Who Leads? Who Follows? Measuring Issue Attention and Agenda Setting by Legislators and the Mass Public Using Social Media Data*

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Abstract

Are legislators responsive to the priorities of the public? Existing research has demonstrated a strong correspondence between the issues about which the public cares and the issues addressed by politicians. But scholars have yet to uncover conclusive evidence about who influences whom and thus sets the political agenda. Here we answer this question with fine-grained temporal analyses of messages transmitted on the Twitter social media platform by members of Congress and the public during the 113th Congress. After employing an unsupervised method that classifies tweets sent by legislators and the public into topics, we use VAR time-series models to explore whose priorities have more influence in the reciprocal relationship between citizens and politicians. We find that legislators are more likely to respond to than to influence discussion of public issues, results that hold even after controlling for the agenda-setting effects of the media. We also find, however, that legislators are more likely to be responsive to their own supporters and attentive voters than to the general public.

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An enduring topic in the study of democratic polities is how responsive governments are to the preferences of the public. Two main lines of inquiry lead this research: Do politicians respond to the issue priorities of the public (Edwards and Wood, 1999; Jones and Baumgartner, 2004; Sulkin, 2005; Neundorf and Adams, 2018)? And if so, do they reflect the policy preferences that citizens have on these issues (Page and Shapiro, 1983; Page, 1994; Stimson, Mackuen and Erikson, 1995; Erikson, Mackuen and Stimson, 2002; Soroka and Wlezien, 2009; Caughey and Warshaw, 2018)? This paper focuses on the first of these two questions, because while a correspondence between public and political agendas has definitively been shown to exist, there is still high uncertainty about who influences whom. Evidence is even more scant on the important question of which citizens have the most influence on the agenda taken up by politicians: the general public (Downs, 1957), attentive citizens (Arnold, 1990; Aldrich, 1995), or politicians' own political supporters (Egan, 2013; Kastellec et al., 2015).

In this paper we aim to shed new light on these classic and relevant political science questions by analyzing the issues to which members of the U.S. Congress and the American public pay attention. Although determining whether politicians are also responsive to constituents' issue preferences and priorities on the policies they *implement*, and if so *which* constituents' issue preferences, is of equal relevance, to say the least, "policy actions cannot be taken unless attention is directed at the matter" (Jones and Baumgartner, 2004, 2). Hence, understanding whether politicians pay attention to issues as a response to public demands is a first and crucial step towards fully understanding political representation in the United States. But we are not addressing the downstream question of: if members of Congress do pay attention to the preferences of their constituents, which constituents are they trying to please.[1]

We measure the expressed agenda of legislators and the American public by looking at the issues they discuss on Twitter. Virtually all members of the U.S. Congress are active Twitter users, and their tweets have been shown to constitute a standardized representation of their issue agenda (Casas and Morar, 2015). The topics discussed by individual users of the platform have in turn been shown to be an accurate measure of the issue priorities of the public. The issues Americans discuss on social media are highly correlated with other measures of issue salience such as the Most Important Problem (MIP) survey question (O'Connor et al.,

[1] See Gilens and Page (2014) for an analysis of the determinants of policy outcomes.

2010).[2]

Twitter data provide two main advantages to address the questions at hand. First, the data allow us to measure public and political agendas using the same source: both members of Congress and their constituents are present on the platform, sending tweets that have the same format and symbolic references such as hashtags. Second, the high granularity of the data allows us to observe swiftly changing temporal patterns in topic salience. We are therefore able to pinpoint with precision the extent to which politicians allocate attention to different issues and respond to shifts in issue attention by the public.

We first analyze all tweets sent by members of the 113th Congress from January 2013 to December 2014. Using a Latent Dirichlet Allocation (LDA) model, we extract topics that represent the diversity of issues legislators discuss on the social networking site. We show that this method is able to classify legislators' tweets into a set of facially valid topics that exhibit meaningful variation over time and across parties. We then explore to what extent legislators' expressed political agendas are affected by what the public discusses. We compare the influence of tweets sent by members of the public who are Democratic and Republican supporters, those who are particularly attentive to politics, as well as a random sample of U.S. Twitter users. Our tests examine the extent to which issue attention changes by these groups of citizens affect policymakers' agendas.

Our findings show definitively that members of Congress are more likely to respond to the issue priorities of the public than to extert influence over these priorities. However, this responsiveness is limited in ways that reinforce polarization and inequality. Lawmakers are highly responsive to the priorities of party supporters, as previous work leads us to expect (Shapiro et al., 1990; Clinton, 2006; Bawn et al., 2012; Egan, 2013; Kastellec et al., 2015). To a lesser extent, politicians are also responsive to the issue priorities of attentive citizens (Arnold, 1990; Aldrich, 1995). But despite well-established models predicting that politicians should reflect the priorities of the general public (Downs, 1957), we find little evidence that ordinary citizens have much influence on the public agenda.

The rest of the paper proceeds as follows. In sections 1 and 2 we discuss the existing literature on issue responsiveness and present the responsiveness models and hypotheses we test. In section 3 we present the data. Sections 4 and 5 introduce our topic modeling method,

[2] We further test this assumption in Appendix A.

describe how we apply it when using Twitter data, and demonstrate how it yields valid estimates of issue attention. Results of our analysis are shown in section 6. The article concludes in section 7 with a summary of findings and a list of possible paths for future research.

1 Politicians' Responsiveness to the Public's Priorities

Empirical studies of democratic responsiveness typically seek to answer one of two questions. First, do the public and politicians hold similar policy preferences? And second, do politicians allocate attention to issues in ways aligned with the public's priorities? Political science research on the first question has been substantially advanced by recent innovations in data collection and measurement (e.g., Lax and Phillips (2011); Gilens (2012); Burstein (2014); Tausanovitch and Warshaw (2014); Caughey and Warshaw (2018)). But without a response to the second question, an evaluation of the extent to which governments are responsive to their citizens is incomplete. As Bryan D. Jones and Frank R. Baumgartner note, "How representative is a legislative action that matches the policy preferences of the public on a low priority issue but ignores high priority issues?" (Jones and Baumgartner, 2004, 2) Agenda correspondence precedes preference alignment: for politicians to be truly responsive to the public, they first need to pay attention to the issues constituents deem relevant, and then their actions must refect people's preferences on those issues.

Research on agenda-setting and political responsiveness in the United States, spearheaded by Baumgartner and Jones's landmark study *Agendas and Instability in American Politics* (Baumgartner and Jones, 1993), has found a strong relationship between the priorities of the public and the agenda of members of Congress. For issues such as the economy, health, environment, and foreign trade, changes in public issue salience (measured using Gallup's long-standing question posed to Americans about the Most Important Problem (MIP) facing the country) correlate at high levels with changes in political attention (measured as the proportion of Congressional hearings on the same issue) (Jones and Baumgartner, 2004). Subsequent work has uncovered reasons for why this strong relationship exists. Jones, Larsen-Price and Wilkerson (2009) for example, study the correlation between the agenda of the public (Gallup's MIP) and the issues discussed in different political venues (Congressional bills and laws, State of the Union addresses, Congressional roll-call votes, and Executive Orders as some examples).

They document higher correlations when there is lower institutional friction (lower transaction costs and fewer actors involved in the decision-making process) and when political actions are more visible (for example, investigative hearings compared to legislative hearings). Scholars have also found a stronger relationship between public and government agendas on issues on which the public is mobilized and clearly expresses its preferences (Brayden, Bentele and Soule, 2007), as well as on issues picked up by electoral challengers that can put a member's reelection at risk (Sulkin, 2005).

However, existing studies comparing the attention paid by the public to that devoted by the government do not clearly address a very important question for political responsiveness research: who influences whom (Page, 1994)? Are policymakers responsive to the issues their constituents deem relevant, or is it the other way around? Research indicates that influence can flow in both directions, but it is unclear who has the largest capacity to influence the issue agenda of the other, politicians or the public. Canes-Wrone (2005), for example, shows how an increase of attention to an issue by the president can drive public attention on that issue, putting pressure on Congress to legislate according to the president's views. An extensive literature on opinion formation and elite cues also highlights the ability of political elites to influence public opinion: politicians not only drive attention to issues but they also influence public perceptions on those issues (Jacobs and Shapiro, 2000; Berinsky, 2007). Building on this literature we expect that (**H$_1$**) **members of Congress will influence the issues to which the public pays attention**. Nevertheless, other studies illustrate a effect in the opposite direction (Geer, 1996; Erikson, Mackuen and Stimson, 2002). For example, Canes-Wrone and Shotts (2004) show that public opinion can influence the president's issue attention and actions, particularly on issues directly related to people's daily life. Building on this other literature we also expect that (**H$_2$**) **the public will influence the issues to which members of Congress pay attention**. A primary contribution of our analysis will be to evaluate the magnitude of these effects to determine who has the largest agenda-setting effect. We explore this question without a theoretically motivated hypothesis, but rather as an open debate that must be addressed in order to truly evaluate the nature of political responsiveness in the American democratic system (Page, 1994; Burstein, 2003).

We believe the lack of clear findings on who influences whom is partly a function of data limitations, as time and issue units available for previous studies did not allow for sufficiently granular measurement of the relationship between politicians' and the public's agendas to establish the direction of greater influence. Most existing research, for example, relies on monthly survey data (typically Gallup's MIP question) to measure the public agenda. However, in our 24-hour media environment, politicians and the public are constantly adjusting the issues to which they devote attention, which means that changes in attention allocation are likely to happen within monthly survey waves. Hence, while survey data allow us to observe whether the public and political agendas covary, they provide limited information on which one moves first. Existing analyses trace attention to issue categories that are very broad, which has the advantage of facilitating comparisons of agenda-setting dynamics across long periods of time and across units such as states and countries. However, broad issue categories (such as "the economy" or "health care") can make it difficult to uncover the direction of responsiveness, as they may categorize together agendas that are in fact quite different. For example, an increase in public attention to the Dakota Access Pipeline followed by Congressional hearings on a fracking bill (e.g. S.785 of the 114th Congress) would be miscategorized as a case of agenda responsiveness by a commonly used issue classification in responsiveness research.[3] Although both energy related, these two issues are distinct, and assuming that Congress is reacting and being responsive to a preceding public attention change can be misleading.

We overcome these previous data limitations by employing advances in communication technology and machine learning. The high granularity of social media data and the ability to extract topics from text using unsupervised machine learning allow us to more clearly distinguish temporal relations between public and political agendas at the issue level than has been possible in previous work.

