number of unique MoCs that mention hashtags from each topic. We see that authors of tweets about energy, the economy, and employment are more likely to be Republicans, while authors of tweets about women's issues, education, and Latino issues are more likely to be Democrats. Topics that Republicans talk about, such as “employment,” are discussed by many MoCs, while most Democrat topics are discussed by fewer people (e.g., “Latino issues”). As Figure 3 shows, the only political issue that most Democrats discussed was healthcare. Their next most popular topics were locative – indicated by hashtags that signal a location such as #ct or #ny. The topics Democrats discuss – healthcare, education, subgroup (women, Latinos, veteran) issues etc. – are personal or micro-level policy issues. On the other hand, Republicans focus on macro-level issues such as the economy and energy policy. The Republican National Committee recognized this pattern as well. In its “Growth and Opportunity Project” report issued in March 2013 (Barbour, Bradshaw, Fleischer, Fonalledas, & McCall, 2013), the RNC claimed, “while Democrats tend to talk about people, Republicans tend to talk about policy.”

RQ4: Which politicians exhibit the highest rate of framing?

We determined which politicians exhibit the highest rates of framing by visualizing the aggregated signed chi-squared scores for each MoC (see Figure 4). As with topics, we computed the aggregated score by summing together the signed scores for each unique hashtag they used. The "U" shape in the graph indicates that people with extreme signed chi-squared results also use many different hashtags. Politicians in the top left and top right quadrants of the graph are both trying to frame often and succeeding at least some of the time. Those near the middle and the bottom are doing less framing on Twitter. It may be that they are not using Twitter very much or that they do use Twitter but not to frame issues. Leaders of the two parties accomplish framing differently. Speaker Boehner, visible near the top right of the graph, uses many distinct hashtags (179), and at least some of them are strongly Republican. Former Speaker Pelosi, on the other hand, uses fewer distinct hashtags (65), but those she uses are strongly Democratic.

We next investigate how Twitter behavior relates to voting behavior. DW-NOMINATE scores are based on roll call voting records and are often used in analyses of political polarization (Lewis and Poole, 2004), and here we compare them to our signed chi-squared measure. The first dimension of DW-NOMINATE roughly maps to the liberal - conservative continuum. Figures 5 and 6 plot our signed chi-square value (x-axis) against the first dimension of the DW-NOMINATE score (y-axis). DW-NOMINATE scores are not comparable across chambers, so we include figures for both the Senate (Figure 5) and House (Figure 6).

We find a strong correlation between signed chi-squared and DW-NOMINATE scores in both the House ($r(331)=0.80$, $p<0.001$) and the Senate ($r(76)=0.83$, $p<0.001$). DW-NOMINATE scores vary little among both Democrats and Republicans. Our signed chi-squared measures may be useful for detecting differences between otherwise similar members of Congress. For instance, we are able to differentiate within the small range of Democrats' DW-NOMINATE scores. Sens. Casey (D-PA) and Shaheen (D-NH) have nearly identical DW-NOMINATE scores (-0.345 and -0.341, respectively) but very different signed chi-squared scores (-85 and -591).

That tells us that, on average, their voting records look similar, but their rhetoric is very different. Sen. Shaheen is much more polarizing in her language than her voting record suggests. She uses hashtags such as #aca, #equalpay, #dontdoublemyrate, #vawa, and #lgbt, all of which are predominantly used by Democrats. On the other hand, Sen. Casey uses a few strongly Democratic hashtags (e.g., #dontdoublemyrate), but also uses some hashtags associated more with Republicans (#dday, #usarmy), resulting in his more moderate chi-squared score.

We see that most politicians are about as polarized in their framing on Twitter as we would expect based on how polarized they are in their voting records. For instance, Rep. Marchant (R-TX) and Sen. Gillibrand (D-NY) had the highest and lowest signed chi-squared scores. Both also had high and low DW-NOMINATE scores, demonstrating their consistent conservative and liberal voting records. They talk and vote along the same polarized lines. We did find 8 MoCs who talked and voted differently: 7 Democrats and 1 Republican (see Table 4). The "Rank Diff" column shows how different a user's chi-squared and DW-NOMINATE scores are based on their rank order under each metric; a negative rank difference indicates a user is more Republican in his talk than in his voting record, and a positive rank difference indicates a user is more Democratic in his talk than in his voting record. We included "Unique Hashtags Used" because some MoCs used just a few hashtags, but those hashtags were very polarizing. Reps. Hinojosa (D-TX), Filner (D-CA) and Harris (R-MD), for instance, seem to use different rhetoric than their voting records would suggest, but they each used only one hashtag. In each case, that particular hashtag was more often used by members of the other party. When we remove MoCs who used just one hashtag, no Republicans appear on the list of people who talk differently from how they vote, and even those Democrats who remain on the list don't have large differences between their ranks according to signed chi-squared and DW-NOMINATE.

