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

PABLO BARBERÁ *University of Southern California*
ANDREU CASAS *New York University*
JONATHAN NAGLER *New York University*
PATRICK J. EGAN *New York University*
RICHARD BONNEAU *New York University*
JOHN T. JOST *New York University*
JOSHUA A. TUCKER *New York University*

Are legislators responsive to the priorities of the public? Research demonstrates a strong correspondence between the issues about which the public cares and the issues addressed by politicians, but conclusive evidence about who leads whom in setting the political agenda has yet to be uncovered. We answer this question with fine-grained temporal analyses of Twitter messages by legislators and the public during the 113th US Congress. After employing an unsupervised method that classifies tweets sent by legislators and citizens into topics, we use vector autoregression models to explore whose priorities more strongly predict the relationship between citizens and politicians. We find that legislators are more likely to follow, than to lead, 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 supporters than to the general public.

Pablo Barberá, Assistant Professor, School of International Relations, University of Southern California, pbarbera@usc.edu.
Andreu Casas, Moore-Sloan Research Fellow, Center for Data Science, New York University, andreucasas@nyu.edu.
Jonathan Nagler, Professor, Wilf Family Department of Politics, New York University, jonathan.nagler@nyu.edu.
Patrick J. Egan, Associate Professor, Wilf Family Department of Politics, New York University, patrick.egan@nyu.edu.
Richard Bonneau, Professor, Center For Genomics and Systems Biology, Courant Institute of Mathematical Sciences, Computer Science Department, and Center for Data Science, New York University; and Flatiron Institute, Center for Computational Biology, Simons Foundation, bonneau@nyu.edu.
John T. Jost, Professor, Department of Psychology, New York University, john.jost@nyu.edu.
Joshua A. Tucker, Professor, Wilf Family Department of Politics, New York University, joshua.tucker@nyu.edu.
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INTRODUCTION

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; Neundorf and Adams 2018; Sulkin 2005)? And, if so, do they reflect the policy preferences that citizens have on these issues (Caughey and Warshaw 2018; Page and Shapiro 1983; Soroka and Wlezien 2009; Stimson, Mackuen, and Erikson 1995)? Our manuscript 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 leads and who follows in the agenda-setting process. Evidence is even more scant on the important question of which citizens have the strongest ability to set political agendas: the general public (Downs 1957), attentive citizens (Aldrich 1995; Arnold 1990), or politicians' own supporters (Egan 2013; Kastellec et al. 2015).

We aim to shed new light on these classic and relevant political science questions by analyzing the issues to which members of the US Congress and the American public pay attention. Although determining whether politicians also follow 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, disentangling whether politicians devote more time discussing an issue after attention to that issue by the public increases is a first and crucial step toward fully understanding political representation in the United States.[1]

We believe the lack of clear findings on who leads public opinion 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. Most existing research relies on monthly survey data (typically Gallup's "Most Important Problem" [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. Moreover, existing analyses trace attention to issue categories that are very broad (such as "the economy" or "immigration"), which has the advantage of facilitating comparisons across long periods of time and units, such as states and countries, but can make it difficult to uncover who leads public opinion by grouping together issues that are in fact quite different.[2]

In an effort to address previous data limitations, we pursue a novel empirical strategy by using the microblogging social media platform Twitter to measure the expressed agenda of legislators and the American public. To be clear, our goal is not to assess whether a social media platform such as Twitter is a useful agenda setting tool for politicians or the public but rather to use their "tweets" as a proxy to measure attention being paid to political issues. We are reassured in pursuing such a measurement strategy because virtually all members of the US Congress are active Twitter users and their tweets have been shown to constitute a standardized representation of their expressed issue agenda (Casas and Morar 2015). Moreover, the issues Americans discuss on social media are highly correlated with other measures of issue salience such as the MIP survey question (O'Connor et al. 2010).[3]

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 before or after shifts in issue attention by the public (or whether they devote attention to the issue at all). Although previous work has used Twitter data to evaluate the issues to which politicians and constituents pay attention (particularly, the work by Lilly Hemphill and colleagues: e.g., Hemphill and Roback (2014) and Shapiro and Hemphill (2017)), this work has examined a limited number of issues and has primarily focused on issue *congruence* rather than issue *responsiveness*.

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 100 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 validated topics that exhibit meaningful variation over time and across parties. We then employ a vector autoregression (VAR) approach to explore the extent to which legislators' expressed political agendas adapt after a change in issue attention by three different subgroups of the public: partisans, people who are particularly attentive to politics, and a random sample of US Twitter users. Our tests examine the extent to which changes in issue attention by these groups of citizens predict policy makers' agendas.

Our observational analysis is necessarily of a descriptive rather than a causal nature. Our VAR approach takes advantage of multiple lags of data to distinguish when groups lead conversations about particular topics and by contrast when they are joining debates that are already established, but it cannot rule out confounding by unobservable factors. Nevertheless, our analyses provide revealing information about the configuration of political agendas and public opinion in the United States. Further, it allows us to ascertain in ways not previously possible whether observable data conform to empirical implications of theories specifying how the agendas of different sets of actors impact those of others, providing corroborative evidence for some of these theories.

Our findings show definitively that members of Congress are more likely to follow the issue priorities of the public than to lead them. However, this responsiveness is limited in ways that reinforce polarization and inequality. Lawmakers are more likely to change their behavior after shifts in attention by party supporters, as previous work leads us to expect (Bawn et al. 2012; Clinton 2006; Egan 2013; Kastellec et al. 2015; Shapiro et al. 1990). To a lesser extent, politicians are also responsive to the issue priorities of attentive citizens over those less inclined to follow politics (Aldrich 1995; Arnold 1990). But despite well-established models predicting that politicians should

[1] To be clear, we are not, however, addressing the downstream question of whether policy *outcomes* reflect the preferences of the public or particular groups of the public; see Gilens (2012) and Gilens and Page (2014) for an analysis of the determinants of policy outcomes.

[2] 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, the Policy Agendas Project issue classification (Jones and Baumgartner 2004): both actions would be categorized into Natural Gas & Oil (803) within the Energy category. 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.

[3] We further test this assumption in Online Appendix A.

reflect the priorities of the general public (Downs 1957), we find little evidence for this. Our findings also suggest that mainstream media is in part to blame for this inequality on issue responsiveness: mass media are more likely to cover those issues that are of interest to partisans, and they often lead the political agenda.

POLITICIANS' RESPONSIVENESS TO THE PUBLIC'S PRIORITIES

Empirical studies on policy (not issue) responsiveness have substantially advanced due to great innovations in data collection and measurement (Burstein 2014; Caughey and Warshaw 2018; Gilens 2012; Lax and Phillips 2011; Soroka and Wlezien 2009; Tausanovitch and Warshaw 2014), but without a more clear understanding of issue responsiveness, an evaluation of the extent to which governments are responsive to their citizens is incomplete. As Jones and Baumgartner (2004) 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?" (p. 2). 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 reflect people's preferences on those issues.

Research on agenda setting and political responsiveness in the United States has found a strong relationship between the issue priorities of the public and the agenda of members of Congress (Baumgartner and Jones 1993). For issues such as the economy, health, environment, and foreign trade, changes in public issue salience (measured using Gallup's long-standing MIP question) correlate at high levels with changes in political attention (measured as the proportion of Congressional hearings on the same issue) (Jones and Baumgartner 2004).

However, existing studies on issue responsiveness do not clearly address a very important question: who leads whom (Page 1994)? Are policy makers more likely to follow than to lead changes in issue attention by their constituents, or is it the other way around? Research indicates that both scenarios are possible, but it is unclear who (if any) has the largest capacity to lead the issue agenda of the other.

On the one hand, research on policy responsiveness argues that politicians have strong incentives to be responsive to the preferences of the public (Erikson, Mackuen, and Stimson 2002; Geer 1996; Stimson, Mackuen, and Erikson 1995). Building on the "retrospective voting" idea, (Campbell, Dettrey, and Yin 2010), scholars, such as Stimson, Mackuen, and Erikson (1995), argue (and find) that electorally oriented politicians update their preferences to maximize reelection prospects once they perceive a shift in public opinion: "when politicians perceive public opinion to change, they adapt their behavior to please their constituents" (p. 545). Canes-Wrone and Shotts (2004) also show that public opinion can influence the preferences of political figures, such as the president, particularly on issues directly related to people's daily life. Overall, this literature suggests that politicians are responsive to public priorities and leads to the expectation that **(H_1) the public's priorities predict the issues to which members of Congress subsequently pay attention.**

On the other hand, another body of research argues the opposite. Building on the image of "policy-oriented" politicians, scholars argue that most politicians are mainly motivated by policy goals rather than by the goal of seeking reelection (Jacobs and Shapiro 2000). Research shows that most citizens are not interested in (Hibbing and Theiss-Morse 2002) and know very little (Delli Carpini and Keeter 1996) about politics, and that instead of evaluating politicians based on their past actions and performance, they make decisions based on group attachments (Campbell et al. 1960) and elite cues (Lupia, McCubbins, and Arthur 1998; Sniderman, Brody, and Tetlock 1993). Authors such as Lawrence R. Jacobs, Robert Y. Shapiro, and Benjamin I. Page draw on this literature and their own empirical evidence to show that policy-oriented politicians take advantage of people's political disconnect to set the agenda to their liking. In interviews with administration officials, the authors are repeatedly told that the government tracks public opinion "not to 'pander' but to educate, lead, or otherwise influence public attitudes" (Jacobs and Shapiro 1997, 3). Overall, this other body of research leads to the expectation that **(H_2) members of Congress initiate debates about issues that are subsequently followed by the public.**

Thus, there are good reasons to believe that politicians follow the issue preferences of the public, but also that the public responds to politicians' issue priorities. But who has the strongest ability to lead the issue agenda of the other? A primary contribution of our analysis will be to evaluate the magnitude of these effects to determine who has the largest agenda-setting effect (if any). We explore this question without a theoretical preference for either hypothesis, but rather as an open debate that must be addressed to truly evaluate the nature of political responsiveness in the American democratic system (Burstein 2003; Page 1994).