2 Models of Responsiveness

To whom should we expect members of Congress to responsive? Despite a substantial number of studies on the issue, the answer is not as straightforward as one might think. As Burstein (2003, 30) points out, "one might hope that 20 years of research would enhance the credibility of some [political responsiveness] theories and reduce that of others. But this does not seem to have happened." In particular, we observe three main theoretical models to pose three

[3]Policy Agendas Project issue classification (Jones and Baumgartner, 2004).

different answers to our question of interest. We call them here the *Downsian*, the *Attentive*, and the *Supporter* models.[4]

In an *An Economic Theory of Democracy*, Anthony Downs (1957) argued that, in a bipartisan democratic system, policymakers interested in reelection should be responsive to the median voter. The implications for political responsiveness research are easier to envision from a policy preference than an attention allocation perspective: assuming that citizens' preferences for a given policy fall into a right-left continuum, members of Congress maximize their chances of reelection by adopting the policy preference of their median constituent. However, how does this apply to responsiveness research interested in attention allocation? We argue that if we follow Downs's logic, we should expect members of Congress to increase their chances of reelection by focusing on issues that a majority of the general public deem relevant. A main testable hypothesis that derives from the argument is that (**H**$_3$) **changes in attention allocation by the *general public* should influence changes in issue attention by members of Congress.**

Other scholars however disagree with this premise as being too optimistic about the public's influence. Instead of responding to the median voter or the general public, some believe members of Congress have incentives to be mostly responsive to attentive voters. Studies of opinion formation show that most voters do not desire to pay much attention to politics (Hibbing and Theiss-Morse, 2002) and that many do not have clear issue priorities nor policy preferences Converse (2006). Nevertheless, this is not the case for all citizens. Some attentive voters care a great deal about the political world, and according to theoretical models such as Katz and Lazarsfeld (1955)'s two-step communication flow and Page and Shapiro (1992)'s rational public, these attentive voters have the potential to influence the issue priorities and preferences of less attentive citizens. This type of logic leads congressional scholars such as Arnold (1990) and Aldrich (1995) to argue that members of Congress should be particularly concerned about the issues to which attentive voters pay attention. A testable hypothesis that derives from this logic is that (**H**$_4$) **changes in attention allocation by *attentive publics* should influence allocation changes by members of Congress.**

Other scholars propose a third alternative: members of Congress should be mostly inter-

[4]There is a fourth main theoretical model that for data limitations we are unable to test in this paper: the argument that policymakers are responsive to wealthier constituents (Gilens, 2012).

ested in responding to core party supporters. They have issue priorities that are easier to distinguish and represent Wright (1989), they play a very active role in nomination processes (Bawn et al., 2012), their support is crucial not only to win primaries (Fenno, 1978; Gerber and Morton, 1998) but also general elections (Holbrook and McClurg, 2005), and the priorities of policy-oriented members are more likely to align with theirs (Egan, 2013; Kastellec et al., 2015). Some empirical research finds that in fact members are more likely to represent the policy preferences of their supporters (Shapiro et al., 1990; Clinton, 2006; Kastellec et al., 2015; Neundorf and Adams, 2018) but no research yet exists showing whether that is the case for issue attention allocation. From this model, however, we can derive that ($\mathbf{H}_5$) **changes in attention allocation by *party supporters* should influence allocation changes by members of Congress.**

As a final theoretical consideration, a large number of scholars and existing research on policy preference congruence point out that the more salient an issue becomes in the eyes of the public, the larger the degree of political responsiveness we should expect (Jones, 2004; Burstein, 2003; Canes-Wrone and Shotts, 2004; Sulkin, 2005; Soroka and Wlezien, 2009). Hence, in the previous models we should expect ($\mathbf{H}_6$) **the general public, attentive citizens, and party supporters to have a larger ability to influence political agendas on issues that are most relevant to them.**

3 Data

3.1 Members of Congress on Twitter

To test our hypotheses, we use tweets sent by members of the 113th House and Senate of the U.S. (2013–2014). Twitter use in Congress has increased steadily over the past years (Golbeck, Grimes and Rogers, 2010; Chi and Yang, 2010; Shapiro, Hemphill and Otterbacher, 2012; Evans, Cordova and Sipole, 2013). Of all legislators that served in the 113th Congress, around 95% of all Representatives (417 of 440)[5] and Senators (100 of 105)[6] had active Twit-

[5]We include in our analysis Jason T. Smith (MO-8), who won a special election in June 2013 after the previous incumbent resigned; David Jolly (FL-13), who substituted Bill Young; Catherine Clark (MA-5), who substituted Edward Markey after he was elected senator; Bradley Byrne (AL-1), who substituted Jo Bonner after he resigned; and Vance McAllister (LA-5), who substituted Rodney Alexander after his resignation.

[6]We include in our analysis William Cowan, who substituted John Kerry as junior Senator from Massachusetts; Edward Markey, who substituted William Cowan after he declined to run in a special election; Jeffrey Chiesa, who substituted Frank Lautenberg as junior senator from New Jersey; and was in turn substituted substituted for Cory

ter accounts.[7] This proportion was similar across parties: 94% of Republicans (268 of 284 serving members) and 94% of Democrats (248 of 264 serving members).

The interest that members of Congress show in using Twitter to communicate with their constituents is illustrated by the high number of tweets they send, a total of 651,116 during our period of study (from January 1st, 2013 to December 31st, 2014), which results in approximately 900 tweets per day. Golbeck, Grimes and Rogers (2010) argue that members of Congress use Twitter primarily to advertise their policy positions and to provide information about their activities. However, more recent studies have shown that the platform can also be a tool for members of Congress to be responsive to their constituents (Hemphill, Otterbacher and Shapiro, 2013), to exercise control of the offline and online political agenda, to interact publicly with other Representatives and Senators, and to report on their constituency service (Evans, Cordova and Sipole, 2013).

The frequency and variety of use of online networking tools by members of Congress suggests that tweets can be considered a meaningful representation of how legislators communicate with their constituents: both members of Congress themselves and their constituents show interest in this platform, and a preliminary analysis of the content of the messages they exchange shows a sophisticated use of this tool. In fact, as Casas and Morar (2015) demonstrate, there is a high correlation between the issues discussed by legislators on tweets, press releases, and floor speeches, which supports our claim that tweets are a good representation of the overall communication strategies of members of Congress.

3.2 Citizens on Twitter

In addition to tweets sent by members of Congress, we also collected tweets sent by different samples of Twitter users. These allow us to test our hypotheses ($H_{3,4,5}$) regarding the part of the public to which politicians are more likely to be responsive. We consider four samples of Twitter users:

1. **General Public**: includes about 25,000 Twitter users, sampled by generating random numeric user IDs, then checking whether the users existed, and then checking whether

Booker; and John Walsh, who substituted Max Baucus after his appointment as U.S. Ambassador in China.

[7] The list of Twitter handles of members of Congress was collected through the New York Times Congress API and then revised for errors. All the figures in this section are reported as of December, 2014.

the users resided in the United States.[8]

2. **Attentive Public**: a randomly generated sample of 10,000 Twitter users that follow at least one of five major media outlets in the United States (CNN, Wall Street Journal, New York Times, Fox News, and MSNBC). We apply a geographic restriction based on the time zone on users' profiles, which is available for most users. In particular, we exclude users whose time zone indicates they are likely to be located outside U.S. We also filter based on activity: only users who have ever sent 100 tweets or more are included.

3. **Republican Supporters**: a random sample of 10,000 Twitter users who follow 3 or more Republican members of Congress and no Democrat in Congress. The same geographic and activity filters as in the attentive public sample are applied here.

4. **Democratic Supporters**: a random sample of 10,000 Twitter users who follow 3 or more Democratic members of Congress and no Republican in Congress. The same geographic and activity filters as in the sample of Republican supporters applies.

After identifying these four samples, we then collected all the tweets they sent during our period of analysis (January 2013 to December 2014) using Twitter's REST API.[9]

3.3 Media

One limitation of the research design up to this point is that it does not consider the role of the traditional mass media. It may well be that both public and political agendas are influenced by the mass media.[10] To account for this possibility, we also collected tweets from a sample of media outlets, and use them to control for media effects.

In particular, we collected all tweets sent over the same time period from the Twitter accounts of the 36 largest media outlets in the U.S. (print, broadcast, online), as identified by the Pew Research Center. Table 1 provides descriptive statistics for all the data collected.

[8] A description of the procedure we followed to build this randomly generated sample can be found in Appendix B.

[9] We conducted the data collection for this random sample in 2015 and were constrained by Twitter's rate limits, which do not allow downloading all of user's tweets. In this case, part of the tweets sent by some users in early 2013 will not be included in our sample.

[10] See Gerber, Karlan and Bergan (2009); Ladd and Lenz (2009), Habel (2012) or King, Schneer and White (2017) for examples of studies documenting media effects on voters and political actors. See also Feezell (2018) for a study on how mainstream media can shape the issue attention distribution of the public via social media.

Table 1: Description of the tweets in the dataset.

Group	N	Avg.	Min	Max	Tweets
House Republicans	238	1,215	70	8,857	267,311
House Democrats	207	1,177	113	5,993	222,491
Senate Republicans	46	1,532	73	6,627	67,412
Senate Democrats	56	1,616	150	10,736	87,307
Random Sample	25K	465.2	1	8,926	11,316,396
Informed Public	10K	948	100	5,861	9,487,382
Republican Supporters	10K	1,091	100	8,804	10,911,813
Democratic Supporters	10K	1,306	100	5,122	13,058,947
Media outlets	36	7,803	8	15,858	273,121

Period of analysis: January 1, 2013 to December 31, 2014.

4 Measuring Attention to Political Issues with Topic Models

Our purpose in this paper is to characterize the different issues that members of Congress, ordinary citizens, and media outlets discuss on Twitter, and how their importance varies over time and across groups defined by their partisanship and political interest. To extract these categories, we estimate a probabilistic model of word occurrences in documents called Latent Dirichlet Allocation (Blei, Ng and Jordan, 2003), which belongs to a general category of latent variable models that infer topics from documents using a "bag-of-words" approach. The alternative to using an unsupervised topic model would be for the analyst (ourselves) to choose the topics. But we are not omniscient. The purpose of the analysis is to determine if members of the public and members of Congress are discussing the same topics. We are *not* trying to see if they are talking about topics known by the analyst. And since we are working on topics that may appear and dissappear on a relatively short time-scale, we are not trying to see if members of the public and members of Congress are each only discussing broad ongoing policy areas such as defense or health-care. Rather we want to let the data describe what topics were discussed. We note that having the analyst choose topics is often perfectly sensible, and in many cases preferable, to deriving the topics from the data. But here we are interested in topics that are not necessarily known in advance. And, as we show in Appendix Appendix C, it is possible to map the topics derived from the data to an existing set of topics (the topics used in (Jones and Baumgartner, 2004)), with similar results.[11] And as we demonstrate below, the topics generated by the model pass standard tests of validity.

The LDA model considers each document as a sequence of N tokens (which in our case are n-grams, or combinations of one and two words), denoted by $\mathbf{w} = (w_1, w_2, \ldots, w_N)$, extracted from a vector of length V containing all possible tokens in the corpus. Our definition of "document" is the aggregated total of tweets sent by members of Congress each day, by party and chamber.[12] LDA treats each document as a random mixture over latent topics, and each topic as a probability distribution over tokens. Each document w in the corpus is the result of the following generative model (Blei, Ng and Jordan, 2003, p.96):

1. The topic distribution for document w is determined by: $\theta \sim \text{Dirichlet}(\alpha)$
2. The token distribution for topic k is determined by: $\beta \sim \text{Dirichlet}(\delta)$
3. For each of the tokens in document w
   (a) Choose a topic $z_n \sim \text{Multinomial}(\theta)$
   (b) Choose a token w_n from $p(w_n|z_n, \beta)$, a multinomial probability conditioned on z_n.

This model requires us to fix K, the number of possible topics. There are two main parameters of interest: β, a matrix of dimensions $K \times V$ indicating the distribution of tokens over topics; and θ, a matrix of dimensions $K \times N$ indicating the distribution of topics over documents.

Note two additional features of our analysis. First, we fit the model at first only for members of Congress and then use the estimated parameters to compute the posterior topic distributions of citizens and media outlets, also aggregated by day, based on their observed words. We do so to make sure the topics we estimate are political in nature, and because our main focus is language use by members of Congress.[13] Second, in our estimation we assume that

[11]For a general overview of the use of text-as-data methods in political science research, see Grimmer and Stewart (2013) and Wilkerson and Casas (2017).

[12]There are two reasons for this decision. First, LDA assumes that each document is a mixture of topics, which is appropriate for our conceptualization of each day's tweets as the political agenda that each party within each legislative chamber is trying to push for that specific day. Second, conducting an analysis at the tweet level is complex, given its very limited length. The existing literature on topic modeling of tweets has found that applications that aggregate tweets by author or day outperform those that rely on individual tweets (Hong and Davison, 2010).