Among those remaining Democrats who talk differently than they vote are some of Congress's most conservative Democrats. For instance, Rep. John Barrow's (D-GA) signed chi-squared ranking is lower than we would expect because he used hashtags such as “jobs”,“NoShowNoPay”, and “CutTheFleet”. “Jobs” was used far more often by Republicans. “NoShowNoPay” and “CutTheFleet” both refer to bills aimed at cutting spending[4]. It is not surprising to see him talk this way because Rep. Barrow is widely recognized as a conservative Democrat and has a mixed voting record that accounts for his nearly-zero DW-NOMINATE score. Sen. Manchin and Reps. Altmire and Levin are similarly conservative compared to their Democratic colleagues, and we expect them to use some Republican frames.

Discussion

A rich body of research suggests that framing has incredible potential to influence public opinion and political behavior (Entman, 1993; Pan & Kosicki, 1993; Scheufele & Tewksbury, 2007). Social media offers politicians an opportunity to circumvent traditional media and to directly influence their audience's opinions and behavior by establishing their own frames for issues. Using data from Twitter about how members of the U.S. Congress use hashtags, we examined to what extent politicians were doing their own framing, which issues received the most framing efforts, and which politicians exhibited the highest rates of framing. We found that politicians are indeed actively using social media to frame issues. They do so by selectively choosing topics to discuss and hashtags within those topics to use. Recognizably divisive issues - healthcare and the economy - received the most framing efforts. In both parties, those who voted most liberally or conservatively were also the most likely to exert framing efforts. For the most

[4] “NoShowNoPay” refers to a bill that would cut Congressional pay for missing votes, and “CutTheFleet” refers to a bill co-sponsored by Rep. Barrow and Rep. Richard Hanna (R-NY) that reduces the number of vehicles the federal government owns.

part, MoCs were about as polarizing on Twitter as they are in their voting records.

Politicians Framing in Social Media

Earlier work suggests framing can impact public opinion in two ways: by highlighting issues (McCombs & Shaw, 1993) and by highlight aspects of issues (Nelson et al., 1997). Our analysis reveals that politicians accomplishing framing of both types: first, by choosing which issues to discuss, and second, by using different hashtags to highlight aspects of issues. Given (a) voters take the first interpretation if it is marginally acceptable (Lau et al., 1991) and (b) we follow people like us on Twitter (Himelboim et al., 2013): if politicians do framing on Twitter, then their efforts likely amplify ideological divides through *frame alignment*. Frame alignment is a process through which our attitudes and values become increasingly similar to those around us (Kim and Bearman, 1997). The potential to amplify ideological divides is greatest for those issues that are most aggressively framed, and we identified them using signed chi-square scores. Those topics are jobs, energy policy, equal pay, and immigration. Topics that exhibited little controversy included foreign affairs, natural disasters, technology, and sports. Our method of frame analysis is able to determine not just that frames are being used but to measure the relative influence a frame is likely to have given its frequency, persistence, and use.

Politicians signal the salience of issues by talking about them frequently and using hashtags within them broadly. Our results indicate that Democrats are more likely to highlight women's issues, education, and Latino issues. Republicans, on the other hand, signal that jobs, the economy, and energy policy are most salient. Earlier research found that users are unlikely to be exposed to cross-ideological content on Twitter (Himelboim et al., 2013) and warns of the dangers of selective exposure and lack of diversity of political information (see e.g., Garrett, 2009a; Garrett, 2009b). Ideological amplification is just one potential implication. Others include polarization, reduced tolerance, and less effective deliberation.

Polarization is a likely outcome of both types of framing. Our results indicate disagreement not just about the aspects of issues that are important but that different issues are important to different groups. As mentioned above, for instance, the Lilly Ledbetter Fair Pay Act received quite a bit of attention from Democrats but none from Republicans. This suggests that Republicans did not think pay equity needed to be discussed. It is difficult to have a broad discussion about an issue when the parties disagree about whether we should talk about it at all.