MODELS OF RESPONSIVENESS

Beyond whether politicians or the public have the largest agenda-setting effect, a second question is also crucial for advancing a more complete picture of issue responsiveness in the United States: to whom should we expect members of Congress to be 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 different answers to our question of interest. We call them here the *Downsian*, the *Attentive*, and the *Supporter* models.[4]

In *An Economic Theory of Democracy*, Downs (1957) argued that, in a bipartisan democratic system, policy makers interested in reelection should be responsive to the median voter or "centrist opinion" (Jacobs and Shapiro 2000). The implications for political responsiveness are easier to envision from a policy—as opposed to from an issue responsiveness—perspective: members of Congress should adopt the policy preference of their median constituent. Following the same logic, we should also expect legislators to increase their chances of reelection by focusing on issues that a majority of the general public deems relevant. Some strongly disagree and argue that politicians have very little incentives to devote attention to the preferences of the median voters: only a small proportion of the mass public pays attention to, know about, and participate in politics; and those who do are more likely to be partisans than the typical median voter (Hibbing and Theiss-Morse 2002; Delli Carpini and Keeter 1996; de Vreese and Boomgaarden 2006).[5] Nevertheless, existing empirical evidence still gives some credit to the Downsian logic. An extensive literature on cue-taking argues that even the least informed and attentive public often draws on multiple sources of information to make decisions about politics, also keeping politicians in check (Lau and Redlawsk 2006; Lupia, McCubbins, and Arthur 1998). In fact, in their exhaustive work on policy responsiveness in the United States and Canada, Soroka and Wlezien (2009) find "roughly the same degree [of policy responsiveness] across groups. In most cases, representation is neither markedly better nor markedly worse when we look solely at certain groups" (p. 165).[6] Hence, given the conflicting arguments and evidence, it is pertinent to test whether a Downsian logic is still in place. A main testable hypothesis that derives from the argument is that **(H_3) changes in attention allocation by the *general public* predict changes in issue attention by members of Congress.**

Other scholars, however, disagree with this premise as being too optimistic about the public's agenda-setting role. 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 follow day-to-day 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* predict allocation changes by members of Congress.**

Another group of researchers proposes a third alternative: legislators should be mostly interested 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 to win not only 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 legislators are more likely to represent the policy preferences of their supporters (Clinton 2006; Kastellec et al. 2015; Neundorf and Adams 2018; Shapiro et al. 1990), but no research yet exists showing whether that is the case for issue attention allocation. From this model, however, we can derive that **(H_5) changes in attention allocation by *party supporters* predict allocation changes by members of Congress.**

As a final theoretical consideration, scholars argue (and find) that the more salient an issue becomes in the eyes of the public, the larger the degree of political responsiveness we should expect (Burstein 2003; Canes-Wrone and Shotts 2004; Jones 2004; Soroka and Wlezien 2009; Sulkin 2005): "the public importance of policy domains may tell us a lot about policy makers' responsiveness. There is good reason, after all, to expect policy makers to reflect the importance of the different domains because of possible electoral consequences" (Wlezien 2004, 7). If politicians aim to be responsive to a certain group of the public, they should be interested in reacting to shifts in attention involving issues that are particularly salient to that group. In other words, if members of Congress are mainly responsive to their party supporters (or to the attentive or general public), they should be more likely to react to shifts in attention by party supporters on issues that take on 10% rather than 1% of their supporters' discussion. Hence, building on this literature, if the previous responsiveness models apply, we should expect that **(H_6) to the extent that particular issues are more salient among the general public** (according to the Downsian model), **attentive citizens** (according to the Attentive model), **and party supporters** (according to the Supporter model), **these**

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

[5] Delli Carpini and Keeter (1996), for example, found that only 30% of Americans know the name of at least one of the two Senators representing their State.

[6] The authors do find, however, that when discrepancies exist between the policy preferences of some groups, politicians do tend to be more responsive to some groups: those with a higher income, education, and political sophistication.

publics' priorities will more strongly predict the politicians' agenda.[7]

THE MECHANISMS OF ISSUE RESPONSIVENESS

Here, we use messages sent on Twitter by politicians and the public as measures of these individuals' issue priorities, allowing us to evaluate the extent to which reciprocal relationships exist among these priorities. Previous research has suggested several mechanisms by which politicians might become informed about the public's priorities, and vice versa. In particular, this literature puts forward a set of mechanisms through which the issue priorities of politicians and the public can directly lead the priorities of the other, as well as ways in which the mass media can channel these reciprocal dynamics.

One mechanism by which politicians and citizens learn about one another's priorities is direct interaction and communication between lawmakers and their constituents, which include town halls, "lobby days" organized by interest groups and offline and online correspondence. For example, about 24% of Americans report having written a letter to a public representative (Schlozman, Verba, and Brady 2012). Surveys indicate that politicians pay some attention to social media messages from constituents as well, although these messages are not weighed as heavily as other constituent communications (Chen, Lee, and Marble 2018). Another way that politicians learn about citizens' priorities is by tracking public opinion. Polling organizations, such as Gallup and the Pew Research Center, regularly release polls revealing the public's issue priorities. Political parties, campaign staff, and government agencies run their own polls to assess the issues that are of interest to the public (Jacobs and Shapiro 2000). Modern practices also include using dashboards to track the issues that are mostly discussed by citizens in social media (Webster and Ksiazek 2012).

In this study, we focus on what is arguably the primary mechanism by which politicians and the public learn about each other's issue priorities: the news media. First, the media's powerful role in this regard derives from the fact that lawmakers are incentivized to expend effort to generate media coverage of their priorities, while at the same time media outlets are incentivized to cover issues that resonate with their audiences' priorities. A wide range of factors determine media content, including assigned "beats," journalistic practices, and the occurrence of newsworthy events (Graber 1997; Shoemaker and Reese 1996). Among these factors, audience preferences and political institutions play a very important role, ensuring that media covers issues that are of interest to both the public and politicians. And second, the media's substantive role derives from its ability to drive both public and political attention (McCombs and Shaw 1972; Zaller 1992).

The media is responsive to political elites in part because political institutions represent an important source of constant newsworthy information (Shoemaker and Reese 1996). Media outlets regularly appoint correspondents to institutions such as the White House and Congress, ensuring that major issues discussed in these political venues achieve media attention. Media outlets are responsive to public demands in part because of market pressures: particularly in a context in which most outlets face economic hardships, discussing the issues that are of interest to the public increases their chances of getting the readers and viewers needed to generate profits. More than ever, media outlets today have a wide range of instruments in their hands to measure, and respond to, the issues in which the public is interested (including tracking social media attention) (Anand and Peterson 2000; Webster and Ksiazek 2012). In addition, public sentiment is often reflected by newsworthy political events in themselves, including election results, strikes, and demonstrations (Gitlin 1980). To be sure, neither the public nor politicians have exclusive control over the agenda, which is frequently set by external unexpected shocks (such as natural disasters) (Birkland 1998) and recurrent events (and expiring statutory provisions) (Adler and Wilkerson 2012) that simultaneously affect the attention distribution of politicians but also of the media and the public.

There is clear evidence showing that not only politicians and the public lead media attention but also that the media can drive political agendas and public opinion (Soroka 2002; Walgrave, Stuart, and Nuytemans 2008; Walgrave and Van Aelst 2006). The media "construct" and highlight problems for politicians to solve, and they increase the salience of issues that voters might consider relevant, which reelection-seeking politicians should address in other to please them (Wouters and Walgrave 2017). Moreover, a long-standing literature also shows that the issues covered in the media are very likely to lead public opinion and preferences (Boydstun 2013; Iyengar and Kinder 2010; McCombs and Shaw 1972; Zaller 1992).

Exploring all the mechanisms through which groups of the public and politicians influence the agenda of the other is outside the scope of this study. Nevertheless, given that research points to mass media as playing a crucial agenda setting role, in our analysis we will control for potential media effects as well as explore the extent to which mass media coverage favors particular responsiveness models.

DATA

Members of Congress on Twitter

To test our hypotheses, we use tweets sent by members of the 113th House and Senate of the US Congress (2013–14). Twitter use in Congress has increased steadily over the past years (Chi and Yang 2011; Evans, Cordova, and Sipole 2014; Golbeck, Grimes, and

[7] As will be explained below in the *Issue Attention Congruence* section, we measure the salience of an issue by calculating the average relative daily attention that different groups of the public paid to each political issue.

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	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

Note: Period of analysis: January 1, 2013, to December 31, 2014. *N* corresponds to the number of Twitter accounts in each sample. *Avg*, *Min*, and *Max* correspond to the average, minimum, and maximum number of tweets, respectively, sent by individual users in each group during the whole period of analysis. *Tweets* corresponds to the total number of tweets sent by all users in each group during the period of analysis.

Rogers 2010; Shapiro, Hemphill, and Otterbacher 2012). Ninety-five percent of legislators that served in the 113th Congress had active Twitter accounts, sending a total of 651,116 messages (excluding retweets), about 900 tweets per day.[8]

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, exercise control of the political agenda, express party loyalty, engage in partisan taunting, and report on their constituency service (Hemphill, Otterbacher, and Shapiro 2013; Evans, Cordova, and Sipole 2014; Russell 2018b, 2018a). Moreover, research indicates that the topics discussed in tweets are a fair representation of the legislators' overall expressed agenda: there is a very high correlation between the issues they discuss on social media and their press releases, for example (Casas and Morar 2015).

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 ($H_{3,4,5,6}$) regarding the part of the public whose shifts in attention politicians are more likely to follow. 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 the users resided in the United States.[9]
2. **Attentive Public**: a randomly generated sample of 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 the United States. We also filter based on activity: only users who have ever sent 100 tweets or more are included. After applying these filters, the final sample size is 10,000 users.
3. **Republican Supporters**: a random sample of 10,000 Twitter users who follow three 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. In Online Appendix F, we demonstrate why this sampling method is able to select party supporters.
4. **Democratic Supporters**: a random sample of 10,000 Twitter users who follow three or more Democratic members of Congress and no Republican in Congress. The same geographic and activity filters as in the sample of Republican supporters apply.

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.[10] The final number of users and tweets in each group is available in Table 1. Retweets are excluded from our sample to avoid inflating the correlations we observe between politicians and the public regarding the issues they discuss.

Media

As discussed previously, it may well be that both public and political issue agendas are led by the mass media (Gerber, Dean, and Bergan 2009; Habel 2012; King, Schneer, and White 2017; Ladd and Lenz 2009), particularly so on social media (Feezell 2018). To account for

[8] See Online Appendix F for information regarding the data collection process.

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

[10] We conducted the data collection for the random sample (General Public group) 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 in 2013 by about 44% of the random users are not included in the sample.

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 United States (print, broadcast, online), as identified by the Pew Research Center.

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 discussed 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 an LDA (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.

As we explain in greater detail in Online Appendix G.1, this method treats each document as a random mixture over latent topics, and each topic as a probability distribution over tokens. In our analysis, tokens are *n*-grams (combinations of one and two words). Our definition of "document" is the aggregated total of tweets sent by members of Congress each day, by party and chamber.[11]

The alternative to using an unsupervised topic model would be for the analyst to choose the topics and then build a supervised classifier predicting them. Despite the existence of well-known categories of political issues,[12] training an accurate classifier would be an incredibly arduous task, given the large number of categories, making unsupervised models a preferable option. However, as we show in Online Appendix E.2, it is possible to map the topics derived from the data to an existing classification of political topics—the topics used in Jones and Baumgartner (2004)—with similar results.[13] And as we demonstrate in Online Appendix G.3, the topics generated by the model pass standard tests of both predictive and semantic validity (Quinn et al. 2010).

Note two additional features of our analysis. First, we fit the model at first only for members of Congress (instead of fitting it to the messages sent by all groups) to increase the likelihood of discovering topics that were politically salient during the 113th Congress, and then use the estimated parameters to compute the posterior topic distributions for citizens and media outlets, also aggregated by day, based on their observed words. However, a replication of the results based on an LDA model fit to the tweets of politicians, the media, and the public leads to similar conclusions (see Online Appendix E.4). Second, in our estimation we assume that topic distributions are independent over time, and that the number of topics and the content of each topic is constant over time.

We fix the number of topics to $K = 100$ after exploring a wide range of values by running 10-fold cross-validations and computing common goodness-of-fit measures (Chang et al. 2009) (see Online Appendix G.2 for a detailed description of how we chose K).

In general, we find that most of the 100 resulting topics 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.). Because we are not interested in these topics, in our analysis we will only include political issues, of which 53 were identified.[14] After reviewing their content, we noted 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 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.

RESULTS

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 following their constituents? And if so, are they following 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 3 displays Pearson correlation coefficients, indicating how similar the issue distribution of

[11] 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).

[12] Such as the ones from the Comparative Agendas Project or Manifesto Project.

[13] 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).

[14] To identify the list of relevant political topics, five coders used the information contained in our topic dashboard (pablobarbera.com/congress-lda) to classify each of them into three categories: non-political topics (e.g., Valentine's Day), political topics but not related to issues (e.g., public communication by House Republicans), and political issues (e.g., gun violence, government shutdown, obamacare). Average intercoder agreement was 83% and Cronbach's alpha was 0.92. We chose as political issues those where the modal classification (three or more coders) agreed to classify as such.

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	Malaysia 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	Twenty-first 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 parentheses indicate issues that have been created *ad hoc* by merging very similar topics from the topic model.