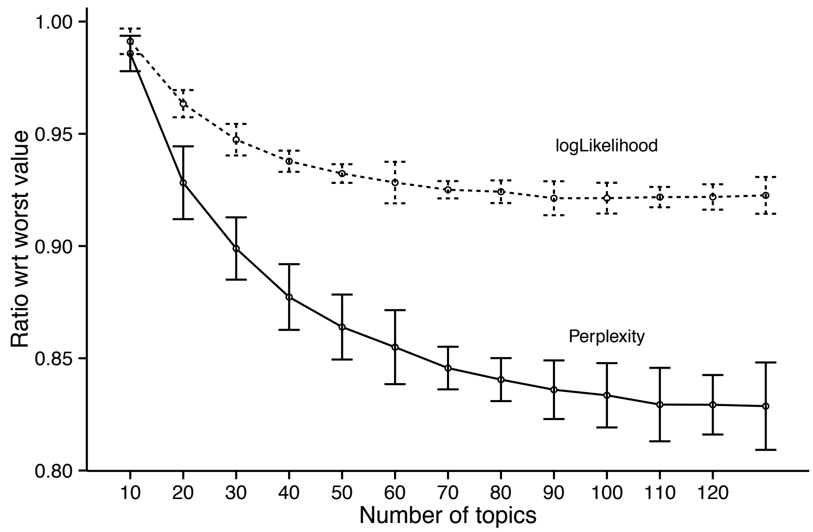
[13]We note that there is a limitation to this approach. If the public discusses some political topics that members of Congress never mention, we will not observe them. However, the public talks about many non-political issues

topic distributions are independent over time, and that the number of topics and the content of each topic is constant over time.

To fix the number of topics, we ran our model multiple times with different values of the number of tpoics (K), using 10-fold cross-validation and computing the log likelihood and estimated perplexity on the holdout sample (two common goodness of fit measures for LDA models, (Chang et al., 2009) – where smaller values indicate a better model fit). Figure 1 reports these two measures of model fit when estimating the model with different numbers of topics, from 10 to 130. We find that K=100 fits the data best. A higher value of K would minimize the loglikelihood and the perplexity measures, but we choose a conservative K in order to avoid overfitting (Hastie, Tibshirani and Friedman, 2009). We fit the model with a collapsed Gibbs sampler (Griffiths and Steyvers, 2004; Phan, Nguyen and Horiguchi, 2008), implemented in R (Grün and Hornik, 2011). We ran a single chain for 1,000 iterations. We apply the usual pre-processing text techniques (converting all words to lowercase and removing stopwords, all words shorter than 3 characters, and all n-grams that appear in less than 10 documents, but keeping hashtags and user handles), and then select as features the N=75,000 most frequent unigrams, bigrams, and trigrams.

that are not relevant for our analysis. Using unsupervised topic modeling techniques to discover political issues discussed by the public but not by politicians turned out to be unfeasible. This study however already represents a significant step-forward in understanding political responsiveness dynamics. We encourage future research to find ways to address the shortcoming mentioned here.

Figure 1: LDA model fit with different number of topics



5 Validation of Discovered Topics

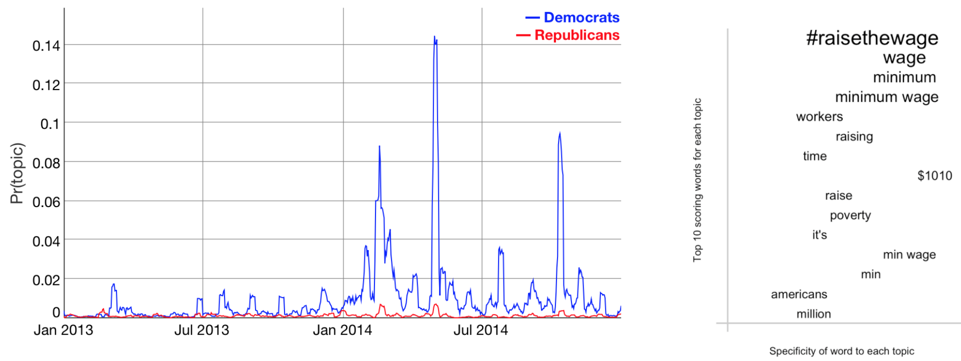
This section demonstrates that the topics that are discovered by the Latent Dirichlet Allocation model are valid representations of the political issues that legislators and citizens discuss. Following Quinn et al. (2010), we discuss how our results meet different notions of validity. First, we analyze the top scoring words for each topic to demonstrate that the topics that emerge from the model have a coherent meaning (semantic validity). Then, we examine whether topic usage corresponds correctly to external events (predictive validity). We will focus on whether topic usage is coherent with party identification for both legislators and citizens, and on whether spikes in their probability distribution can be matched to relevant political events.

To facilitate this validation exercise we have prepared an online appendix (or *dashboard*) where we offer a visualization of each of the topics that results from our analysis. The dashboard is available in the following URL, which we have anonymized for the peer review process: https://s3.amazonaws.com/lda-demo/lda/index.html. A screenshot of one the topics is shown in Figure 2. We provide five different elements to interpret the issue that is associated with each topic: a plot indicating topic use by each of the groups we consider, the total estimated proportion of tweets from each group that belong to this topic, a graph with the top 15 n-grams most associated with that topic, the list of the five members of Congress who most often used this topic, and a sample of tweets by politicians and media outlets with a high probability to belong to this topic.

As we show in Figure 2, it is easy to identify that this particular topic refers to debates about the minimum wage. From the time series plot, we learn that it started to be mentioned by Democratic legislators after January of 2014, when Barack Obama made this issue a central part of his State of the Union address. Democratic legislators and Democratic supporters are around 5 times more likely to discuss this topic than Republicans. The most common n-grams (#raisethewage, minimum wage, it's time, $10.10, workers, etc.) are also related to this issue. The sample of tweets also supports this interpretation.

Figure 2: Visualization of Topics with Online Dashboard

Topic Usage Over Time:



Display: ☑ Democrats ☑ Republicans ☐ Media ☐ Public ☐ Dem. Supporters ☐ Rep. Supporters ☐ Random Sample • **Smoothing period:** 7 days

Topic usage by elites: 0.59% all, 0.75% Senate Democrats, 0.20% Senate Republicans, 1.32% House Democrats, 0.09% House Republicans.
Top Members of Congress: @janschakowsky (D-IL), @keithellison (D-MN), @JuliaBrownley26 (D-CA), @SenatorHarkin (D-IA), @askgeorge (D-CA)
Topic usage by media and public: 0.52% Media, 0.07% informed public, 0.01% random users, 0.55% Democratic supporters, 0.14% Republican supporters.

Sample of representative tweets by Members of Congress:

Ed Markey @SenMarkey Follow
Close to 2/3 of min wage workers are women. #RaiseTheWage will help nearly 15 million women & thousands in #MA.
4:35 PM - 24 Jul 2014
5 3

Nancy Pelosi @NancyPelosi Follow
In marking 75 years of Fair Labor Standards Act, Congress must raise minimum wage so all workers get a fair day's pay for a fair day's work.
11:00 PM - 25 Jun 2013
111 34

Tom Harkin @SenatorHarkin Follow
Today is the 75th anniversary of the minimum wage – it's time to #raisethewage again to help millions of Americans earn a living.
3:09 PM - 25 Jun 2013
31 5

Rosa DeLauro @rosadelauro Follow
We need to respect workers and pass Fair Minimum Wage Act. Long past time to raise minimum wage to $10.10 #RaiseTheWage
7:11 PM - 25 Jun 2013
4 3

Sample of representative media tweets:

NBC News @NBCNews Follow
Seattle's $15/hr minimum wage increase will be more than double the federal minimum wage of $7.25/hr. nbcnews.to/1wX5NGU
1:00 AM - 3 Jun 2014
151 84

Mother Jones @MotherJones Follow
The GOP just a filibustered a bill to raise the minimum wage to $10.10.
Reminder: The minimum wage is pretty damn low
bit.ly/1bbqLqq
2:00 AM - 1 May 2014
82 23

ThinkProgress @thinkprogress Follow
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Although not all topics have such a straightforward interpretation, in general we find that most topics that emerge from the analysis can be easily labeled. However, not all of them are political in nature: for example, we find topics about anniversaries and celebrations (Valentine's Day, Flag Day, Constitution Day, Thanksgiving, etc.). Since we are not interested in these topics, in our analysis we will only include political issues: we identified 53 of them.[14] After reviewing their content, we noticed that some topics that referred to a single issue were classified as different topics because distinct words were being used by different groups when talking about the same issue. For example, we found separate separate topics for Republican and Democratic members of Congress discussing the 2013 Government Shutdown. This may influence our results by overestimating how often parties in Congress respond to their supporters. To avoid this potential source of bias, we decided to merge some topics and focus our analysis on 46 political issues. Table 2 displays the list of all these topics we have classified as political issues.

We also compare the topics that emerge from the analysis to the list of key votes in Congress according to the Congressional Quarterly Almanac (see Table 3). This yearly publication selects a series of key votes in the House and Senate that are considered the "major issues of the year".[15] We find that only 16 (28%) out of 57 key votes in 2013 and 2014 cannot be matched to topics; and those that are not matched correspond to votes on relatively less important or less divisive issues, such as confirmations of presidential appointees, foreign policy decisions, and decisions on Senate rules. We also find that of the 46 political issues we identified in Table 2, 23 do not appear in the list of key votes, but in all cases because they're related to political action by other institutions (the Supreme Court or the President), or to external events, such as wars or attacks.

[14]To identify the list of relevant political topics, 5 coders used the information contained in our dashboard to classify each topic into three categories: non-political topics, political topics but not related to issues, and political issues. Average intercoder agreement was 83%. We chose as political issues those where 3 or more coders agreed to classify as such.

[15]As defined in the publication, each vote is judged based on the extent to which it represents: 1) a major controversy, 2) a matter of presidential or political power, and 3) a potentially great impact on the nation and the lives of Americans.

Table 2: List of political issues.

Topic Number	Label	Topic Number	Label
3	Investigation of Benghazi Attack	50	Climate Change
7	100 Days of #BringBackOurGirls campaign	51	Lame Duck Congress
9	Gender Wage Gap	53	Minimum Wage
12	Republican Issues Spring 2013	58	Affordable Care Act
14	Marriage Equality	62	Border Crisis in Texas
15	Gun Violence	63	Obamacare (Employer Mandate)
16	Abortion (Pro-Life)	64	FAA Furloughs Cause Flight Delays
18	Veteran Affairs Delays Scandal	66	Malaysian Airlines Crash in Ukraine
20	NSA Surveillance Scandal	67	Comprehensive Immigration Reform
23	#BringBackOurGirls campaign	70	#MiddleClassFirst campaign
28	Employment Non-Discrimination Act	75	Military Justice Improvement Act
32	Islamic State	81	Poverty (SNAP program)
33	Use of Military Force in Syria	83	21st Century Cures Initiative
36	Ebola	85	Unemployment Insurance
37	Social Security	88	IRS Scandal
39	Keystone XL Pipeline	89	Obamacare (Website and Implementation)
41	Immigration (Border Security)	93	Jobs Bills Omnibus
43	Executive Action on Immigration	96	Violence Against Women Act
46	Unemployment Numbers Reports	97	Protests in Ukraine and Venezuela
47	Paul Ryan Budget Proposal	99	CIA Detentions and Interrogations Report
48	Black History Month	100	#ObamacareInThreeWords Campaign
(101)	Student Debt	(102)	Hobby Lobby Supreme Court Decision
(103)	Budget Discussion	(104)	2013 Government Shutdown

Note: The topic number in parenthesis indicate issues that have been created *ad-hoc* by merging very similar topics from the topic model.

6 Results

6.1 Issue Attention Congruence

The key substantive question we want to answer is whether the distribution of topics discussed by members of Congress leads or follows that of their constituents, and vice-versa. Are members reacting to their constituents? And if so, are they reacting to particular types of constituents?

Similar to previous studies on the issue, we start by examining simple congruence in the way members of Congress and citizens allocate attention to the 46 political issues we identified. In this issue congruence framework, a correlation between the public and the political agenda is a necessary condition for political responsiveness to be present. Table 4 displays Pearson correlation coefficients indicating how similar the issue distribution of Democratic and Republican supporters, attentive publics, and the general public are to the expressed agenda of Republicans and Democrats in Congress over the two year period studied. Higher coefficients indicate that groups tend to discuss the same issues.