Reduced tolerance and less effective deliberation are likely results of the combination of framing and selective exposure. Exposure to contrasting perspectives can foster tolerance by making users familiar with opposing rationale (Mutz, 2002; Price, Cappella, & Nir, 2002). Himelboim and colleagues (2013) found that Twitter users are not likely exposed to contrasting perspectives, so it is likely that the audiences of Democratic and Republican representatives are seeing only one party's framing efforts. Repeated exposure to these frames reinforces existing opinions rather than fostering tolerance of other opinions.

Similarly, exposure to only a single viewpoint reduces the likelihood that users will seek additional information or scrutinize their own views (Carpini, Cook, & Jacobs, 2004; Mendelberg, 2002). Because we know that users are likely to accept the first viewpoint they encounter, as long as it is not too far from their existing view (Lau et al., 1991), the danger here is that the first frame users encounter will be the one they adopt. So, frames such as “#jobs” and “#Obamacare” that are used by many MoCs have greater reach than those used by fewer MoCs.

Limitations and Future Work

We recognize that politicians' tweets are not the only, or even the primary, source of political news for most Americans (Rainie et al., 2012). People may also follow multiple politicians, and readers likely access political news from a number of sources (Garrett, 2009a). Therefore, the impact of politicians' framing efforts of Twitter is limited. However, prior research suggests that political elites and journalists share frames, in part to provide efficient ways of covering topics (Shah et al., 2002). The frames politicians use may get adopted by others, potentially increasing the frames' impacts. Future research should examine whether the frames politicians establish in social media are eventually picked up by others and diffuse through traditional political news coverage.

Unlike traditional measures of polarization, such as DW-NOMINATE (Lewis and Poole, 2004), that rely on roll call votes or bill co-sponsorship, our signed chi-squared algorithm can analyze tweets or other public statements at any point in time. Therefore, it can be used to compare rhetoric over time and at any point in the legislative process; for instance, we could examine whether framing efforts increase around elections or early in a policy debate. It can also be used to compare one's rhetoric to one's voting behaviors.

Conclusion

As we increasingly turn to social media for news and rely less on traditional media for help understanding policy debates, it is important that we understand how politicians use social media to frame our discussions. We demonstrated that politicians do use hashtags to frame policy discussions, and they can do so without relying on traditional media. We found a strong correlation between politicians' framing efforts and voting records, indicating that politicians talk and vote along similarly polarized lines. Given the increasing use of social media for accessing news, studies like ours are important for understanding how existing models of media effects must change to account for new arrangements of authors, sources, and audiences. Algorithmic approaches that rely on actual texts offer promising methods for examining these effects.

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Tables and Figures

	Mean	S.D.	Median	Min	Max
Users/hashtag	2.8	8.9	1	1	260
Total uses	9.0	68.9	1	1	3415

Table 1. Summary statistics of users/hashtag and total uses of hashtags

Total users		**Total tweets**		**Top Tags (Democrats)**		**Top Tags (Republicans)**	
Tag	Users	Tag	Tweets	Tag	Count	Tag	Count
JOBS	260	4jobs	3415	ACA	783	4jobs	3413
SCOTUS	215	tcot	3070	DontDoubleMyRate	634	tcot	3047
Obamacare	202	JOBS	2080	JOBS*	558	Obamacare	1926
gop	191	Obamacare	2054	VoteReady	539	smallbiz	1691
FF	186	smallbiz	1834	VAWA	502	JOBS*	1456
4jobs	165	gop	1383	gop*	462	stopthetaxhike	1260
smallbiz	153	stopthetaxhike	1268	EqualPay	425	FastAndFurious	1082
ACA	153	FastAndFurious	1115	FF*	421	ar2	1017
DontDoubleMyRate	149	FF	1027	hcr*	366	gop*	916
tcot	146	ar2	1017	p2	350	Energy	749
VAWA	142	ACA	865	FarmBill	332	FullRepeal	727
FullRepeal	132	Energy	857	netDE	331	FF*	604
Veterans	132	SCOTUS	745	Veterans	322	SCOTUS*	450
hcr	130	DontDoubleMyRate	739	SCOTUS*	254	Holder	408
Energy	126	FullRepeal	730	NJ	236	stribpol	385