TABLE 3. Correlation in Issue Attention Between Members of Congress and Groups of the Public and the Media Over 46 Political Issues

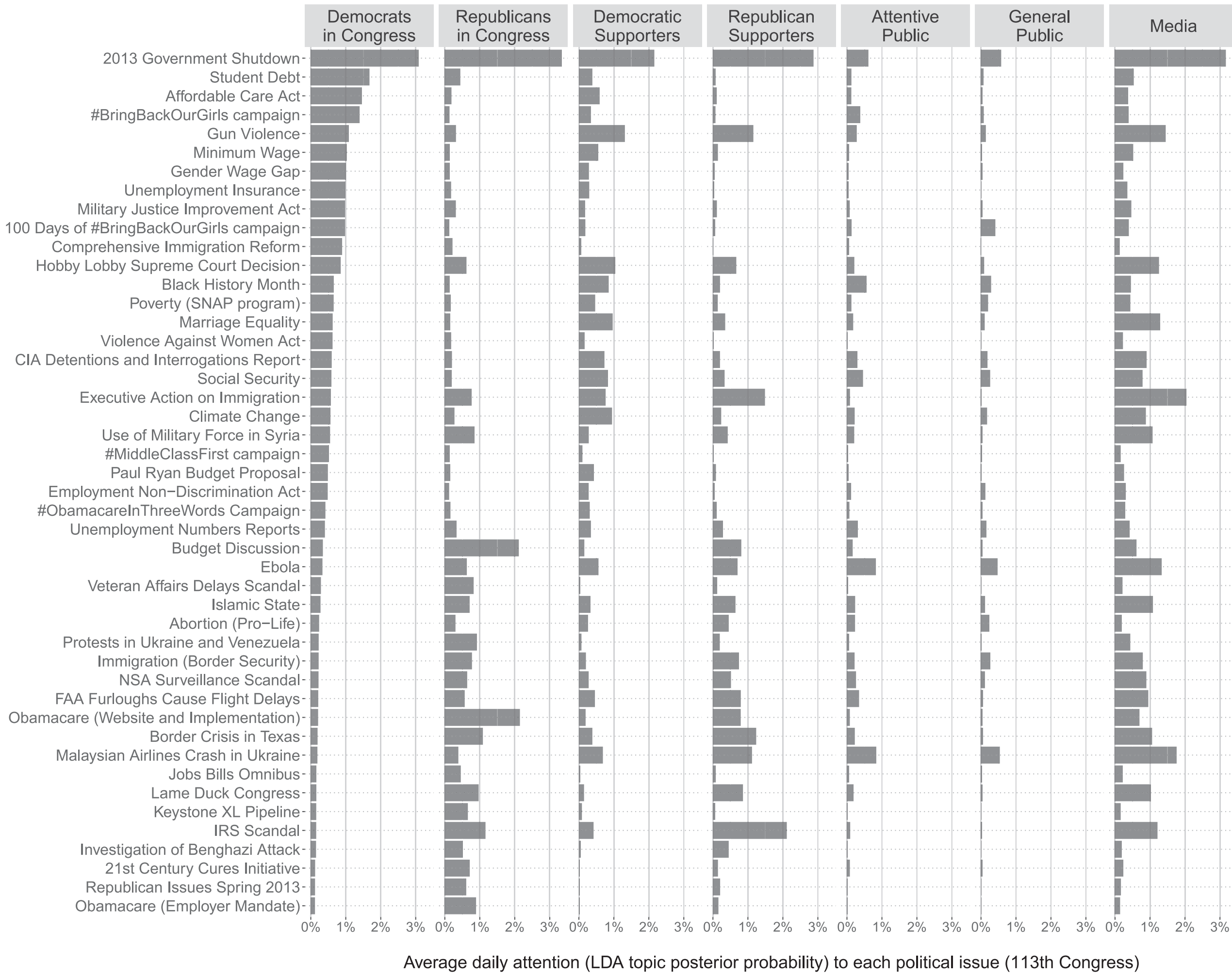
Group	Democrats in Congress	Republicans in Congress
Democratic supporters	0.69	0.51
Republican supporters	0.41	0.77
Attentive public	0.49	0.52
General public	0.38	0.34
Media	0.52	0.63

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.

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 models, 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 to be between members and their party supporters (0.69 for Democrats and 0.77 for Republicans) and between members and the attentive public (0.49 for Democrats and 0.52 for Republicans). The correlation between the expressed agenda of legislators and the attention allocation of supporters of the other party is much lower (a 0.41 correlation between Democratic members and Republican supporters, and 0.51 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. As expected, the issue attention distribution of the media is also highly correlated to the agenda of members of Congress, emphasizing mass media's agenda-setting and mediating role.

In Figure 1, we provide information about the average daily attention that each party in Congress, each public group, and the media paid to the political issues under study. This figure provides a more detailed understanding of the agenda level correlations we observe in Table 3 and some potential reasons as to why we observe a particularly strong relationship between the issue agenda of members of Congress and the attention

FIGURE 1. Average Issue Attention by Groups of Politicians, the Public, and the Media



Note: Attention is represented as daily posterior LDA topic probabilities expressed in percentages. These are percentages based on all 100 topics of the LDA model.

distribution of their party supporters. We see, for example, how Democrats in Congress and Democratic supporters paid much more general attention to the Affordable Care Act (row 3 of figure 1) and Marriage Equality (row 15) 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 (11th to the last row), its employer mandate clause (last row), and to the Border Crisis in Texas (10th to the last row). The attentive public, and especially the general public, paid less attention not only to these issues but also to all political issues in general. (See Online Appendix G.4 for further discussion of these results.)

Who Leads? Who Follows?

The previous correlations and percentages, however, are not sufficient evidence to conclude that members of Congress lead the issue attention distribution of their constituents nor to adjudicate between the competing Downsian, Attentive, and Supporter models. Here, we take advantage of the time series nature of our dataset to establish who puts issues on the agenda first by estimating a VAR models with topic-fixed effects. These models are well-suited to capture the relationship between endogenous variables (Freeman, Williams, and Lin 1989; Sims 1980) and have been used in previous political science studies with similar objectives (Edwards and Wood 1999; Enders and Sandler 1993; Wood and Peake 1998).[15]

[15] In this paper, we do not control for the agenda of the President for two main reasons. First, Edwards 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. Needless to say, revisiting the question of agenda-setting power of the President in the era of Trump would likely be a good idea for future research.

In our VAR model, we have a set of stationary time series Y_i representing the proportion of daily attention each of our groups i[16] paid to each topic j in day t of the 113th Congress.[17] 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 on Twitter, we would theoretically expect members of Congress to follow changes in public issue attention quite rapidly. However, to account for the potential of longer-term decay we use a seven-lag structure.[18] The final model can be & formally expressed as follows:

$$Z = \log\left(\frac{Y}{1-Y}\right)$$
$$Z_{i,j,t} = \alpha_j + \sum_i \sum_{p=1}^{7} \beta_{i,p} Z_{i,j,t-p} + \varepsilon_{i,j,t}. \quad \textbf{(1)}$$

Note that given the issue-fixed effects structure of the model (α_j), we are assuming that the estimates of interest are 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 changes in issue attention by a given group to predict subsequent attention allocation of the other groups.[19]

The results of the estimated VAR model can be best expressed using cumulative impulse response functions (IRFs). These cumulative IRFs indicate how an x-unit increase in attention to a given topic by a group predicts the cumulative 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 2 two different types of IRFs for a 15-day period.[20] 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 the effect of 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.[21] Each single panel in Figure 2 shows how much more cumulative attention to the issue the group in the panel title is predicted to pay after a one-time (in gray) and permanent (in black) 10 percentage point increase by the groups along the y-axis (the row groups) 15 days ago. The predicted responses (95% confidence interval lines) are expressed in percentage points (0–100 scale). Most one-time effects (gray coefficients) range from 0 to 4. We believe these are meaningful and substantive responses. As we know from the long-standing literature on agenda setting, politics is often a fight for attention and simply getting an issue into the agenda is extremely difficult (Jones and Baumgartner 2005; Schattschneider 1975). Moreover, dynamics of attention often follow nonlinear functions with tipping points, where small amounts of additional attention around the tipping point can have large political implications (Baumgartner and Jones 1993; Kingdon 2013).

The results in Figure 2 corroborate the first two expectations in regard to the ability of members of Congress and the public to predict each other's issue attention. Politicians from both parties (first two rows in all the panels in Figure 2) are able to predict the attention distribution of the public (H_2). Specifically, they are able to lead the issue attention of party supporters and attentive publics, although both parties lead the issue attention of their own supporters than supporters of the opposing party. And we see in the far right panel that the issues prioritized by both parties appear to be very poor predictors of the issue attention of the general public.

We also find strong evidence supporting a political responsiveness dynamic (H_1): we see changes in issue attention by citizens to be positive predictors of the issues members of Congress discuss, and we also see these effects to always be of a larger magnitude than the ability of members of Congress to lead the agenda of the public. The ability of Republican supporters to set political issue agendas represents the most extreme case. This group of the public is predicted to increase the cumulative amount of attention to an issue only by 0.75 and 1.25 percentage points 15 days after a 10-point increase in attention by Democrats and Republicans in Congress, respectively (first and second gray estimates from the top in the fourth panel from the right).

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

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

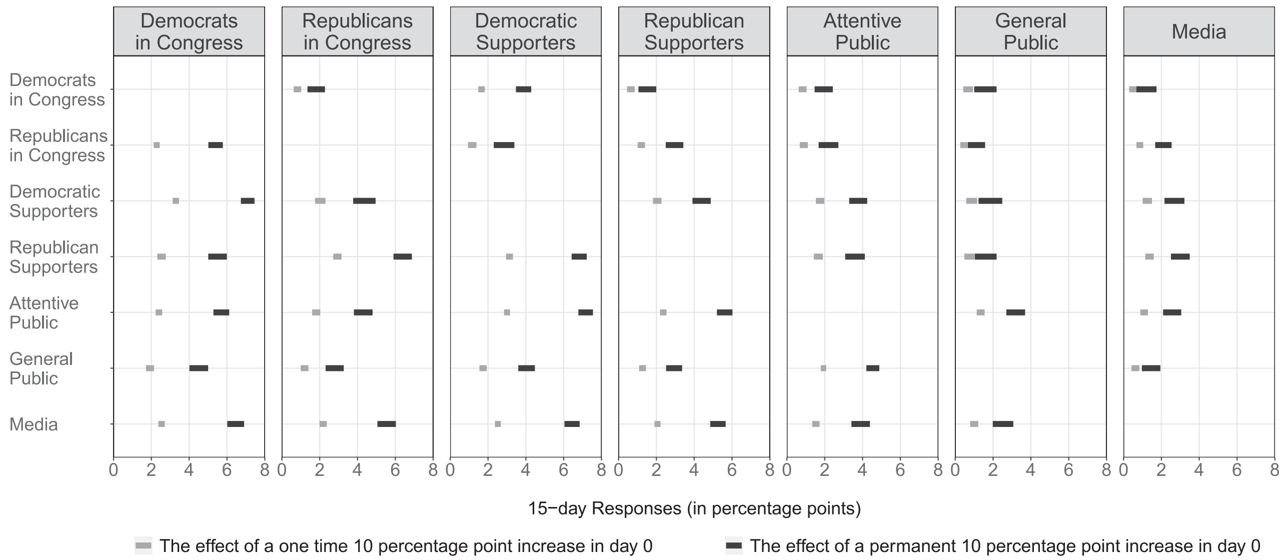
[18] Autocorrelation and partial autocorrelation functions vary depending on the group and issue series one explores. However, on average we observe autocorrelations to go below 0.1 after 5–9 days, and partial autocorrelations to be below this level after 3–5 days; which indicates that by using a seven-lag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

[19] As we point out in the *Discussion*, we believe that future work should focus on studying how the effects presented here are conditional on the issue or issue type at hand. The methods advanced here can, for example, be used to clearly test hypotheses on the relationship between issue responsiveness and issue ownership. This is not, however, the immediate purpose of this study.