Table 3: Correspondence between key votes in Congress and our discovered political issues

2013 Key votes	Topics?	2014 Key votes	Topics?
H23 Superstorm Sandy Disaster Aid	**No**	H21 Omnibus Appropriations for 2014	103
H30 Debt limit	103	H30 Abortion Funding	16
H55 Violence Against Women Act	96	H31 Farm and Nutrition Programs	81
H89 Fiscal 2013 Appropriations	104	H61 Debt Limit	103
H125 Air Control Furloughs	64	H106 Climate Change Rules	50
H208 Immigration Enforcement	41	H156 Health Law Employer Mandate	63
H251 Abortion	16	H248 Medical Marijuana	**No**
H286 Farm and Nutrition Programs	81	H322 A-10 Airplanes	**No**
H325 Yucca Nuclear-Waste Storage	**No**	H327 Electronic Surveillance	20
H412 Electronic Surveillance	20	H452 Iraq Policy	**No**
H427 Iran Sanctions	**No**	H463 Endangered Species	**No**
H550 Government Shutdown	104	H507 Arming Syrian Rebels	33
H587 Health Insurance Implementation	63, 89	H519 Keystone XL Pipeline	39
H640 Budget Agreement	49	H550 Immigration Deportations	43
S24 Chuck Hagel Confirmation	**No**	H562 Tax Deductions for Charities	**No**
S92 Fiscal 2014 Budget Resolution	104	H563 Omnibus Appropriations for 2015	103
S97 Firearms Background Checks	15	S1 Janet Yellen Confirmation	**No**
S145 Farm and Nutrition Programs	81	S13 Omnibus Appropriations for Fiscal 2014	59
S168 Immigration Overhaul	67	S21 Farm and Nutrition Programs	81
S185 Student Loan Interest Rates	101	S33 Debt Limit	59
S199 Transportation-Hud Appropriations	**No**	S48 Debo Adegbile	**No**
S219 Government Shutdown	104	S59 Military Prosecutions	75
S232 Employee Nondiscrimination	28	S117 Minimum Wage	53
S242 Senate Filibuster Rules	**No**	S252 Child Migrants	**No**
S245 Defense Authorization	75	S262 Equal Pay for Women	9
S281 Budget Agreement	104	S280 Keystone XL Pipeline	39
		S282 Electronic Surveillance	20
		S354 Omnibus Appropriations for 2015	**No**
		S356 Surgeon General Nomination	**No**

These initial results show potential for corroborating the presence of political responsiveness at the issue attention level, and they seem to indicate that some responsiveness models have a stronger explanatory power than others. In particular, these results provide stronger support for the Supporter and, to a lesser extent, the Attentive model, than for the Downsian argument. There is a positive, and in some cases large, correlation between the agenda of members of Congress and the issues discussed by their constituents. Nevertheless, when paying attention to the coefficients for specific groups, we observe the highest correlations

Table 4: Correlation in issue attention between members of Congress and groups of the public and the media over 46 Political Issues

Group	Democrats in Congress	Republicans in Congress
Democratic Supporters	0.58	0.34
Republican Supporters	0.18	0.62
Attentive Public	0.32	0.38
General Public	0.24	0.30
Media	0.41	0.62

to be between members and their party supporters (0.58 for Democrats and 0.62 for Republicans) and between members and the Attentive Public (0.32 for Democrats and 0.38 for Republicans). The correlation between the expressed agenda of legislators and the attention allocation of supporters of the other party is substantially lower (a 0.18 correlation between Democratic members and Republican supporters, and 0.34 between Republican members and Democratic supporters). We observe the lowest correlation coefficients when comparing the agenda of lawmakers and the issues the General Public discuss.[16]

In Figure 3, we provide information about the average daily attention that each party in Congress and each public group paid to the political issues under study.[17] These issue-level comparisons between groups help explain the agenda level correlations we observe in Table 4. We see for example how Democrats in Congress and Democratic supporters paid much more general attention to the Affordable Care Act (row 2 of the figure) than did Republicans, whereas Republicans in Congress and Republican supporters paid more attention than did Democrats to the (troubled) release and implementation of the ACA website and its employer mandate clause (last and third to the last rows). The attentive public, and the general public particularly, paid less attention to all these issues; about 9% and 5% of their overall attention during the 113th Congress respectively, compared to 19% and 21% by Democratic and Republican supporters.

6.2 Who Influences Whom?

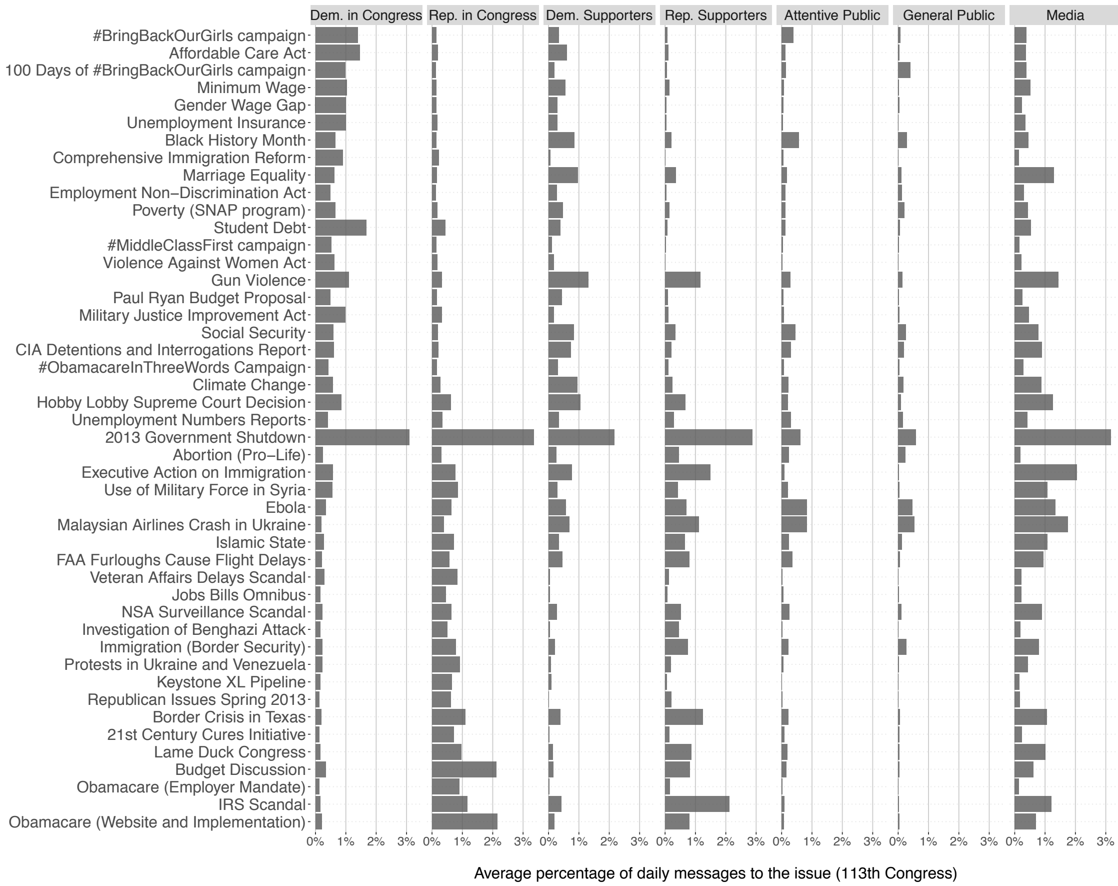
The previous correlations however are not sufficient evidence to conclude that members of Congress are responsive to their constituents nor to adjudicate between the competing Downsian, Attentive and Supporter models. The direction of the effect is still to be determined, and the influence of each group needs to be conditioned on the potential effects of the other groups and of the media. In other words, we have not yet determined whether, on average, Republicans and Democrats in Congress decide to increase their attention to an issue as a result of their supporters, attentive voters, and/or the general public doing so, or if the causation is in the other direction, or if both the public and the members of Congress simply follow

[16]As expected, we also observe a high correlation between the issues members of Congress and the Media discuss, which corroborates the need to control for media effects when estimating how public and political agendas influence each other.

[17]The figure is sorted by the amount of attention paid to the issue by Democrats in congress.

the media.

Figure 3: Average Issue Attention by groups of politicians, public, and the media



In this section we aim to determine the direction and size of these effects by estimating a vector autoregressive (VAR) model with topic-fixed effects. These models are well-suited to capture the relationship between endogenous variables (Freeman, Williams and min Lin, 1989; Sims, 1980) and have been used in previous political science studies with similar objectives (Enders and Sandler, 1993; Wood and Peake, 1998). In *Who influences Whom?* for example, Edwards and Wood (1999) use a VAR model to study the ability of United States presidents to set the Congressional and media agendas.[18]

In our VAR model we have a set of stationary time series Y_i representing the proportion of

[18]In this paper we do not control for the agenda of the President for two main reasons. First, in the mentioned article Edward III and Wood (1999) do not find the President to have a relevant agenda-setting capacity; and second, the method we employ in this paper to measure agendas (proportion of daily tweets on a set of issues) is well suited to measure group but not individual agendas, given that single individuals do not tweet frequently enough to build unbiased measures.

daily attention each of our groups i[19] paid to each topic j in day t of the 113th Congress (we are also controlling for media effects).[20] The values of these random variables range from 0 to 1 but neither of the extreme values are present ($0 < Y_{ijt} < 1$). Their distributions are right skewed, with few days of very high issue attention and much lower attention during the rest of the two year period. We follow a common practice in time series analysis of skewed proportions (Wallis, 1987) and model the log odds Z_i of the described series Y_i instead of the raw proportions.

We then express the autoregressive and endogenous relationship of these variables as a system of equations in which each variable Z_i is a function of its previous lags plus the lags of the other variables. Given that there are no time restrictions when it comes to posting messages in Twitter, we would theoretically expect members of Congress to react to changes in public issue attention quite rapidly. However, to account for potential longer term effects, we use a 7-lag structure.[21] The final model can be formally expressed as:

$$
\begin{aligned}
Z &= \log\left(\frac{Y}{1-Y}\right) \\
Z_{i,j,t} &= \alpha_j + \sum_i \sum_{p=1}^{7} \beta_{i,p} Z_{i,j,t-p} + \varepsilon_{i,j,t}
\end{aligned}
\tag{1}
$$

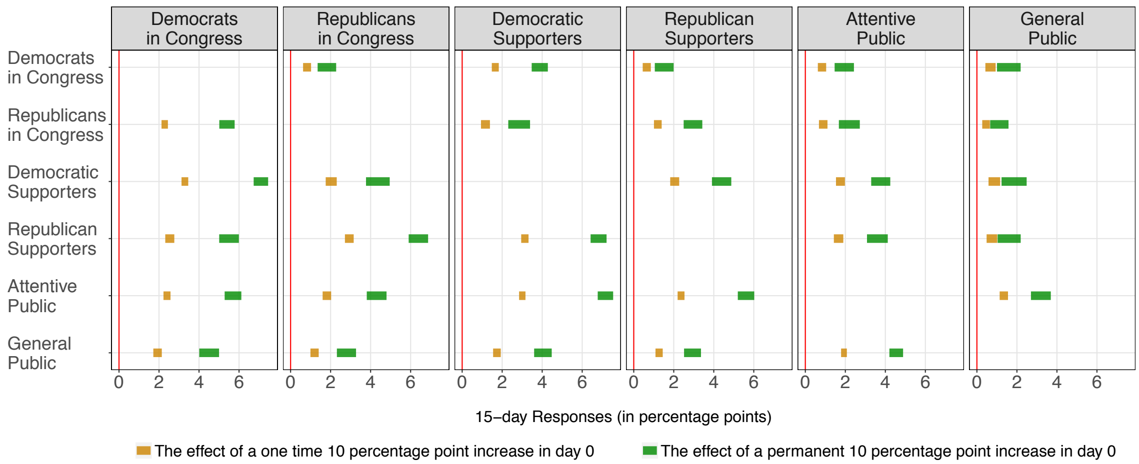
Notice that given the issue-fixed effects structure of the model (α_j) we are assuming that the influence that one group has on the others is constant across issues. Although this is an inaccurate assumption, it is a useful one for what we intend to accomplish here. It allows us to estimate how much on average we should expect each group to influence the attention allocation of the others. As we point out in the Discussion section 7, we believe that future work should focus on studying how the effects presented here are conditional on the issue or issue type at hand. This is not however the immediate purpose of this study.