* tag appears on both parties' top 15 lists

Table 2. Most used tags along a number of measures of use

Hashtag	Chi-squared	# MoCs
4jobs	129.7	162
aca	111.0	150
fullrepeal	99.3	128
equalpay	86.1	80
tcot	84.3	140
dontdoublemyrate	75.7	144
stopthetaxhike	74.8	118
middleclasstaxcuts	62.7	53
lgbt	55.6	47
gopnmc	49.9	59
equalpayday	47.3	40
disclose	44.4	48
vawa	44.3	136
voteready	44.2	41
obamacare	43.1	194

Table 3. Top 15 framing hashtags: tags are ranked by their chi-squared results, and we indicate how many MoCs ever used the tag

MoC	Signed Chi-Squared	DW-NOMINATE	Rank Diff	Unique Hashtags
Rep. John Barrow (D-GA)	111.9	-0.086	6	35
Sen. Joe Manchin (D-WV)	58.4	-0.128	7	6
Rep. Jason Altmire (D-PA)	33.3	-0.137	7	16
Rep. Sandy Levin (D-MI)	12.9	-0.337	7	29
Rep. Larry Kissell (D-NC)	9.9	-0.161	8	5
Rep. Ruben Hinojosa (D-TX)	1.1	-0.323	8	1
Rep. Bob Filner (D-CA)	1.1	-0.654	8	1
Rep. Andy Harris (R-MD)	-0.5	0.900	8	1

Table 4. MoCs whose chi-squared and DW-NOMINATE signs differ, indicating that they tweet and vote differently.

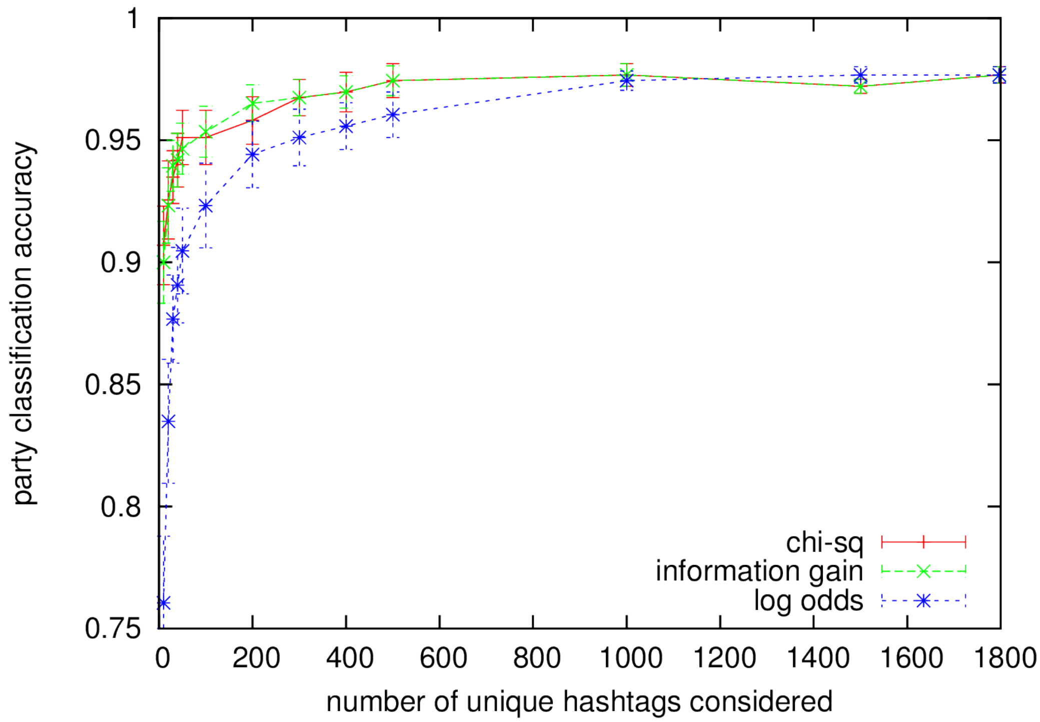

Figure 1. Comparing Classification Algorithms. The graph shows average accuracy (and standard error) for each algorithm using feature sizes in {10, 20, 30, 40, 50, 100, 200, 300, 400, 500, 1000, 1500, 1797}