[20] In Online Appendix D, we provide results based on shorter and longer term IRFs.

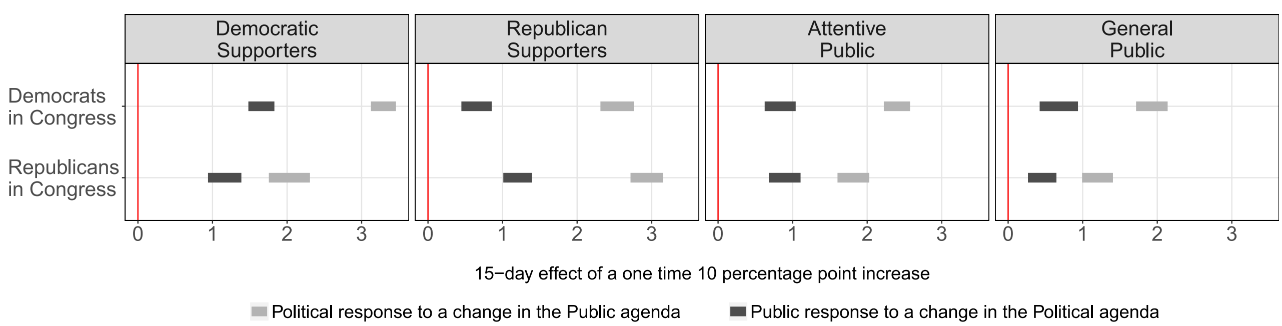
[21] When calculating the IRFs for the permanent 10-percentage-point change, we insert a new increase of attention every day to the covariate of interest until the predicted attention for that group reaches 10% without the need of any extra shock. If we let ϕ represent the attention increase we introduce 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: $\phi_{i,t} = \begin{cases} 10, & \text{if } t \text{ is } 0 \\ 10 - \hat{y}_{i,t} & \text{if } t \text{ is } > 0 \end{cases}.$

FIGURE 2. 15 Day Cumulative IRFs: Predicted Issue Responsiveness Across Groups



Note: The coefficients (with 95% confidence intervals) indicate (in percentage points) how much more cumulative attention the groups in the panel titles paid to a given issue as a result of the groups in the *y*-axis increasing the attention to the same issue by 10 percentage points once (in gray) and permanently (in black) 15 days ago.

FIGURE 3. Politicians' Ability to Set Public Agendas versus the Ability of the Public to Influence Political Agendas



Note: The coefficients (with 95% confidence intervals) indicate (in percentage points) how much more cumulative attention the groups in the panel titles paid to a given issue as a result of the groups in the *y*-axis increasing the attention to the same issue by 10 percentage points (in black) 15 days ago. The gray coefficients indicate the vice versa effect.

The changes in the opposite direction, however, are two to three times larger: both Democrats and Republicans in Congress are predicted to increase their cumulative attention by about 3 percentage points (Republican supporters' gray estimates in the two most left panels).

These differential effects can be better appreciated in Figure 3, where we rearrange the one-time attention changes estimates (gray responses) from Figure 2 to more easily compare who has the largest ability to lead the issue agenda of the other, members of Congress or the public. However, there is an additional factor we need to take into consideration when interpreting these results. As we observed in Figure 5 and Table A.6, politicians devote more attention to political issues than their party supporters (and much more than the attentive and general public). This means that although an increase in attention of the same size has a larger effect when it goes from the public to politicians, we are more likely to observe members of Congress, rather than the public, to make large shifts in political attention.

Our results also provide strong evidence in favor of the Supporter model of responsiveness (H_5). If we focus only on the variables predicting the agenda of members of Congress the most (two left panels in Figure 2), 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 a cumulative attention of 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 some 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 cumulative attention by 2.25 and 5.75 percentage points, respectively, and Republican policy makers 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 cumulative attention of Democratic lawmakers by 2.5 and 5.5 points. However, the estimated effects are of smaller size than the effects we observed in favor of the Supporter model.

Finally, the results show weak support for the Downsian model (H_3). Democratic members of Congress are only predicted to increase their cumulative 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—their cumulative attention increases 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 lead the agenda of members of Congress. The effect of a permanent increase of attention by the general public (black general public estimates in the two left panels) is of a similar magnitude to a one-time attention increase by party supporters (Democratic supporter gray estimate in the left panel and Republican supporter gray coefficient in the second panel from the left). Moreover, given the low attention the general public pays to politics, attention shifts of this magnitude (10 percentage points) are unlikely to take place. Nevertheless, when comparing the results of fitting the same model only to data from 2013 with data only from 2014, we interestingly find that politicians are slightly more responsive to the general public during election year (2014) than during a non-election year (although even during an election year politicians are also more likely to follow shifts in attention by party supporters and the attentive public).[22]

Overall, the results show that politicians are more likely to follow changes in issue attention distribution by their own party supporters than to attentive voters, and that they rarely follow the issue priorities of the general public.

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 salient to these groups. To test this hypothesis, we first need to estimate by how much each group led 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 lead the agenda of the others is constant across issues, and we model the data in a different way. In the previous model, 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 seven-lag structure. Then, for each of the VAR issue models, we calculate 15-day cumulative IRFs capturing how a one-time 10 percentage point increase in attention by a specific group predicts the attention of the other groups.

Figure 4 shows the results (15-day IRFs) for each of these 46 VAR models. Each panel reports how the groups in the panel titles are predicted to respond to changes in attention by the other groups: the circles represent the predicted effects (with lines representing a 95% confidence intervals), the colors of the circles show the group to which they are reacting, and the labels on 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 lead 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 lead public issue attention. We only include the predicted effects for issues where the confidence intervals do not cross zero.[23]

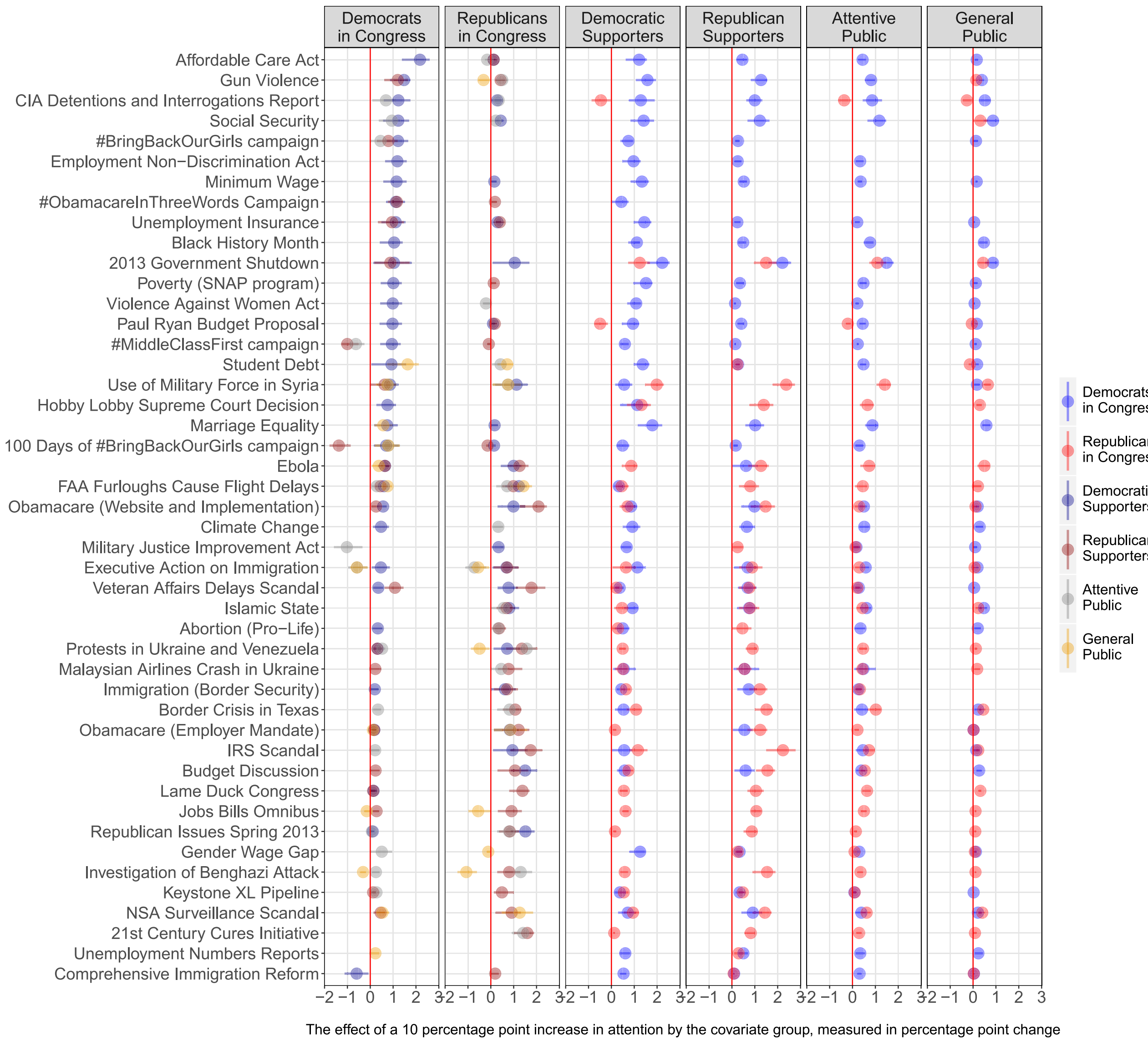
The issues are sorted based on the predicted impact of Democratic Supporters on Democrats in Congress: from the issues with the largest estimated impact to the issues with the smallest. Among the top rows, we find issues such as healthcare reform ("Affordable Care Act," row 1), gun violence (row 2), and minimum wage (row 7). A one-time 10-percentage-point increase on these issues by Democratic supporters is predicted to increase the cumulative attention that Democratic members of Congress pay to them by 2, 1.5, and 1 percentage points.

In the second panel from the left, we see the issues in which Republican supporters more strongly led the agenda of Republicans in Congress by looking at the red circles. The discussions around the IRS scandal (row 35) that took place around mid-2013 and the implementation of the Affordable Care Act and its website problems (row 23) were the issues on which Republican members of congress seemed to follow their supporters the most. In both cases, a one-time 10 percentage point shift is predicted to translate into an increase of cumulative attention of about 2 percentage points 15 days

[22] See Online Appendix E.1.

[23] In Online Appendix C, we show predicted effects for all issues.