[19] Democratic and Republican members of Congress, Democratic and Republican Supporters, Attentive Public, General Public, and Media

[20] We run Augmented Dickey-Fuller unit root tests and confirm that the series are stationary.

[21] Autocorrelation and Partial Autocorrelation Functions vary depending on the group and issue series one explores. However, on average we observe autocorrelations to go below 0.1 after 5-9 days, and partial autocorrelations to be below this level after 3-5 days; which indicates that by using a 7-lag structure we are accounting and controlling for the autocorrelative nature of these variables.

Figure 4: 15 day Cumulative IRFs: Predicted Issue Responsiveness Across Groups*



***Note**: *each coefficient indicates the cumulative predicted change in the issue salience of political topics for each group (as indicated in the facet headers), measured in percentage point changes, as a result of a one-time and permanent ten-unit increase in issue salience by the group in the y axis.*

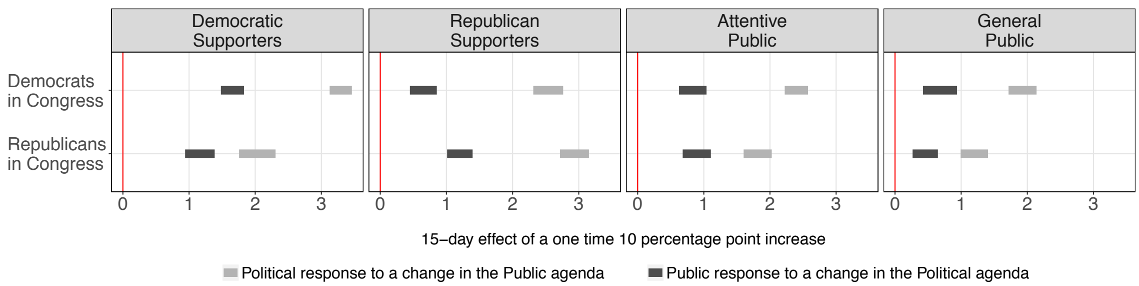
The results of the estimated VAR model can be best expressed using cumulative impulse response functions (IRFs). These cumulative IRFs indicate how a x-unit increase in attention to a given topic by a group influences the attention that other actors dedicate to the same topic over time. Cumulative IRFs can be calculated for a varying number of subsequent days. We calculate and report in Figure 4 two different types of IRFs for a 15 day period. In both cases we assume that at day 0 none of the groups is paying attention to a given issue j. First, we want to explore responsiveness to brief changes in attention and we calculate how a 10 percentage point increase in attention to an issue by each group (going from 0 to 10% of attention in day 0) affects future issue attention by the other groups. We are also interested in the effect of attention changes that last longer and calculate how a permanent attention change to a given issue from 0 to 10% by one group affects the attention of the others.[22] Each single panel in Figure 4 shows how much more attention to the issue the group in the panel

[22] When calculating the IRFs for the permanent 10-percentage-point change, we insert a new increase of attention every day to the covariate of interest until the predicted attention for that group reaches 10% without the need of any extra shock. If we let ϕ represent the attention increase we introduce in the covariate, and $\hat{y}$ the resulting predicted value-attention for that same covariate, then we can formally express ϕ during the 15 day period as follows :

$$\phi_{i,t} = \begin{cases} 10, & \text{if } t \text{ is } 0 \\ 10 - \hat{y}_{i,t} & \text{if } t \text{ is} > 0 \end{cases}$$

title is predicted to pay as a response to a one-time (in orange) and permanent (in green) 10 percentage point increase by the groups along the y-axis (the row groups) 15 days ago. The predicted effects (95% confidence interval lines) are expressed in percentage points (0-100 scale).

Figure 5: Politicians' Ability to Set Public Agendas *versus* the Ability of the Public to influence Political Agendas



The results in Figure 4 corroborate the first two expectations in regards to the ability of members of Congress and the public to influence each other's issue attention. Politicians from both parties (first two rows in all the panels in Figure 4) are able to influence the attention distribution of the public (H_1). Specifically, they are able to influence the issue attention of party supporters and Attentive Publics, though both parties have much more influence on their own supporters than supporters of the opposing party. And we see in the far right panel that both parties appear to influence very little the issue attention of the General Public.

We also find strong evidence supporting a political responsiveness dynamic (H_2): we see changes in issue attention by citizens to have a positive and significant effect on the issues members of Congress discuss, and we also see these effects to always be of a larger magnitude than the effects members of Congress have on the agendas of the public. The ability of Republican Supporters to influence political issue agendas represents the most extreme case. This group of the public is predicted to increase its attention to an issue only by .75 and 1.25 percentage points 15 days after a 10 points increase in attention by Democrats and Republicans in Congress respectively (first and second orange estimates from the top in the third panel from the right). The changes in the opposite direction however are three and two times larger: both Democrats and Republicans in Congress are predicted to increase their attention by about 3 percentage points (Republican Supporters' orange estimates in the two most left panels). These differential effects can be better appreciated in Figure 5, where we re-arrange the one-time attention changes estimates (orange responses) from Figure 4 to more easily compare who has the largest ability to influence the issue agenda of the other, members of Congress or the Public.

Our results also provide strong evidence in favor of the Supporter model of responsiveness (H_5). If we focus only on the variables that influence the agenda of members of Congress the most (two left panels in Figure 4), we observe that the strongest predictors of a positive attention change by lawmakers is a change of attention by their own party supporters. The VAR model predicts Democrats in Congress to go from paying no attention to an issue to dedicating approximately 3% as a result of a one-time 10 point attention shift by Democratic Supporters, and 7% as a result of permanent 10 point change by their party supporters (Democratic Supporter estimates in the left panel). We see Republicans in Congress respond similarly to changes in attention by their own supporters (Republican Supporter estimates in the second panel from the left). All the other IRFs for the one-time and permanent attention shocks are of smaller magnitude.

We also find support for the Attentive model (H_4). For example, after a one-time and a permanent 10 percentage point change in attention by the Attentive Public, Democratic members of Congress are predicted to increase their attention by 2.25 and 5.75 percentage points, respectively, and Republican policymakers by about 1.75 and 4.25. If we treat the supporters of the other party also as an attentive public (they follow not one but at least three members of Congress in Twitter), we observe a similar pattern. Changes in attention by Democratic Supporters are also predicted to have a positive effect of 2 and 4.25 points on Republican members, and changes by Republican Supporters are predicted to increase the attention of Democratic lawmakers by 2.5 and 5.5 points. However, the estimated effects are of smaller size than the effects we observed for the responsiveness model.

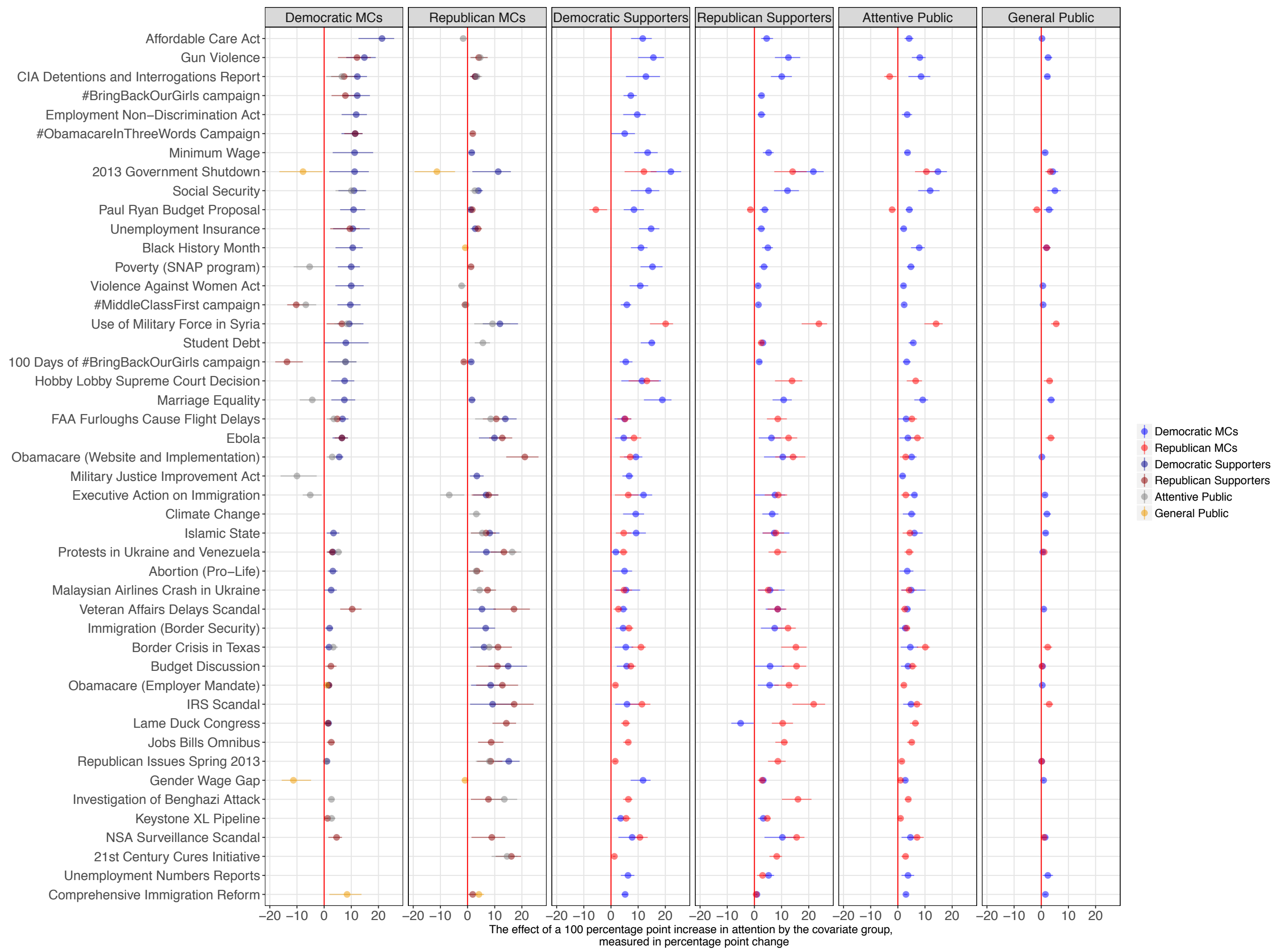
Finally, the results show weak support for the Downsian model (H_3). Democratic members of Congress are only predicted to increase their attention to an issue by 2 and 4.5 percentage points after a one-time and a permanent 10-point increase of attention by the General Public. The Republican members' response is expected to be even lower, and to increase their attention only by 1.5 and 3 percentage points. This means that among the different groups of the public, the General Public has the lowest ability to set the agenda of members of Congress. The effect of a permanent increase of attention by the General Public (green General Public estimates in the two left panels) is of similar magnitude than a one-time attention increase by party supporters (Democratic Supporter orange estimate in the left panel and Republican Supporter orange coefficient in the second panel from the left). Overall, the model shows that politicians are mostly responsive to their own party supporters, then to attentive voters, and that they are only slightly responsive to the general public.

6.3 Responsiveness and Issue Relevance

If members of Congress have an interest in being responsive to specific groups of constituents, then we expect that (**H**$_6$) they should be particularly interested in responding to changes in attention involving issues that are relevant to these groups . In order to test this hypothesis we first need to estimate how each group influenced the attention that all other groups paid to each separate political topic. To do so we relax our assumption that the ability of one group to influence the agenda of the others was constant across issues, and we model the data in a different way. In the previous model 1 we included topic-fixed effects (α_j). In this section we instead estimate 46 separate VAR models, one for each political issue. We include the same endogenous variables into the model, again apply a logit transformation to all time series, and use the same 7-lag structure. Then, for each of the VAR issue models, we calculate 15 day cumulative Impulse Response Functions capturing how a one-time 100 percentage point increase in attention by a specific group affects the attention of the others.