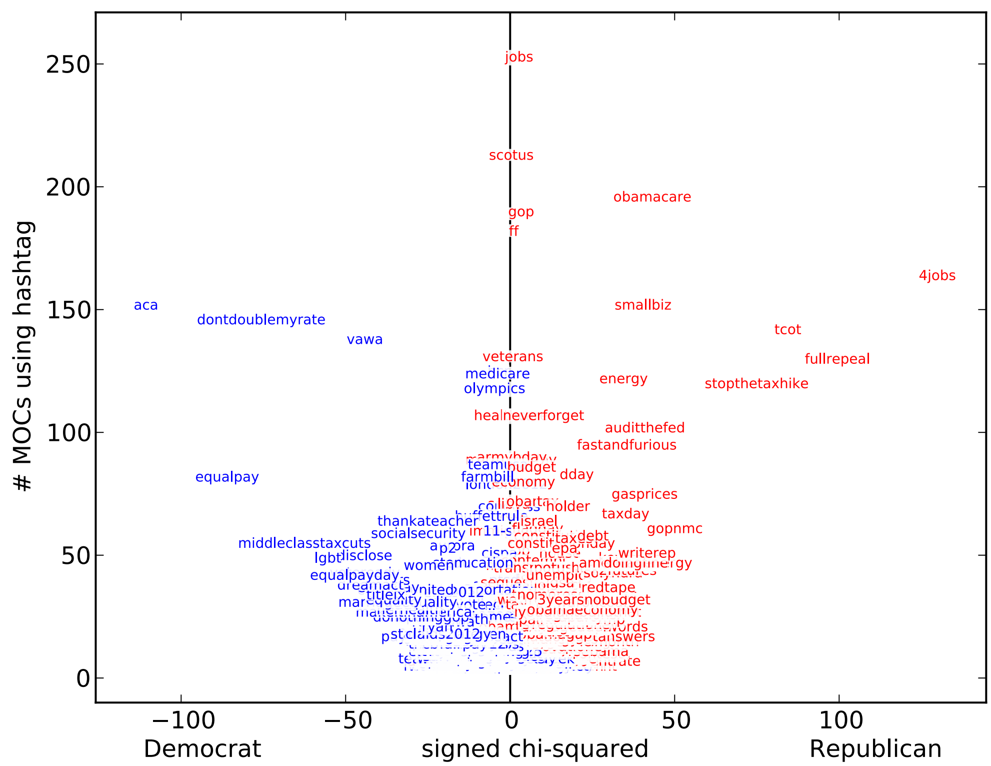

Figure 2. Hashtags' signed chi-squared values and number of MoCs who used them. Red tags have positive signed chi-squared values (more likely used by Republicans), blue negative (more likely used by Democrats).