FIGURE 4. Predicted Issue Responsiveness Across Issues and Groups (15 Day IRFs)



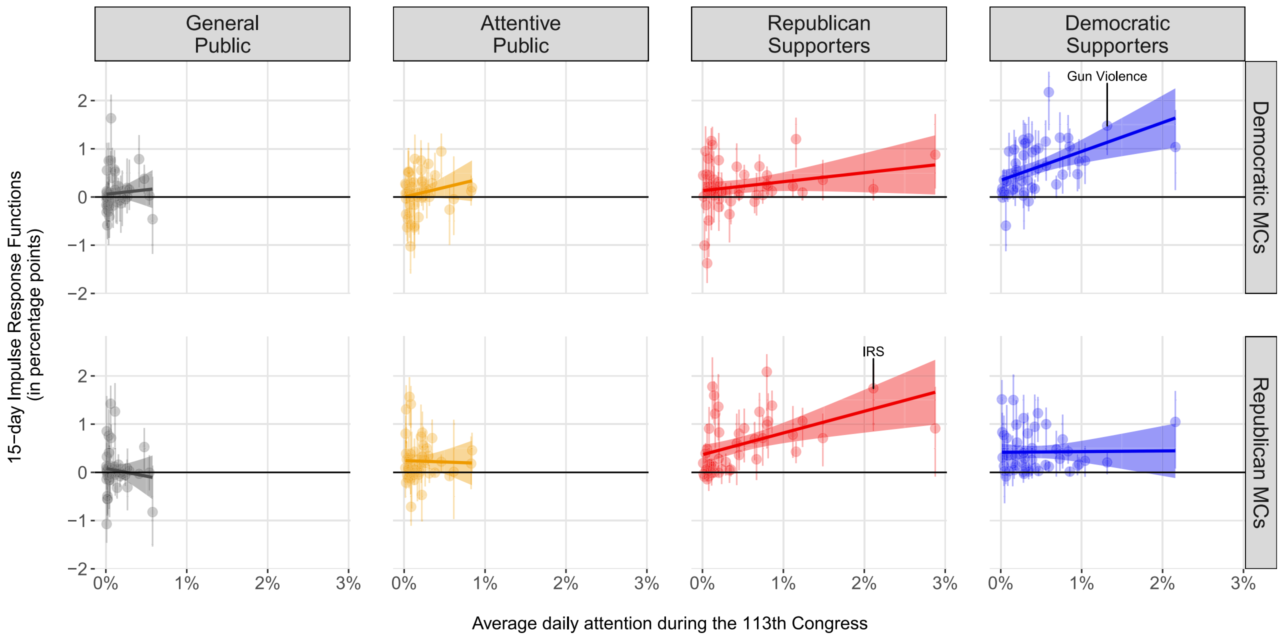
Note: The coefficients (with 95% confidence intervals) indicate (in percentage points) how much more/less cumulative attention the groups in the panel titles paid to the issue in the *y*-axis as a result of a group (identified by the color) increasing the cumulative attention to the same issue by 10 percentage points 15 days ago. Only coefficients not crossing zero have been included. 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. Versions of this figure that also show the coefficients crossing zero are available in Online Appendix C.

later. The effects represented by gray circles in the left-most panel indicate that social security (row 4) is the issue on which the attentive public was able to lead the discussion of Democratic members the most, and in the second panel, we see that they particularly led the attention that Republican members paid to the protests in Ukraine and Venezuela (row 30). The effects represented by orange circles in the two left panels indicate that discussions by Democratic and Republican members of congress on student debt (row 16) and the use of military force in Syria (row 17), respectively, were among the ones that the general public was able to positively lead the most.

To test the last of our hypothesis, that members of Congress will be more likely to follow shifts in attention on issues to which constituents pay more attention (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 (these averages are displayed in Figure 1). 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 and to capture instead how important the issue was for that specific group in general.

With this measure of average attention and the estimates from Figure 4 in hand, we can now move to

FIGURE 5. Correlation Between Public Issue Relevance and the Ability of the Public to Set Political Agendas



Note: The *x*-axis indicates the average attention the groups in the top panel titles paid to each political topic during the 113th Congress. The *y*-axis indicates how much more/less cumulative attention Democrats (top four panels) and Republicans in Congress (bottom four panels) paid to these topics as a result of the groups in the top panel titles increasing the attention to the topic by 10 percentage points 15 days ago. Each dot represents a different political issue and the lines around the dots represent 95% confidence intervals. Rows are sorted by the largest effect of Democrats in Congress (left panel).

a direct test of H_6 by examining correlations between the two. Accordingly, in Figure 5 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 cumulative attention members of Congress are predicted to pay to each issue as result of the groups in the panel title increasing their attention by 10 percentage points 15 days ago (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 predicted response of Democratic members of Congress, whereas the bottom ones illustrate the predicted reaction of Republican lawmakers.

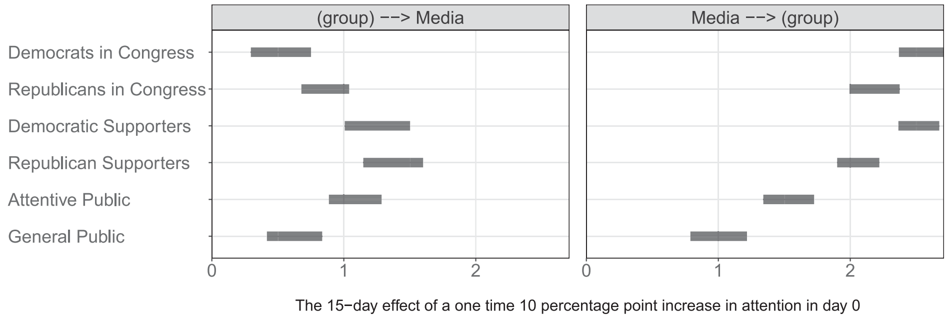
We find support for the issue relevance hypothesis (H_6) only as it relates to the Supporter model. In the top right panel, we observe that changes in attention by Democratic supporters have a larger effect on the agenda of Democrats in Congress when they involve issues Democratic supporters deem relevant (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 lead the expressed agenda of Republicans in Congress on issues that are important to them (such as the discussion around the Internal Revenue Service—IRS). Thus, members of congress appear to behave as if they are more likely to pay attention to the views of their supporters on issues their supporters care more about than on issues they care less.

In Figure 5, 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 follow 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 of a very small magnitude. For Republicans in Congress, we do not even see a positive correlation between how much they follow shifts in attention on particular topics and the average attention the attentive public and supporters of the other party paid to the issues (flat yellow and blue lines at the bottom). Finally, we observe no correlation between how much the general public leads politicians' agenda and the amount of average attention the general public devotes to any given issue. Overall, these results validate the strong findings from Figure 2 in favor of the Supporter model, as well as the lack of evidence in support of the Downsian model of responsiveness.

The Role of the Media

We now turn to an evaluation of the role played by news media in mediating the dynamics identified in this paper. Our data and methods allow us to examine in detail whether the mass media is equally likely to lead, and be led by, politicians and the public—or whether, in contrast, the media strengthens the voice of some groups and increases their ability to lead political agendas.

FIGURE 6. Predicted Media Effects



Note: The effects (with 95%) in the left panel indicate how much the media outlets increased their attention to a given issue (in percentage points) 15 days after the groups in the *y*-axis increased their attention to the same issue by 10 percentage points. The coefficients in the right panel indicates the vice versa effects, how much the groups in the *y*-axis increase their attention to an issue 15 days after the media increased the attention to the same issue by 10 percentage points.

TABLE 4. Correlation in Issue Attention Between Media Outlets and the Other Groups of Analysis

Group	Media
Democrats in Congress	0.52
Republicans in Congress	0.63
Attentive public	0.74
Democratic supporters	0.79
Republican supporters	0.79
General public	0.55

As a first cut, Table 4 confirms previous work indicating that media coverage reflects both politicians' and the public's issue priorities. The table displays correlations between the distribution of attention to issues by the media and that of the other groups under study. We find a particularly strong relationship between media issue attention and the issue attention of politically engaged Americans—that is, party supporters and the attentive public. Less substantial, but still very strong, relationships exist between the issue attention of mass media and that of members of Congress and the general public.

These correlations, of course, do not provide information about the directions of these relationships. For a clearer picture of the role of the media, we take a closer look at the IRF coefficient estimates regarding the media originally displayed in the final column and bottom row of Figure 2, plotting them in more detail in Figure 6. In this figure's left panel, media coverage is the dependent variable. Plotted here are the estimated impacts of changes in the attention to issues given by politicians and the public on the attention given to these issues by media. Here, we observe that demand-side forces (namely, the priorities of the most politically engaged Americans) are stronger predictors of what the media covers than supply-side forces (i.e., the priorities of members of Congress). These results corroborate the argument that media outlets are particularly likely to follow shifts in attention by the public due to market pressures (Anand and Peterson 2000; Webster and Ksiazek 2012) and suggest that the effort expended by lawmakers to raise the salience of their favored issues is relatively less influential.

In the right panel of Figure 6, media coverage is the independent variable. This panel displays the estimated impacts of changes in media issue attention on the attention given to these issues by politicians and the public. Shifts in issue attention by media outlets have the strongest impact on the issue agendas of members of Congress and of party supporters. Notably, in each case, the power of shifts in media attention to predict subsequent shifts in attention among all audiences is greater than the reverse, confirming that media outlets play a crucial role in leading political attention (Soroka 2002; Walgrave, Stuart, and Nuytemans 2008; Walgrave and Van Aelst 2006). Finally, the media effects in Figure 6 suggest that news media contribute to the promotion of a Supporter responsiveness model. Not all groups of the public are equally likely to lead the issues covered by media outlets. The "voice" of Democratic and Republican supporters is stronger than the voice of the attentive citizens and the general public. This is particularly relevant given that, as we observe in the right panel in Figure 6, the issues covered by the media are strong predictors of the subsequently expressed issue agenda of members of Congress.

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 leads 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 follow shifts in issue attention by their constituents when deciding what issues to discuss, but also to adjudicate between three competing models of political responsiveness: whether public representatives follow changes in attention by their party supporters, the attentive public, or the general public.

We modeled how public and political agendas predict 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. The public was not only able to lead the expressed agenda of members of Congress, but the magnitude of this phenomenon was greater than that associated with politicians' ability to lead public agendas: an attention shift from party supporters preceded a larger shift by members of Congress than the attention shift from party supporters following an attention shift by members of Congress. 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. The findings also suggest that mainstream media promote similar dynamics: they are particularly likely to follow the issue preferences of party supporters, and they are likely to lead the issue agenda of members of Congress. In addition, we observed Democrats and Republicans in Congress to particularly follow 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.

These issue responsiveness findings align with the literature on policy and policy preference responsiveness that shows that political and policy agendas in the United States are mainly driven by the priorities of strong partisans (Clinton 2006; Kastellec et al. 2015; Shapiro et al. 1990). The study also supports the claim that, due to existing representation and responsiveness dynamics, political agendas are more polarized than is the American public (Grimmer 2013). While others show that this is in part a function of geographic sorting and an increasing number of clearly partisan districts (Bishop and Cushing 2008; Grimmer 2013), we show that low political attention by the general public and a higher media coverage of partisan issue preferences is also in part to blame. This has important normative implications for democratic politics, as it could be an indirect factor contributing to political polarization.

Our analysis is limited to the 113th Congress, but we argue that our findings are likely to be generalizable to the current context. Social media usage by members of Congress was already almost universal in 2013. In addition, data from the Pew Research Center show that Twitter penetration among online US adults has remained around 20% for the last five years (Smith and Anderson 2018). The fact that Twitter has become more central in US politics (Gainous and Wagner 2013), particularly after Trump was elected President, means that we would expect our findings to be more valid today and lead to more precise estimates. However, one result that may not hold today may be the notable partisan asymmetry we observe regarding the relationship between legislators and the media, which appears to be stronger for Republicans than for Democrats. This pattern could be a function of the political context, and in particular of which party is in the opposition, or it could be related to structural factors, such as the asymmetric fragmentation of the media system—currently larger on the left than on the right in the United States.

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 (Lawrence and Boydstun 2017; Wells et al. 2016)—a finding that may be worth revisiting in the era of Trump's presidency. Do politicians running in safe versus marginal districts respond to different types of constituents? Do politicians respond differently to constituents' issue priorities depending on the issues they own? And how would these results differ across institutional or political contexts? In particular, we might have reason to expect higher levels of responsiveness in countries with higher levels of political contestation (Hobolt and Klemmensen 2008).

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 (Erikson, Mackuen, and Stimson 2002; Jones and Baumgartner 2004; Page and Shapiro 1983; Stimson, Mackuen, and Erikson 1995). A relevant number of political decisions, however, are made at the state level. Are state policy makers 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-grained temporal measure that Twitter data offer 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 related to political representation in the future.