Figure 6 shows the results (15-day IRFs) for each of these VAR issue models for each of the 46 issues. Each panel reports how the groups in the panel titles are predicted to respond to changes in attention by the other groups: the dots represent the predicted effects (with a 95% confidence interval), the colors show the group they are reacting to, and the labels in the y-axis (the row labels) indicate the specific issue. To avoid overcrowding the plot, in the two left-most panels we only show the ability of the public groups to influence the expressed agenda of Democrats and Republicans in Congress, and in the four panels on the right we show the reverse effects, the ability of members of Congress to influence public issue attention. We only include the predicted effects for issues where the confidence intervals do not cross zero.

Figure 6: Predicted Issue Responsiveness Across Issues and Groups (15 day IRFs)

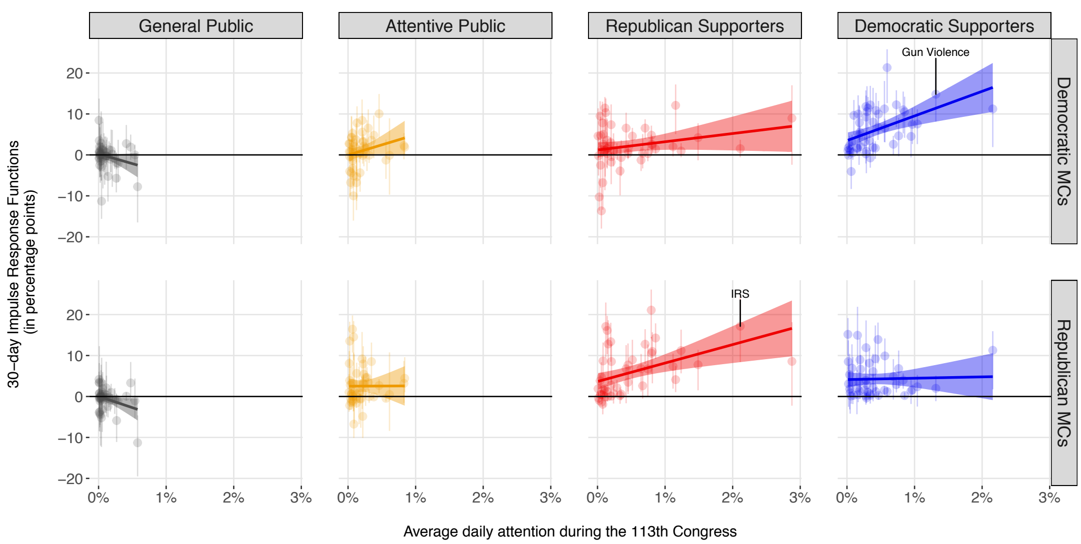


***Note**: *The two left-most panels show the influence of the public on Members of Congress. The four right-most panels show the influence of Democratic and Republican members of congress on the public.*

The top effects in the left panel indicate the issues in which the ability of Democratic Supporters to set the agenda of Democratic members of Congress was higher. These include issues such as health care reform (Affordable Care Act), gun violence, and minimum wage (row 7). In the second panel from the left we see the issues in which Republican supporters were able to influence the agenda of Republicans in Congress the most. For example, the discussions around the IRS scandal (row 36) that took place around mid-2013 and the implementation of the Affordable Care Act and its website problems (row 23). The gray effects in the left-most panel indicate that the Attentive Public was able to influence the Democratic members' discussion on social security issues (row 9), and in the second panel we see that the Attentive Public was able to influence Republican members' attention on student debt (row 17). The orange effects in the two left panels indicate that the General Public was able to influence both parties' discussion around immigration reform (two left panels, last row).

In order to test the last of our hypothesis, that members of Congress will pay attention to constituents when the constituents write about issues of particular importance to those constituents ($\mathbf{H}_6$), we build a measure of group issue relevance by calculating the average daily attention each group paid to each topic during the 113th Congress (see these averages in Figure 3). By taking the average we intend to focus less on how much attention a group paid to a given issue at a particular point in time (as a result maybe of an external shock) and to capture instead how important the issue was for that specific group in general.

Figure 7: Correlation between Public Issue Relevance and the Ability of the Public to set Political Agendas



With this measure of average attention and the estimates from Figure 6 in hand, we can now move to a direct test of $\mathbf{H}_6$ by examining correlations between the two. Accordingly, in Figure 7 we plot on the x-axis the average daily attention paid to each issue by each group of the public (see panel titles). In the y-axis we plot the attention members of Congress are predicted to pay to the each issue 15 days after an attention change (15 day cumulative IRFs). Each dot is a single predicted response and the lines around them represent 95% confidence intervals. The four top panels show the response of Democratic members of Congress while the bottom ones illustrate the reaction of Republican lawmakers.

We find support for the issue relevance hypothesis (H_6) only as it relates to the Supporter model. In the top right panel we observe that changes in attention by Democratic supporters have a larger effect on the agenda of Democrats in Congress when they involve issues Democratic supporters deem relevant (such as gun violence). In the second from the right bottom panel we also observe a similar pattern for Republicans, with Republican supporters being more likely to influence the expressed agenda of Republicans in Congress on issues that are important to them (such as the discussion around the Internal Revenue Service – IRS). These relationships between the issue relevance of party supporters and their ability to set political agendas are the only ones in Figure 7 that are statistically significant at conventional levels.

In Figure 7 we see no support for the issue relevance hypothesis as it relates to the Attentive and Downsian models. On average, Democrats in Congress are more likely to react to changes in attention by the attentive public (including supporters of the other party) on issues that are relevant to these groups (two middle panels on the top). However these positive correlations are far from being statistically significant. For Republicans in Congress we do not even see a positive correlation between their level of issue responsiveness and the average attention the attentive public and supporters of the other party party to the issue (flat yellow and blue liens at the bottom). Finally, the issue attention of both parties in Congress is negatively correlated (although not statistically significant) with the amount of average attention the general public devotes to any given issue.

These results validate the strong findings in Figure 4 in favor of the Supporter model, as well as the lack of evidence in support of the Downsian model of responsiveness. At the same time the results in Figure 7 indicate that we should treat the previous evidence supporting the Attentive model with caution. Although in Figure 4 we found that policymakers were significantly likely to be responsive to the attentive and general public, we now observe that this responsiveness does not completely follow the expected logic: lawmakers do not seem to be more responsive to the attentive public on issues that are relevant to them.

7 Discussion and Conclusions

It is well-known in American politics that politicians and the public tend to pay attention to the same political issues (Jones and Baumgartner, 2004), but due to data limitations, the question of who influences whom has previously been unanswered (Burstein, 2003). In this paper we have contributed to answering this open question by characterizing the agenda of members of Congress and their constituents using latent topic modeling applied to the text of the tweets they sent between January 2013 and December 2014 (113th Congress). In doing so, we have been able to create fine-grained political and public agenda measures and to study not only the extent to which members of Congress respond to their constituents when allocating issue attention, but also to adjudicate between three competing models of political responsiveness: whether public representatives respond to the changes in attention by their party supporters, the attentive public, and/or the general public.

We modeled how public and political agendas influenced each other using a VAR model accounting for endogenous and media effects. First, we found a political responsiveness dynamic to be in place during the period of analysis. Groups of the public were not only able to influence the expressed agenda of members of Congress, but their influence was of larger magnitude than the ability of politicians to influence public agendas. Moreover, we found stronger support for some responsiveness models than others. Our findings suggest that members of Congress are mainly responsive to changes in attention allocation by party supporters, and to a lesser extent, attentive publics. In addition, we observed Democrats and Republicans in Congress to be particularly responsive to party supporters on issues that are relevant to them. Finally, we found very little empirical support for the claim that politicians are responsive to the general public.

Overall, we illustrated how researchers can use social media communications to uncover agenda setting and responsiveness dynamics. Due to space constraints we had to limit the scope of our analysis, but other basic questions can be examined using this method. For example - Is the President able to set political and public agendas? Previous research shows that the President's ability is limited (Edwards and Wood, 1999) but more recent studies argue that this pattern may have changed in the last few years (Wells et al., 2016; Lawrence and Boydstun, 2017). Do politicians running in safe *versus* marginal districts respond to different types of constituents? Do politicians respond to some constituents on some type of issues but to other constituents on others?

Another accessible topic of study is issue responsiveness at the state level. Existing responsiveness research in the United States studies how the issues discussed by Federal political elites are shaped by public issue and policy preferences (Jones and Baumgartner, 2004; Page and Shapiro, 1983; Stimson, Mackuen and Erikson, 1995; Erikson, Mackuen and Stimson, 2002). A relevant number of political decisions however are made at the state level. Are state policymakers responsive to their constituents? What type of constituents? Do federal agendas influence political discussions at the state level? Do we see differential responsiveness dynamics across states? And if so, why? In addition, given a longer time period, one could combine the fine-grain temporal measure that Twitter data offers with the curated topics of the Policy Agenda Project to determine who leads and who follows on each of the 19 issues the project has defined (Jones and Baumgartner, 2004). Our hope is that both the findings and methods introduced here can serve as a springboard for research into these and other important topics in political representation in the future.

References

Aldrich, John H. 1995. *Why Parties? the Origin and Transformation of Political Parties in America*. Chicago: The University of Chicago Press.

Arnold, R. Douglas. 1990. *The logic of congressional action*. New Haven: Yale University Press.

Baumgartner, Frank R. and Bryan D. Jones. 1993. *Agendas and Instability in American Politics*. Chicago: University of Chicago Press.

Bawn, Kathleen, Martin Cohen, David Karol, Seth Masket, Hans Noel and John Zaller. 2012. "A Theory of Political Parties: Groups, Policy Demands and Nominations in American Politics." *Perspectives on Politics* 10(3):571âĂŞ597.

Berinsky, Adam J. 2007. "Assuming the Costs of War: Events, Elites, and American Public Support for Military Conflict." *The Journal of Politics* 69(4):975–997.

Blei, David M, Andrew Y Ng and Michael I Jordan. 2003. "Latent dirichlet allocation." *the Journal of machine Learning research* 3:993–1022.

Brayden, King G., Keith G. Bentele and Sarah A. Soule. 2007. "Protest and Policymaking: Explaining Fluctuation in Congressional Attention to Rights Issues, 1960-1986." *Social Forces* 86(1):137–163.

Burstein, Paul. 2003. "The Impact of Public Opinion on Public Policy: A Review and an Agenda." *Political Research Quarterly* 56(1):29–40.

Burstein, Paul. 2014. *American Public Opinion, Advocacy, and Policy in Congress: What the Public Wants and What It Gets*. New York: Cambridge University Press.

Canes-Wrone, Brandice. 2005. *Who Leads Whom?: Presidents, Policy, and the Public*. University of Chicago Press.

Canes-Wrone, Brandice and Kenneth W. Shotts. 2004. "The Conditional Nature of Presidential Responsiveness to Public Opinion." *American Journal of Political Science* 48(4):690–706.

Casas, Andreu and David Morar. 2015. "Different Channel, Same Strategy? Filling Empirical Gaps in Congress Literature." *Paper presented at the 2015 APSA conference* .

Caughey, Devin and Christopher Warshaw. 2018. "Policy Preferences and Policy Change: Dynamic Responsiveness in the American States, 1936âĂŞ2014." *American Political Science Review* 112(2):249âĂŞ266.

Chang, Jonathan, Sean Gerrish, Chong Wang, Jordan L. Boyd-graber and David M. Blei. 2009.

Reading Tea Leaves: How Humans Interpret Topic Models. In *Advances in Neural Information Processing Systems 22*, ed. Y. Bengio, D. Schuurmans, J. D. Lafferty, C. K. I. Williams and A. Culotta. Curran Associates, Inc. pp. 288–296.

Chi, F. and N. Yang. 2010. "Twitter adoption in congress." *Review of Network Economics, Vol. 10, No. 1* .