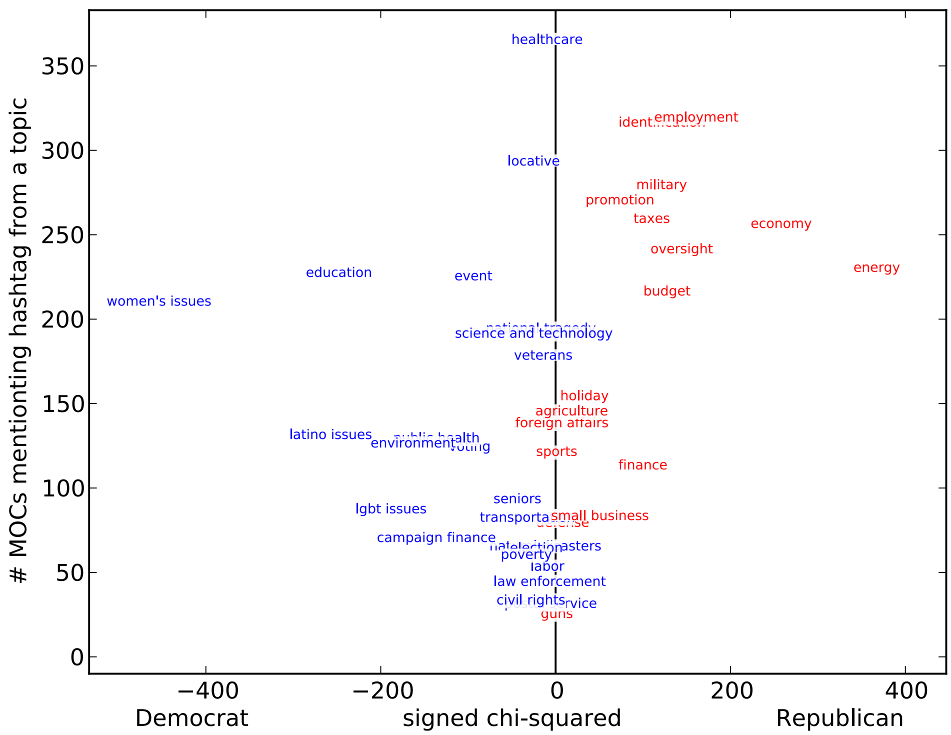

Figure 3. Political topics by their aggregated chi-squared values and number of MoCs who mentioned them. Topics are colored red if their signed chi-squared is positive (more likely mentioned by Republicans), blue if it is negative (more likely mentioned by Democrats).

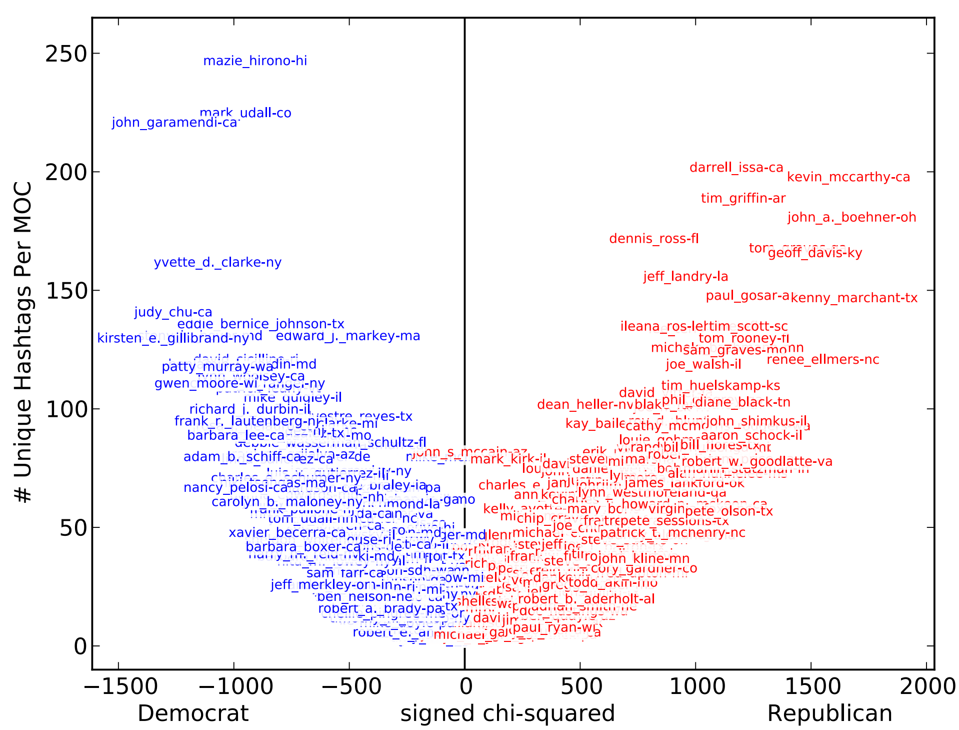

Figure 4. Aggregated signed chi-squared scores for individual MoCs. Individuals are labeled by their name and the state they represent. MoCs are colored red if they are Republicans, blue if they are Democrats.