SUPPLEMENTARY MATERIAL

To view supplementary material for this article, please visit https://doi.org/10.1017/S0003055419000352.

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

CONTENTS

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, 2002, "Number of Responses and the Most Important Problem") and because it is unclear whether it is measuring issue salience or problem perception (Wlezien, 2005, *Electoral Studies*). 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, *Electoral Studies*), we expect such correlation not to be perfect.

We collect Gallup's MIP data from January 2013 though December 2014 from the Roper Center.[1] The data contains individual MIP responses that have been manually coded according to the 19 issue-classification of the Comparative Agendas Project (CAP).[2] 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

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

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

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

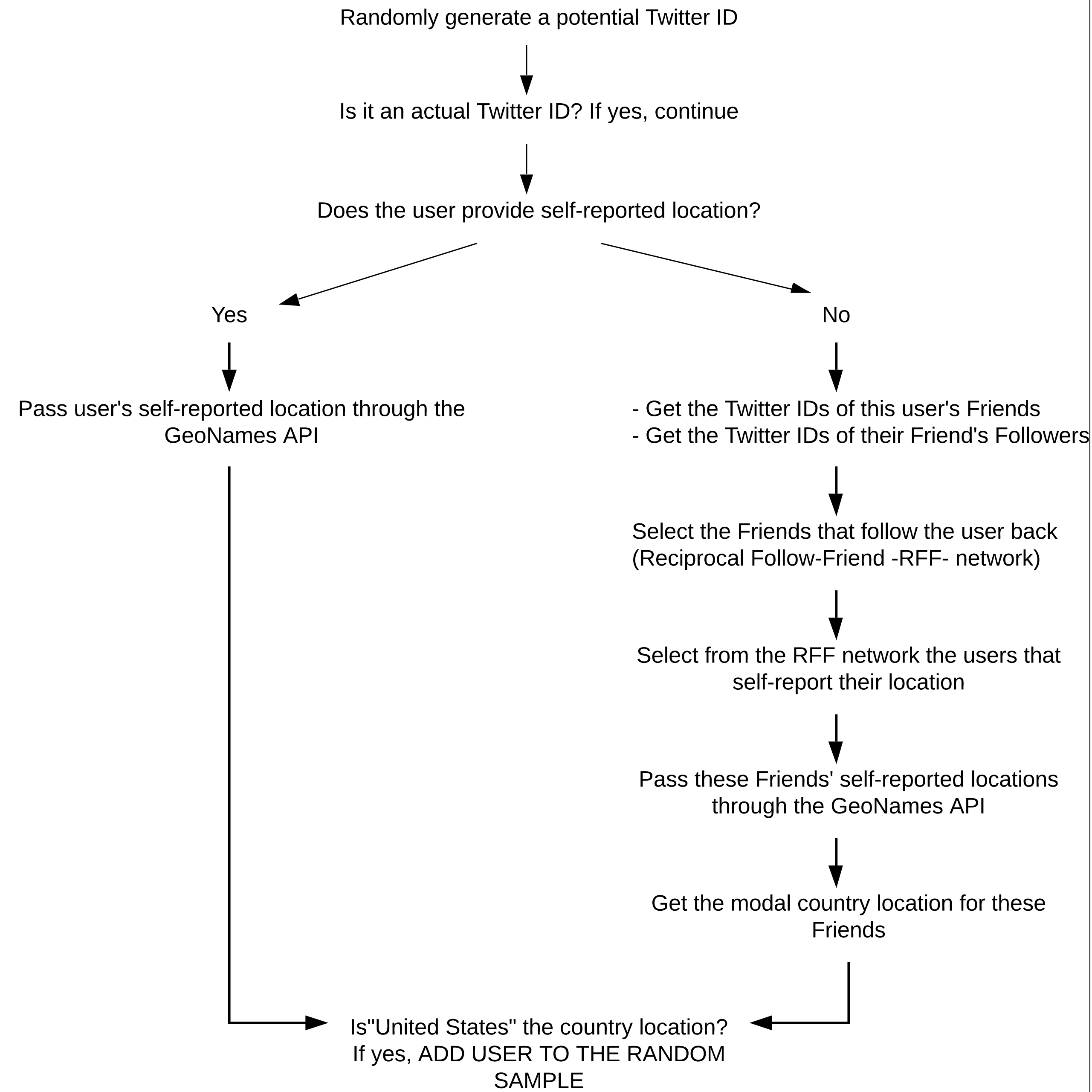
	Gallup MIP Responses					
Twitter Measure	Full Sample	Democrat	Weak Democrat	Independent	Weak Republican	Republican
Democratic Supporters	0.46	0.49	0.46	0.43	0.41	0.45
Republican Supporters	0.69	0.68	0.68	0.66	0.67	0.70
Attentive Public	0.35	0.35	0.34	0.35	0.33	0.35
General Public	0.37	0.39	0.37	0.38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

TABLE A1. Comparative Agendas Project codes assigned to our political issues

Topic #	Our Label	CAP Major	CAP Minor
3	Investigation of Benghazi Attack	16: Defense	1619: Foreign Operations
7	100 Days of #BringBackOurGirls campaign	19: International Affairs	1927: Terrorism
9	Gender Wage Gap	2: Civil Rights	202: Gender Discrimination
11	Hobby Lobby SC Decision (Dem.)	2: Civil Rights	207: Freedom of Speech
12	Republican Issues Spring 2013	6: Education	600: General
14	Marriage Equality	2: Civil Rights	202: Gender Discrimination
15	Gun Violence	12: Law and Crime	1299: Other
16	Abortion (Pro-Life)	2: Civil Rights	208: Right to Privacy
17	2013 Government Shutdown (Rep.)	1: Macroeconomics	105: National Budget
18	Veteran Affairs Delays Scandal	16: Defense	1608: Personnel Issues
20	NSA Surveillance Scandal	16: Defense	1603: Intelligence
23	#BringBackOurGirls campaign	19: International Affairs	1927: Terrorism
26	2013 Government Shutdown (Democrats)	1: Macroeconomics	105: National Budget
27	Student Debt (2014)	6: Education	601: Higher Education
28	Employment Non-Discrimination Act	5: Labor	505: Fair Labor Standards
32	Islamic State	16: Defense	1619: Foreign Operations
33	Use of Military Force in Syria	16: Defense	1619: Foreign Operations
35	2013 Budget Sequestration (Republicans)	1: Macroeconomics	105: National Budget
36	Ebola	3: Health	331: Disease Prevention
37	Social Security	13: Social Welfare	1300: General
38	Budget Discussion (early 2014)	1: Macroeconomics	105: National Budget
39	Keystone XL Pipeline	8: Energy	803: Natural Gas and Oil
41	Immigration (Border Security)	9: Immigration	900: General
42	2013 Budget Sequestration (Democrats)	1: Macroeconomics	105: National Budget
43	Executive Action on Immigration	9: Immigration	900: General
46	Unemployment Numbers Reports	1: Macroeconomics	103: Unemployment Rate
47	Paul Ryan Budget Proposal	1: Macroeconomics	105: National Budget
48	Black History Month	2: Civil Rights	201: Minority Discrimination
49	2013 Budget Agreement	1: Macroeconomics	105: National Budget
50	Climate Change	7: Environment	705: Air Pollution
51	Lame Duck Congress	20: Government Operations	2099: Other
53	Minimum Wage	5: Labor	505: Fair Labor Standards
56	Student Debt (2013)	6: Education	601: Higher Education
58	Affordable Care Act	3: Health	301: Health Care Reform
59	Budget Discussion (mid-2014)	1: Macroeconomics	105: National Budget
62	Border Crisis in Texas	9: Immigration	900: General
63	Obamacare (Employer Mandate)	3: Health	301: Health Care Reform
64	FAA Furloughs Cause Flight Delays	20: Government Operations	2099: Other
66	Malaysian Airlines Crash in Ukraine	19: International Affairs	1921: Specific Country
67	Comprehensive Immigration Reform	9: Immigration	900: Immigration
70	#MiddleClassFirst campaign	1: Macroeconomics	107: Tax Code
74	Hobby Lobby SC Decision (Rep.)	2: Civil Rights	207: Freedom of Speech
75	Military Justice Improvement Act	16: Defense	1608: Personnel Issues
81	Poverty (SNAP program)	13: Social Welfare	1302: Low-Income Assistance
83	21st Century Cures Initiative	3: Health	398: R&D
85	Unemployment Insurance	5: Labor	503: Employee Benefits
88	IRS Scandal	1: Macroeconomics	107: Tax Code
89	Obamacare (Website and Implementation)	3: Health	301: Health Care Reform
93	Jobs Bills Omnibus	5: Labor	500: General
96	Violence Against Women Act	2: Civil Rights	202: Gender Discrimination
97	Protests in Ukraine and Venezuela	19: International Affairs	1921: Specific Country
99	CIA Detentions and Interrogations Report	16: Defense	1603: Intelligence
100	#ObamacareInThreeWords Campaign	3: Health	301: Health Care Reform
101	Student Debt	6: Education	601: Higher Education
102	Hobby Lobby SC Decision	2: Civil Rights	207: Freedom of Speech
103	Budget Discussion	1: Macroeconomics	105: National Budget
104	2013 Government Shutdown	1: Macroeconomics	105: National Budget

B. PROCEDURE TO ELABORATE THE RANDOM SAMPLE OF U.S. TWITTER USERS

FIGURE A1. Flowchart describing the method used to elaborate the random sample of 25,000 U.S. Twitter users