Clinton, Joshua D. 2006. "Representation in Congress: Constituents and Roll Calls in the 106th House." *Journal of Politics* 68(2):397–409.

Converse, Philip E. 2006. "The Nature of Belief Systems in Mass Publics." *Critical Review* 18(1-3):1–74.

Downs, Anthony. 1957. *An economic theory of democracy*. New York: Harper and Row.

Edwards, George C. and B. Dan Wood. 1999. "Who Influences Whom? The President, Congress, and the Media." *The American Political Science Review* 93(2):327–344.

Egan, Patrick J. 2013. *Partisan Priorities: How Issue Ownership Drives and Distorts American Politics*. New York: Cambridge University Press.

Enders, Walter and Todd Sandler. 1993. "The Effectiveness of Antiterrorism Policies: A Vector-Autoregression- Intervention Analysis." *The American Political Science Review* 87(4):829–844.

Erikson, RobertS., Michael B. Mackuen and James A. Stimson. 2002. *The Macro Polity*. Cambrige University Press.

Evans, Heather K., Victoria Cordova and Savannah Sipole. 2013. Twitter Style: An Analysis of How House Candidates used Twitter in their 2012 Campaigns. In *Paper Presented at the 2013 Midwest Political Science Association Conference*.

Feezell, Jessica T. 2018. "Agenda Setting through Social Media: The Importance of Incidental News Exposure and Social Filtering in the Digital Era." *Political Research Quarterly* 71(2):482–494.

Fenno, Richard F. 1978. *Home Syle: House Members in Their Districts*. London: Longman.

Freeman, John R., John T. Williams and Tse min Lin. 1989. "Vector Autoregression and the Study of Politics." *American Journal of Political Science* 33(4):842–877.

Geer, J.G. 1996. *From Tea Leaves to Opinion Polls: A Theory of Democratic Leadership*. New York: Columbia University Press.

Gerber, Alan S, Dean Karlan and Daniel Bergan. 2009. "Does the Media Matter? A Field Experiment Measuring the Effect of Newspapers on Voting Behavior and Political Opinions." *American Economic Journal: Applied Economics* 1(2):35–52.

Gerber, Elisabeth R. and Rebecca B. Morton. 1998. "Primary Election Systems and Representation." *Journal of Law, Economics, and Organization* 14(2):304–324.

Gilens, Martin. 2012. *Affluence and Influence: Economic Inequality and Political Power in America*. Princeton, New Jersey: Princeton University Press.

Gilens, Martin and Benjamin I. Page. 2014. "Testing Theories of American Politics: Elites, Interest Groups, and Average Citizens." *Perspectives on Politics* 12(3):564âĂŞ581.

Golbeck, Jennifer, Justin M Grimes and Anthony Rogers. 2010. "Twitter use by the US Congress." *Journal of the American Society for Information Science and Technology* 61(8):1612–1621.

Griffiths, Thomas L and Mark Steyvers. 2004. "Finding scientific topics." *Proceedings of the National academy of Sciences of the United States of America* 101(Suppl 1):5228–5235.

Grimmer, Justin and Brandon M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(3):267âĂŞ297.

Grün, Bettina and Kurt Hornik. 2011. "topicmodels: An R package for fitting topic models." *Journal of Statistical Software* 40(13):1–30.

Habel, Philip D. 2012. "Following the Opinion Leaders? The Dynamics of Influence Among Media Opinion, the Public, and Politicians." *Political Communication* 29(3):257–277.

Hastie, Trevor, Robert Tibshirani and Jerome Friedman. 2009. *The elements of statistical learning*. Springer.

Hemphill, Libby, Jahna Otterbacher and Matthew Shapiro. 2013. What's congress doing on twitter? In *Proceedings of the 2013 conference on Computer supported cooperative work*. ACM pp. 877–886.

Hibbing, John R. and Elizabeth Theiss-Morse. 2002. *Stealth Democracy: Americans' Beliefs About How Governmnet Should Work*. Cambridge, UK: Cambridge University Press.

Holbrook, Thomas M. and Scott D. McClurg. 2005. "The Mobilization of Core Supporters: Campaigns, Turnout, and Electoral Composition in United States Presidential Elections." *American Journal of Political Science* 49(4):689–703.

Hong, Liangjie and Brian D Davison. 2010. Empirical study of topic modeling in twitter. In *Proceedings of the First Workshop on Social Media Analytics*. ACM pp. 80–88.

Jacobs, L.R. and R.Y. Shapiro. 2000. *Politicians Don't Pander: Political Manipulation and the Loss of Democratic Responsiveness*. Chicago: University of Chicago Press.

Jones, Bryan D. 2004. *Reconceiving Decision-Making in Democratic Politics: Attention, Choice, and Public Policy*. Chicago: The University of Chicago Press.

Jones, Bryan D. and Frank R. Baumgartner. 2004. "Representation and Agenda Setting." *Policy Studies Journal* 32(1):1–24.

Jones, Bryan D., Heather Larsen-Price and John Wilkerson. 2009. "Representation and American Governing Institutions." *The Journal of Politics* 71(1):277–290.

Kastellec, Jonathan P., Jeffrey R. Lax, Michael Malecki and Justin H. Phillips. 2015. "Polarizing the Electoral Connection: Partisan Representation in Supreme Court Confirmation Politics." *The Journal of Politics* 77(3):787–804.

Katz, Elihu and Paul F. Lazarsfeld. 1955. *Personal Influence: The Party Played by People in the Flow of Mass Communications*. New York: Free Press.

King, Gary, Benjamin Schneer and Ariel White. 2017. "How the news media activate public expression and influence national agendas." 358(6364):776–780.

Ladd, Jonathan McDonald and Gabriel S Lenz. 2009. "Exploiting a rare communication shift to document the persuasive power of the news media." *American Journal of Political Science* 53(2):394–410.

Lawrence, Regina G. and Amber E. Boydstun. 2017. "What We Should Really Be Asking About Media Attention to Trump." *Political Communication* 34(1):150–153.

Lax, Jeffrey R. and Justin H. Phillips. 2011. "The Democratic Deficit in the States." *American Journal of Political Science* 56(1):148–166.

Neundorf, Anja and James Adams. 2018. "The Micro-Foundations of Party Competition and Issue Ownership: The Reciprocal Effects of CitizensâĂŹ Issue Salience and Party Attachments." *British Journal of Political Science* 48(2):385âĂŞ406.

O'Connor, Brendan, Ramnath Balasubramanyan, Bryan R. Routledge and Noah A. Smith. 2010. "From tweets to polls: Linking text sentiment to public opinion time series.".

Page, Benjamin I. 1994. "Democratic Responsiveness? Untangling the Links Between Public

Opinion and Policy." *PS: Political Science and Politics* 27(1):25âĂŞ29.

Page, Benjamin I. and Robert Y. Shapiro. 1983. "Effects of Public Opinion on Policy." *American Political Science Review* 77(1):175âĂŞ190.

Page, Benjamin I. and Robert Y. Shapiro. 1992. *The Rational Public: Fifty Years of Trends in American's Policy Preferences*. Chicago: The University of Chicago Press.

Phan, Xuan-Hieu, Le-Minh Nguyen and Susumu Horiguchi. 2008. Learning to classify short and sparse text an web with hidden topics from large-scale data collections. In *Proceedings of the 17th international conference on World Wide Web*. ACM pp. 91–100.

Quinn, Kevin M, Burt L Monroe, Michael Colaresi, Michael H Crespin and Dragomir R Radev. 2010. "How to analyze political attention with minimal assumptions and costs." *American Journal of Political Science* 54(1):209–228.

Shapiro, Catherine R., David W. Brady, Richard A. Brody and John A. Ferejohn. 1990. "Linking Constituency Opinion and Senate Voting Scores: A Hybrid Explanation." *Legislative Studies Quarterly* 15(4):599–621.

Shapiro, M.A., L. Hemphill and J. Otterbacher. 2012. "Doing What I Say: Connecting Congressional Social Media Behavior and Congressional Voting.".

Sims, Christopher A. 1980. "âĂIJMacroeconomics and Reality." *Econometrica* (48):1–48.

Soroka, Stuart N. 2015. "Number of Responses and the Most Important Problem." *Nuffield College Politics Working Paper, 2002-W34* .

Soroka, Stuart N. and Christopher Wlezien. 2009. *Degrees of Democracy: Politics, Public Opinion, and Policy*. Cambridge University Press.

Stimson, James A., Michael B. Mackuen and Robert S. Erikson. 1995. "Dynamic Representation." *American Political Science Review* 89(3):543âĂŞ565.

Sulkin, Tracy. 2005. *Issue Politics in Congress*. Cambridge University Press.

Tausanovitch, Chris and Christopher Warshaw. 2014. "Representation in Municipal Government." *American Political Science Review* 108(3):605–641.

Wallis, Kenneth F. 1987. "Time Series Analysis of Bounded Economic Variables." *Journal of Time Series Analysis* 8(1):115–123.

Wells, Chris, Dhavan V. Shah, Jon C. Pevehouse, JungHwan Yang, Ayellet Pelled, Frederick Boehm, Josephine Lukito, Shreenita Ghosh and Jessica L. Schmidt. 2016. "How Trump

Drove Coverage to the Nomination: Hybrid Media Campaigning." *Political Communication* 33(4):669–676.

Wilkerson, John and Andreu Casas. 2017. "Large-Scale Computerized Text Analysis in Political Science: Opportunities and Challenges." *Annual Review of Political Science* 20(1):529–544.

Wlezien, Christopher. 2005. "On the Salience of Political Issues: The Problem with 'Most Important Problem'." *Electoral Studies* 24(4):555–579.

Wood, B. Dan and Jeffrey S. Peake. 1998. "The Dynamics of Foreign Policy Agenda Setting." *The American Political Science Review* 92(1):173–184.

Wright, Gerald C. 1989. "Policy Voting in the U. S. Senate: Who Is Represented?" *Legislative Studies Quarterly* 14(4):465–486.

Appendix A Validation of Public Agenda Measures

Research studying the correspondence between the issues politicians and the public discuss has traditionally used Gallup's *Most Important Problem* (MIP) polls to measure the issue priorities of the public – see for example Jones and Baumgartner (2004). For decades, Gallup has been asking the same (or very similar) question to the American public "What is the most important problem facing the nation today?" Some have argued that using Gallup's MIP as a measure of the public agenda is problematic because the wording of the question has slightly changed over time (Soroka, 2015) and because it is unclear whether it is measuring issue salience or problem perception (Wlezien, 2005). Others have argued however that, despite its pitfalls, Gallup's MIP is the best data source available to measure what issues are salient to the public (Jones and Baumgartner, 2004).

In the paper we pointed out an additional downside related to Gallup's MIP polls: they aggregate monthly issue attention, which does not facilitate uncovering whether elite political agendas influence public attention, or the other way around, if such influence is happening more quickly than one would observe with monthly data. We also argued that public attention measures created using Twitter data provide more detailed information and facilitate studying temporal patterns. Nevertheless, analyses based on tweets about politics are subject to potential biases: not all citizens have a Twitter account, nor do all those who do tweet often. In this appendix we perform some construct validity tests and asses the extent to which our Twitter-constructed public agendas are a valid measure of the issues different groups of the public pay attention to. To do so, for the period of analysis we correlate monthly MIP responses and our Twitter-constructed public agendas. We expect a positive correlation between the two, but given that MIP polls not only capture salience but also longer-term issue priorities (Wlezien, 2005), we expect such correlation not to be perfect.

We collect Gallup's MIP data from January 2013 though December 2014 from the Roper Center.[23] The data contains individual MIP responses that have been manually coded according to the 19 issue-classification of the Comparative Agendas Project (CAP).[24] These are responses to monthly polls, but as there are a few scattered months for which no data is available, we aggregate these individual responses on a quarterly basis: calculating the proportion of all responses in each three-month period that are about each of the 19 CAP issue categories. We also aggregate the responses by different groups of individuals based on party identification: Democrats, Weak Democrats, Independents, Republicans, and Weak Republicans).