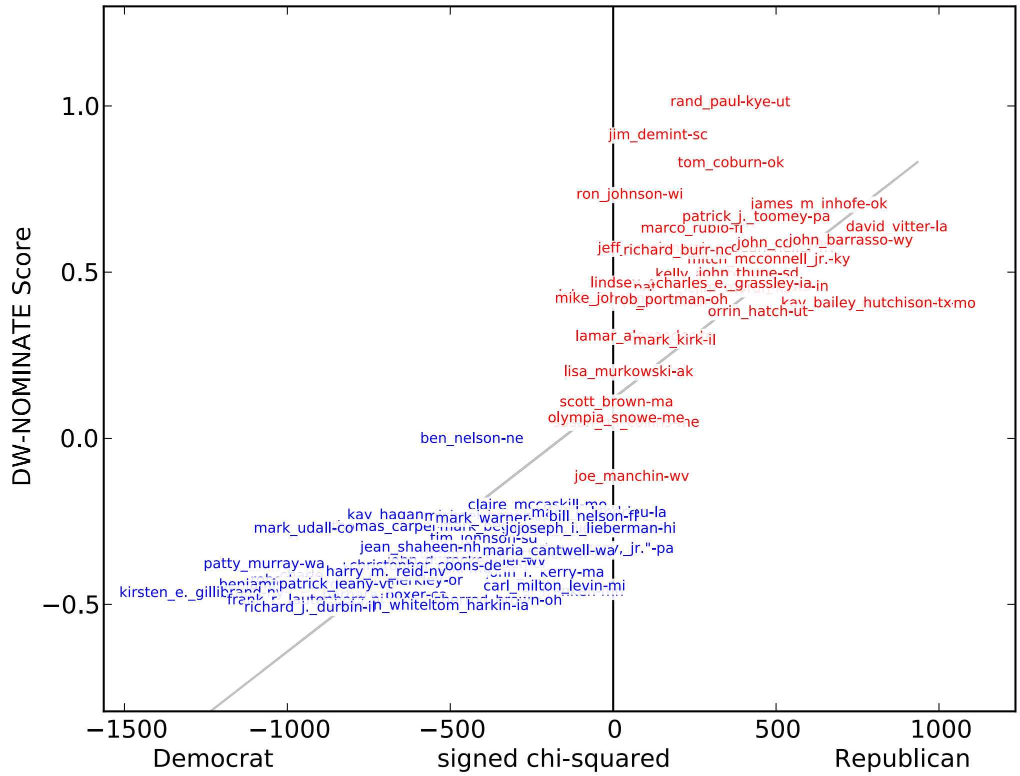

Figure 5. Comparing signed chi-squared and DW-NOMINATE results (Senate).

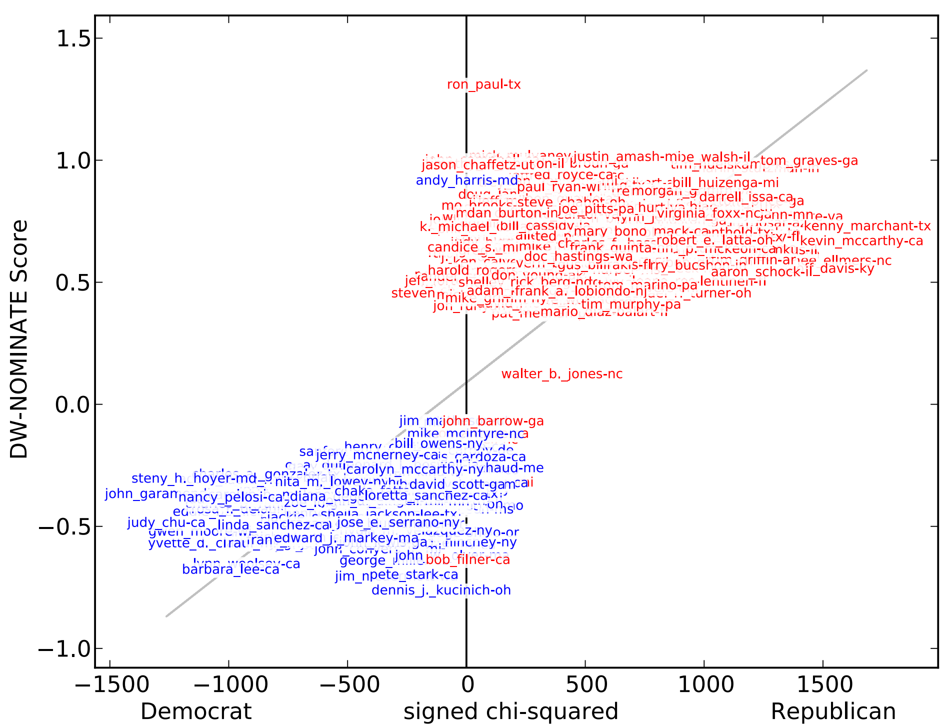

Figure 6. Comparing signed chi-squared and DW-NOMINATE results (House).