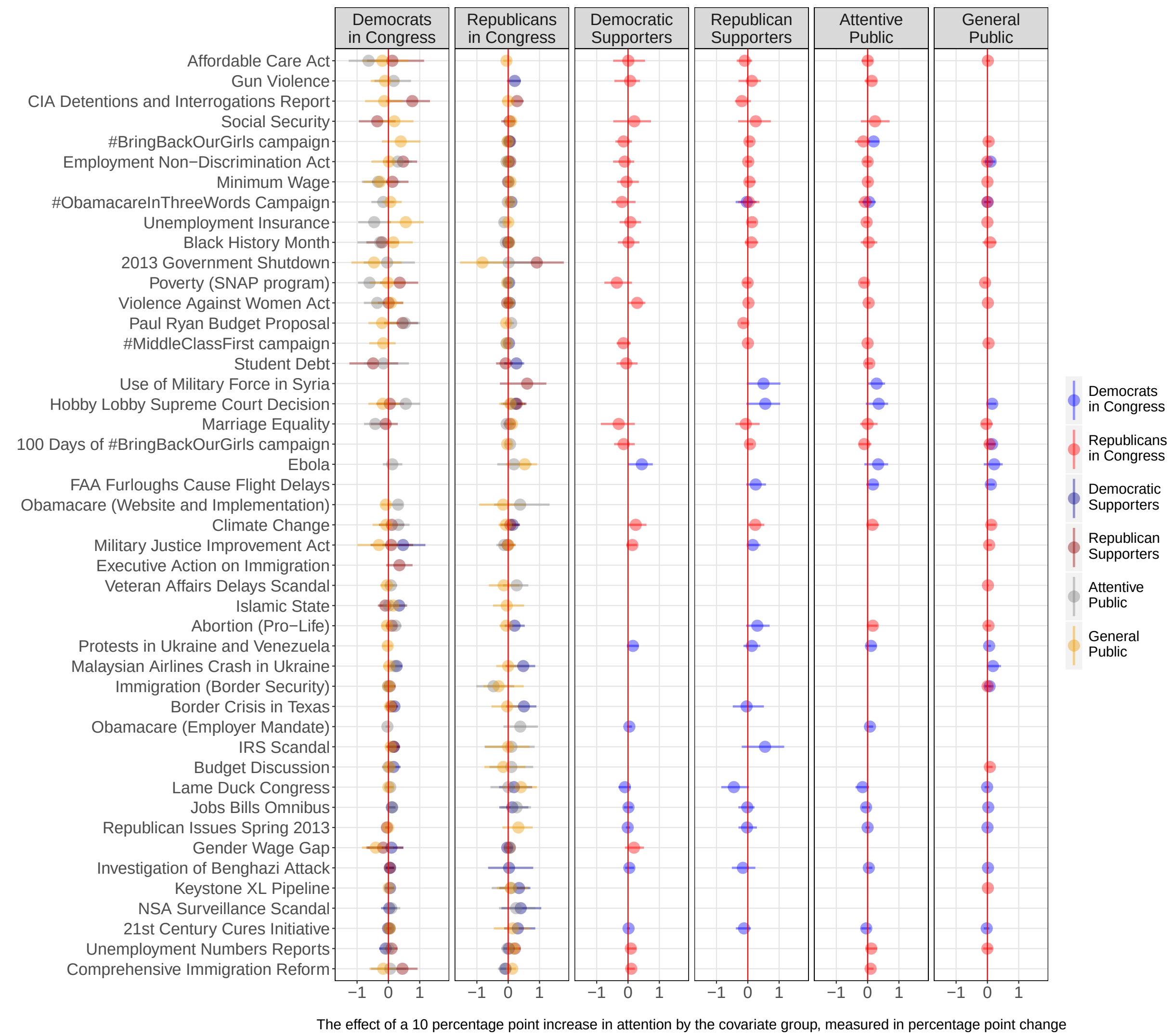
C. COMPLETE ISSUE-LEVEL RESULTS

In Figure 4 we reported issue-level responsiveness results. To avoid overcrowding the figure, we only reported coefficients that did not cross zero. In here we include two new versions of the same figure. Figure A2 reports all the coefficients and Figure A3 shows only those that do cross zero (so the ones not included in Figure 4). Finally, in TableA3 we provide a count of the issues for which a shift in an attention by a given group had a statistically significant effect on another group.

FIGURE A2. Predicted Issue Responsiveness Across Issues and Groups.

Note: The coefficients (with 95% confidence intervals) indicate (in percentage points) how much more/less cumulative attention the groups in the panel titles paid to the issue in the y-axis as a result of a group (identified by the color) increasing the attention to the same issue by 10 percentage points 15 days ago. All coefficients have been included. 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.

FIGURE A3. Predicted Issue Responsiveness Across Issues and Groups.



Note: The coefficients (with 95% confidence intervals) indicate (in percentage points) how much more/less cumulative attention the groups in the panel titles paid to the issue in the y-axis as a result of a group (identified by the color) increasing the attention to the same issue by 10 percentage points 15 days ago. Only coefficients crossing zero have been included. 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.

TABLE A3. Number of topics for which an attention shift by a given group had a statistically significant effect on another group.

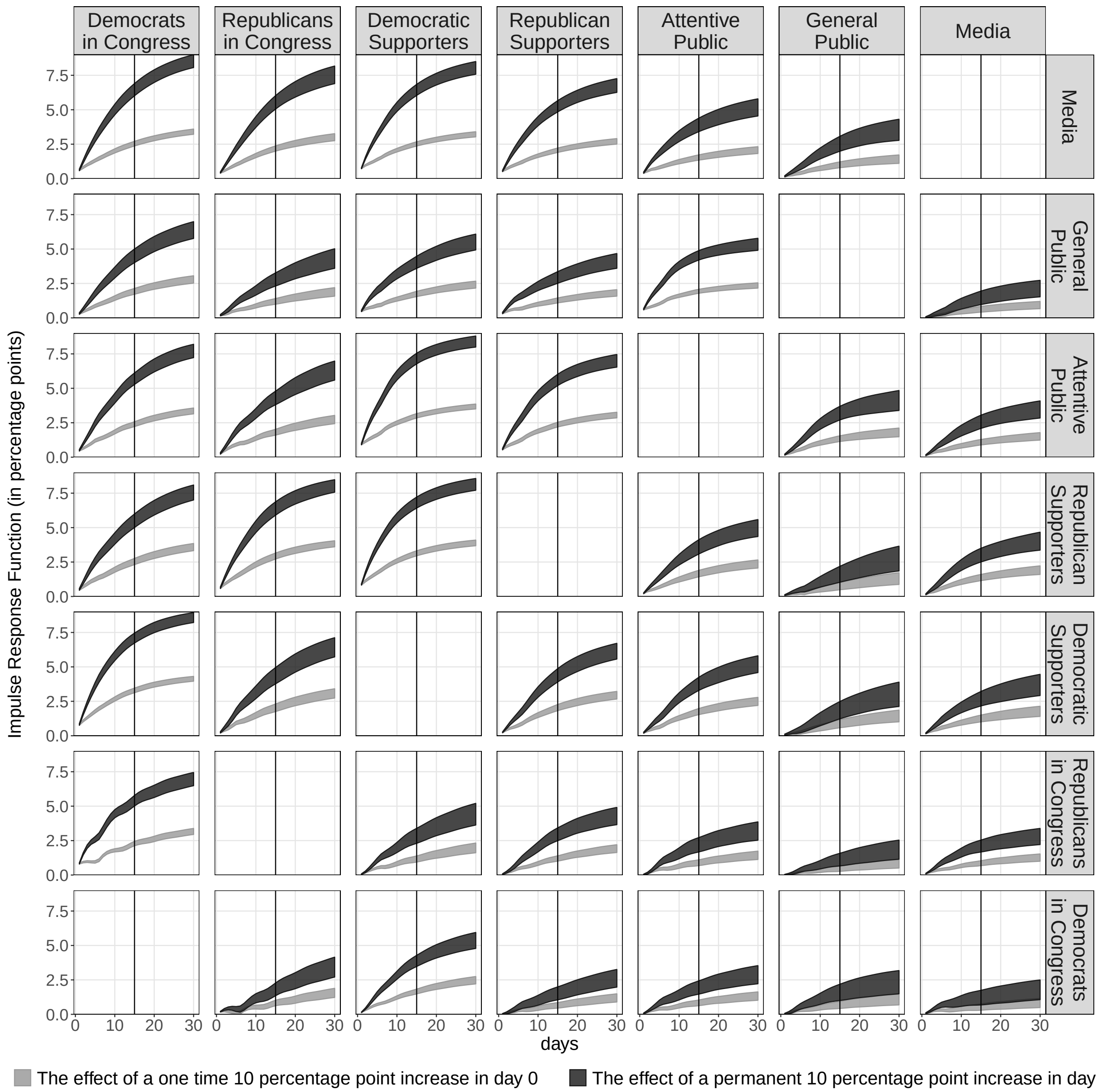
Covariate	Outcome	Num. of Significant Topic Effects
Democrats in Congress	Democratic Supporters	39/46
Democrats in Congress	Republican Supporters	33/46
Democrats in Congress	Attentive Public	34/46
Democrats in Congress	General Public	24/46
Republicans in Congress	Democratic Supporters	24/46
Republicans in Congress	Republican Supporters	28/46
Republicans in Congress	Attentive Public	26/46
Republicans in Congress	General Public	12/46
Democratic Supporters	Democrats in Congress	32/46
Democratic Supporters	Republicans in Congress	22/46
Republican Supporters	Democrats in Congress	18/46
Republican Supporters	Republicans in Congress	28/46
Attentive Public	Democrats in Congress	16/46
Attentive Public	Republicans in Congress	19/46
General Public	Democrats in Congress	4/46
General Public	Republicans in Congress	4/46

D. FULL 60-DAY IMPULSE RESPONSE FUNCTIONS

In the paper we use 15-day Cummulative Impulse Response Functions (IRFs) to study responsiveness dynamics among the different groups of analysis. We could have used shorter or longer term IRFs: shorter-term IRFs would have revealed smaller effects while longer ones would have shown stronger effects. We believe that 15 days is a reasonable time window: it allows for the seven lags included in the model to come into effect and for all the reciprocal channels of influence to be activated, while still keeping the simulated scenario in the realm of what is feasible (we can envision most political discussions to go for about a week or two, but probably not for much longer).

Nevertheless, in this appendix we provide full 60-day cumulative IRFs estimated (Figure A4) to show that the reported 15-day IRFs are indeed a middle ground between low immediate effects and a much stronger (but rather unfeasible) long-term influence.

FIGURE A4. 60 day Cumulative Impulse Response Functions.



Note: The lines in the panels (with 95% confidence intervals) indicate how much more attention the groups in the panel titles pay to a given issue up to 60 days after the groups in the y-axis increased the attention to the same issue by 10 percentage points. The vertical line in each panel indicates the 15-day Cumulative IRFs reported in the paper (Figure 2).

E. ROBUSTNESS CHECKS

In this Appendix we evaluate the extent to which the results presented in the paper depend on a set of modeling choices. In particular, we evaluate the effects of: **a)** having in our sample members of Congress that were up for re-election in 2014 (all House representatives plus a third of the Senators) and Senators that were not (we compare our results when running the model with 2013- and 2014-only data), **b)** using broader rather narrow political issue categories (we compare our results to results based on mapping our issues to the *Comparative Policy Agendas* (CAP) major issue categories), **c)** using narrow topics from an unsupervised model instead of topics from a supervised approach that are based on an existing classification of narrow political issues (we compare the results in the paper to results based on mapping our issues to the CAP minor issue categories), **d)** fitting the LDA model only to tweets from members of Congress instead of the tweets from all the groups in the study (politicians, the public, and the media).

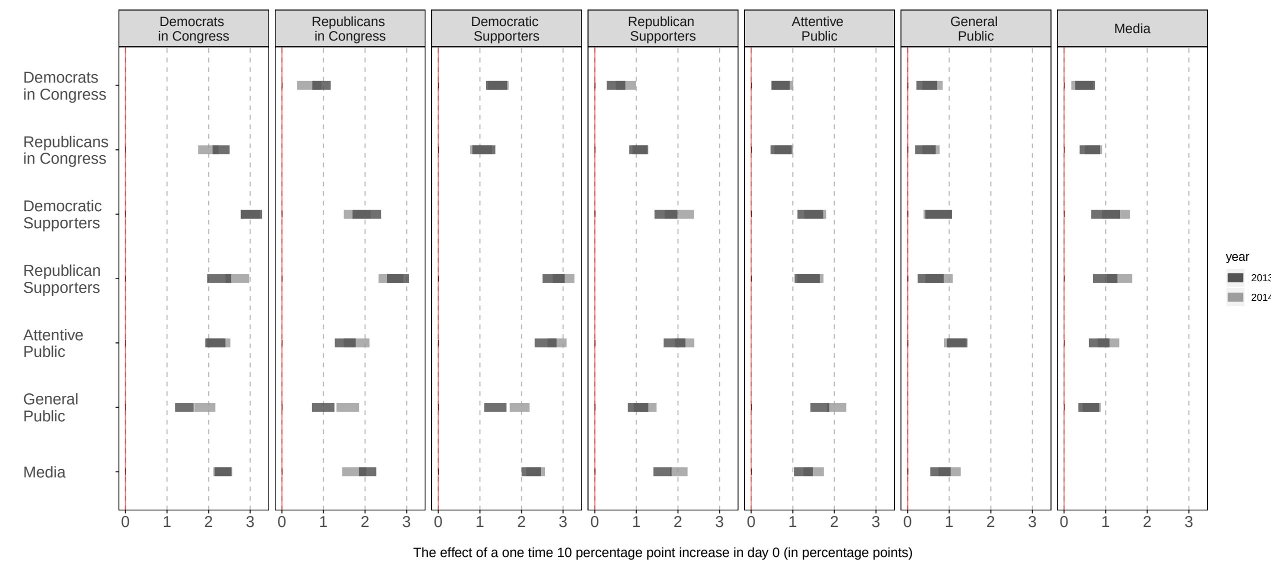
E.1. Exploring Election-Year Effects: Modeling 2013 and 2014 Data Separately

Theoretical accounts (Fiorina, 1973, *American Politics Quarterly*; Mayhew, 1974, *Congress: The electoral connection*) and empirical findings (Soroka and Wlezien 2009; Gilens 2012) indicate that politicians should be more responsiveness to the issue and policy preferences of the public in election years. In this Appendix we first check whether that is the case (its is: politicians are more likely to be responsive to the general public during election years), and then, we explore whether the main findings of the paper hold when looking at results from election *versus* non-election years (they do).