Then we assign one of the 19 CAP issue categories to each of our political issues uncovered from the topic modelling described above. Table A1 shows the CAP codes assigned to our 46 political issues. Then, for each group of the public in our analysis (Democratic and Republican supporters, the attentive public, and the general public), we also aggregate in a quarterly basis the estimated Twitter attention to each of the CAP issues. At this point, both measures (the MIP and Twitter-based measures) are in the same unit of analysis (quarterly attention to the 19 CAP issues) and ready to be compared.

Table A2 shows Pearson correlations between these MIP and Twitter-based public agenda measures. All correlations are positive and most of them are of substantive magnitude. We see a very strong correlation between the Twitter-based measure of the agenda of Democratic and Republican supporters and the issues all poll respondents indicated as the most important (.46 and .69 correlation, respectively). If we break down these correlation by party identification, we see how our measure of the agenda of Democratic supporters is more strongly correlated

[23]The data is available from the following link.

[24]The codebook for the Comparative Agendas Project issue-classification is available using the following link.

with MIP responses by Democrats (.49) than by Republicans (.41). And we observe the same pattern for Republican supporters. Our measure of their agenda is more strongly correlated with MIP responses by Republicans (.70) than by Democrats (.68). Moreover, although of a slightly smaller magnitude, we also observe substantive positive correlations between our Twitter-based measures of the agenda of the attentive and the general public, and Gallup's MIP responses: Pearson correlations of between .32 and .4.

Table A1: Comparative Agendas Project codes assigned to our political issues

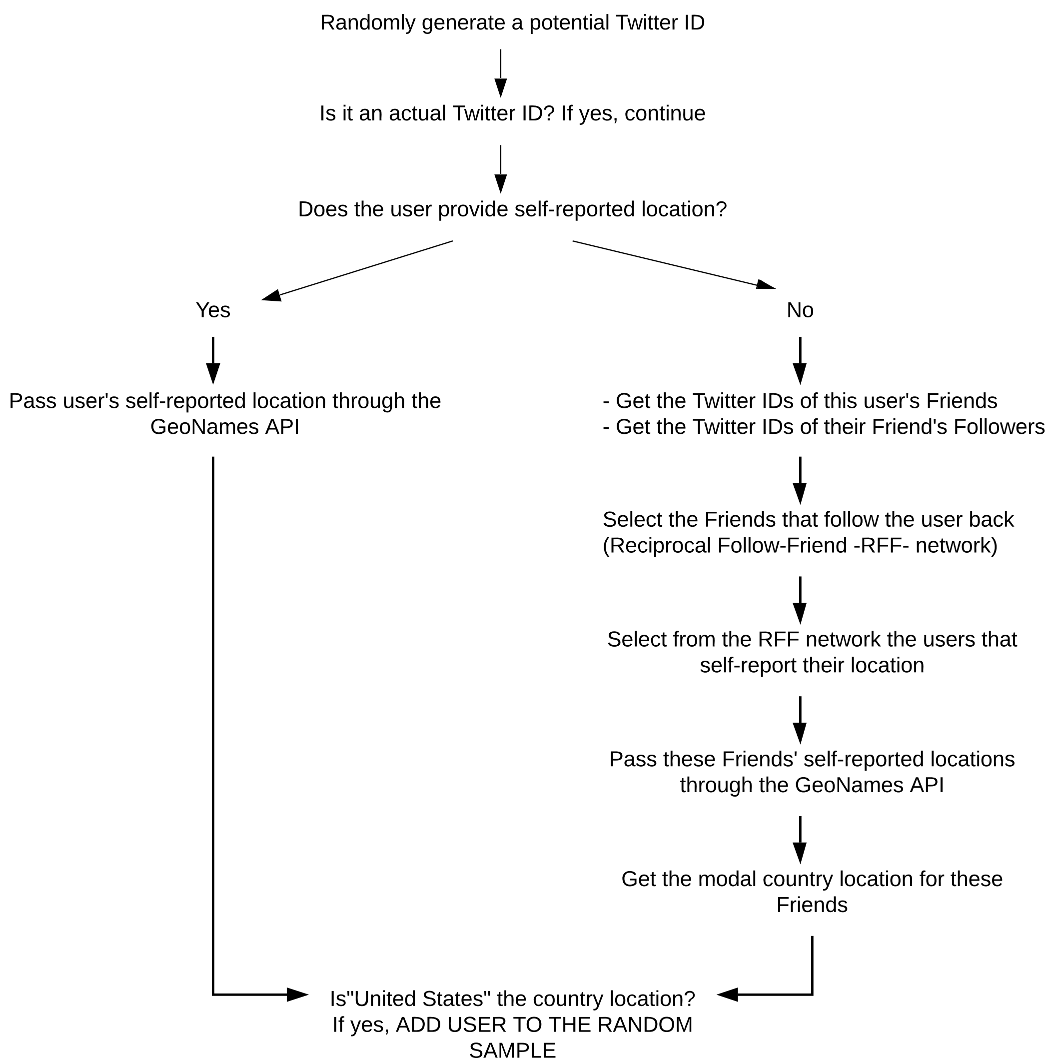
Topic Number	Our Label	CAP Topic Number	CAP Label
3	Investigation of Benghazi Attack	16	Defense
7	100 Days of #BringBackOurGirls campaign	19	International Affairs
9	Gender Wage Gap	2	Civil Rights
12	Republican Issues Spring 2013	6	Education
14	Marriage Equality	2	Civil Rights
15	Gun Violence	12	Law and Crime
16	Abortion (Pro-Life)	2	Civil Rights
18	Veteran Affairs Delays Scandal	16	Defense
20	NSA Surveillance Scandal	16	Defense
23	#BringBackOurGirls campaign	19	International Affairs
28	Employment Non-Discrimination Act	5	Labor
32	Islamic State	16	Defense
33	Use of Military Force in Syria	16	Defense
36	Ebola	3	Health
37	Social Security	13	Social Welfare
39	Keystone XL Pipeline	8	Energy
41	Immigration (Border Security)	9	Immigration
43	Executive Action on Immigration	9	Immigration
46	Unemployment Numbers Reports	1	Macroeconomics
47	Paul Ryan Budget Proposal	1	Macroeconomics
48	Black History Month	2	Civil Rights
50	Climate Change	7	Environment
51	Lame Duck Congress	20	Government Operations
53	Minimum Wage	5	Labor
58	Affordable Care Act	3	Health
62	Border Crisis in Texas	9	Immigration
63	Obamacare (Employer Mandate)	3	Health
64	FAA Furloughs Cause Flight Delays	20	Government Operations
66	Malaysian Airlines Crash in Ukraine	19	International Affairs
67	Comprehensive Immigration Reform	9	Immigration
70	#MiddleClassFirst campaign	1	Macroeconomics
75	Military Justice Improvement Act	16	Defense
81	Poverty (SNAP program)	13	Social Welfare
83	21st Century Cures Initiative	3	Health
85	Unemployment Insurance	5	Labor
88	IRS Scandal	1	Macroeconomics
89	Obamacare (Website and Implementation)	3	Health
93	Jobs Bills Omnibus	5	Labor
96	Violence Against Women Act	2	Civil Rights
97	Protests in Ukraine and Venezuela	19	International Affairs
99	CIA Detentions and Interrogations Report	16	Defense
100	#ObamacareInThreeWords Campaign	3	Health
101	Student Debt	6	Education
102	Hobby Lobby Supreme Court Decision	2	Civil Rights
103	Budget Discussion	1	Macroeconomics
104	2013 Government Shutdown	1	Macroeconomics

Table A2: Pearson correlation between Twitter-based Public Agenda Measures and Gallup's MIP polls

	Gallup MIP Responses					
Twitter Measure	Full Sample	Democrat	Weak Democrat	Independent	Weak Republican	Republican
Democratic Supporters	0.46	0.49	0.46	0.43	0.41	0.45
Republican Supporters	0.69	0.68	0.68	0.66	0.67	0.70
Attentive Public	0.35	0.35	0.34	0.35	0.33	0.35
General Public	0.37	0.39	0.37	0.38	0.32	0.35

Appendix B Procedure to Elaborate the Random Sample of U.S. Twitter Users

Figure 8: Flowchart describing the method used to elaborate the random sample of 25,000 U.S. Twitter users



Appendix C Modeling Broader Political Issues

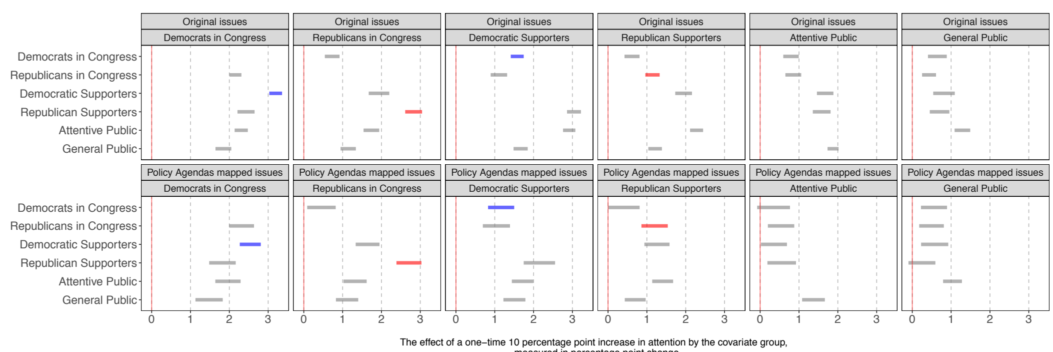
Topics from an unsupervised 100-topic model are of a narrow scope. For example, instead of a broad immigration topic, we discovered a topic on comprehensive immigration reform and a topic on President Obama's executive action on immigration. The advantage of focusing on narrower topic definitions is that we can study attention to specific important issues that dominated the public, media and political agenda for a relevant period of time, and that we can more easily study whether the public responded to a political change in attention by politicians or the other way around.

Focusing on narrow topics has a potential drawback. The goal of the study is to learn about the type of publics politicians are responsive to. If topics are too narrow, we run the risk of studying attention to party frames (how Democrats or Republicans talk about a given issue) instead of topics. This may influence our results in favor of the supporter model and in detriment of the attentive and Downsian arguments.

In the paper we addressed this potential problem by merging issues from the topic model that were closely related: 2 sub-issues about student debt, 2 about the Hobby Lobby Supreme Court decision, 2 on budget discussions, and 5 about the 2013 Government shutdown.

In this Appendix we run a robustness check to evaluate the extent to which our results are a function of studying specific instead of broader issues. First, we used the crosswalk Table A1 from Appendix A to map each of our 46 political issues to a issue-classification based on much broader issues: the 19-topic classification of the Comparative Agendas Project.[25] Then we re-estimated the same VAR model presented in the paper (Model 1). In Figure 9 we compare the results we presented in the paper (six top panels) to the results of a VAR model studying attention to the Comparative Policy Agendas topics (six bottom panels).

Figure 9: A comparison between the VAR results in the paper and the VAR results of a model exploring attention to broader political issues (Comparative Policy Agendas issue classification)



Three main points stand out. First, when modeling attention to Comparative Policy Agendas topics we still observe members of Congress to be first responsive to their party supporters (for Democrats: blue estimates in the top and bottom left panels. For Republicans: red estimates in the second from the left top and bottom panels), and then to attentive voters (attentive publics and supporters of the other party). Second, as we saw in Figure 5 in the paper, we still observe the ability of the public to influence the attention distribution of politicians to be higher than the *vice versa* effect: the blue estimates in the two left panels are of larger magnitude than the blue estimates in the third from the left panels, and the red estimates

[25] http://comparativeagendas.net/

in the second from the left panels are of larger magnitude than the ones in the third from the right panels. Finally, in this new model results we still observe the general public to pay a residual role. They have little ability to set political agendas (bottom estimates in bottom and top left panels) and they do not positively respond to changes in attention by members of Congress.

Overall, the results of the new model show that the main findings presented in the paper hold when modeling attention to broader issues instead of more specific ones.