At the end of 2014, the second year of the 113th Congress (our period of analysis), there was a mid-term election and so all House representatives and a third of the Senators were up for re-election. In a study of policy (not issue) responsiveness in the United States, Gilens (2012) shows that public representatives respond to the policy preferences of the general public only in election years. We follow a similar strategy and use the same exact dataset used in the paper (time-series indicating the attention that Democrats in Congress, Republicans in Congress, Democratic Supporters, Republican Supporters, Attentive Publics, General Public, and the Media paid to 46 political issues) and compare results for the the main VAR model of the paper (Equation 1) when only fitting it to data from a non-election year (2013) *versus* fitting it to data from an election year (2014).

Figure A5 shows the two new model results. Overall, we do not see strong election-year effects. In the two most left panels we observe Democrats and Republicans in Congress to show similar degrees of responsiveness in 2013 and 2014: there is an overlap between most gray and black coefficients. For example, in both years Democrats in Congress were equally responsive to their party supporters. There is however one noticeable difference. In line with Gilens (2012) and Soroka and Wlezien (2009)'s findings on policy (not issue) preferences, we do observe that members of Congress are more likely to respond to the issue preferences of the general public during election years: the gray and black

FIGURE A5. Comparing VAR results and responsiveness dynamics from election (2014, darker coefficients) *versus* non-election years (2013, lighter coefficients).



Note: The coefficients indicate (in percentage points) how much more attention the groups in the panel titles pay to a given issue 15 days after the groups in the y-axis increased the attention to the same issue by 10 percentage points.

coefficients for the General Public in the two most left panels do not overlap. The findings support the argument that when they are not facing an electoral contest, public representatives are mostly responsive to their immediate and mobilized constituents, such as their party base, attentive constituents and interest groups. Nevertheless, in order to increase their chances of reelection, they do pay a bit more attention to the issues preferences of the general public during election years. In Figure A5 we observe how in 2014 the ability of the general public to set the issue agenda of members of Congress was similar to the ability of attentive voters and the media, whereas in 2013 it was much lower than any other group of the public or the media.

Finally, the results in Figure 12 indicate that the main findings of the paper hold when fitting the model to data from an election-year only: we still observe some the public to have a stronger ability to set the issue preferences of members of Congress than the other way around; and we still see members of Congress to be mostly responsive to the issue preferences of their party supporters and attentive public, although we do observe the general public to have a bit more influence on the political agenda during election years.

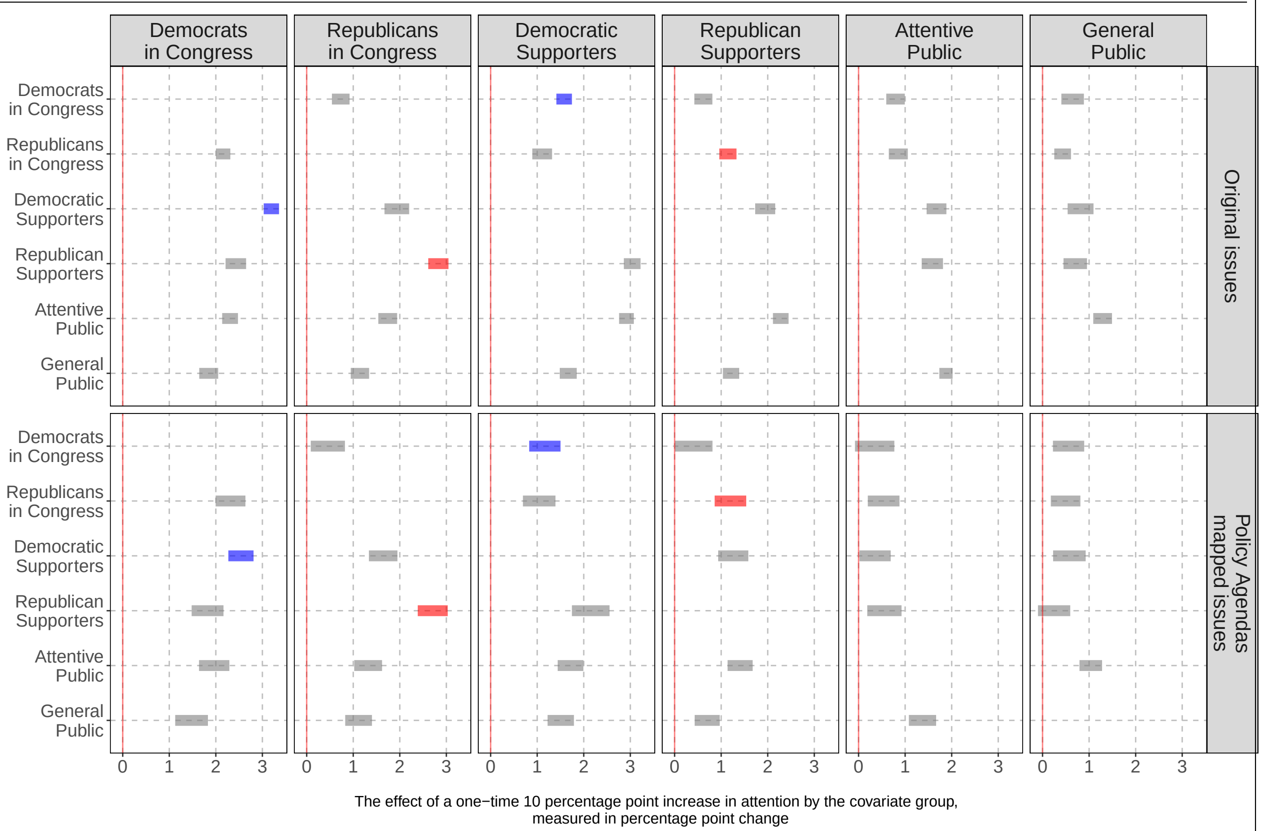
E.2. Modeling Broader Political Issues

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 here we run a robustness check to evaluate the extent to which our results are a function of studying specific instead of broader issues.

FIGURE A6. 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).



Note: The coefficients indicate (in percentage points) how much more attention the groups in the facet titles pay to a given issue 15 days after the groups in the y-axis increased the attention to the same issue by 10 percentage points.

First, we use the crosswalk Table A1 from the *Validation of Discovered Topics* Appendix to map each of our 46 political issues to a issue-classification based on much broader issues: the 19 major topic classification of the Comparative Agendas Project (CAP).[3] Then we re-estimate the same VAR model presented in the paper (Equation 1). In Figure A6 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).

Three main points stand out. First, when modeling attention to CAP major 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 3 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 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.

E.3. Modeling an Existing Classification of Narrow Political Issues

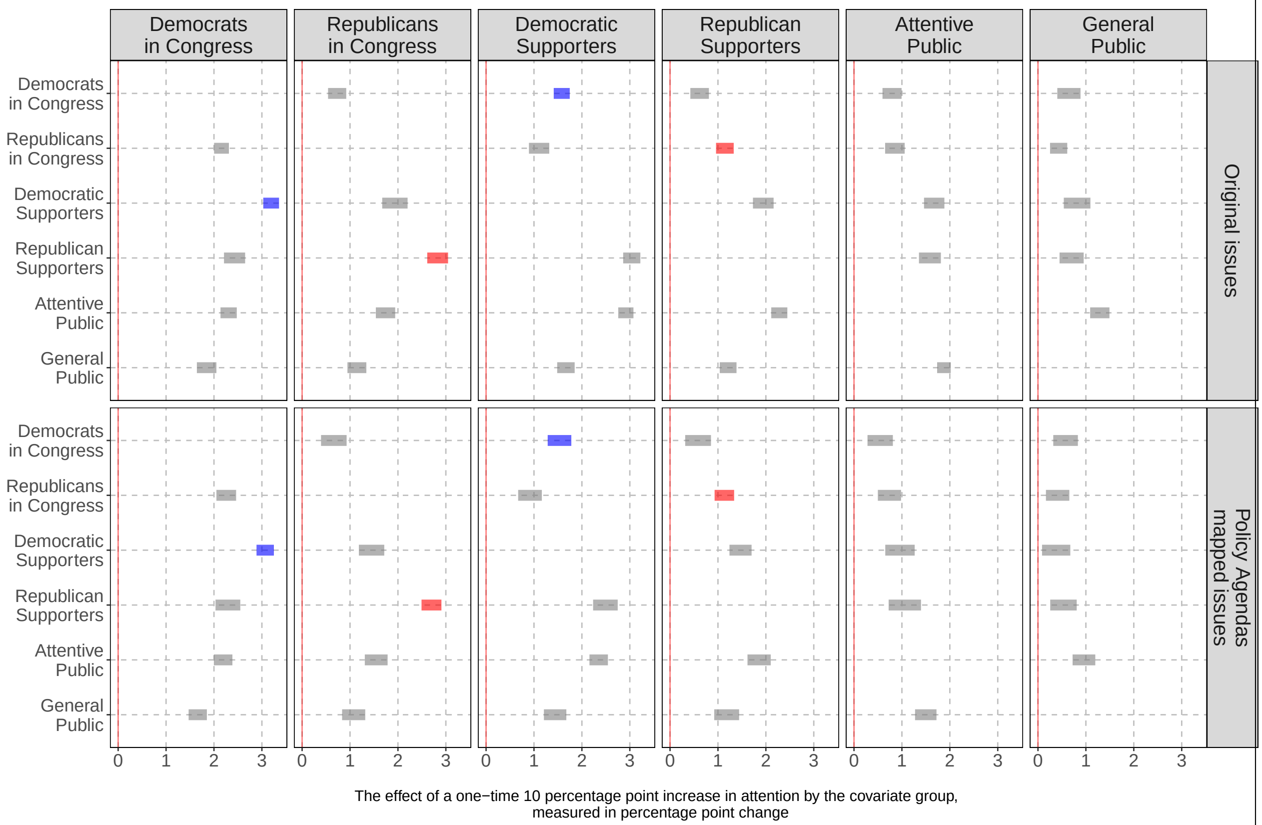
The Comparative Agendas Project has also developed a set of minor issue codes for each of the major issue categories, breaking the 19-issue classification into a 314-(minor)-issue categorization. Hence, instead of using an unsupervised method (LDA) to discover a set of narrow political topics, we could have used the CAP minor issue codes to manually label a set of tweets from our study and then train supervised machine learning classifiers capable of automatically classifying the rest of the tweets.

We decided not to take this path for two main reasons. First, despite the large number of minor topic codes, some are still of a broad nature. For example, there is only one minor *Immigration* topic but, as addressed in the previous subsection, we have discovered that members of Congress discussed more than one immigration-related issue during the 113th Congress. Moreover, training accurate classifiers capable of predicting all minor topic codes would have required to manually label an incredibly large number of tweets.

Nevertheless, here we follow the same procedure described in E.2 to assess whether we reach similar conclusions when we map our issues to the CAP minor issue codes and then re-run the analysis (see Table A1 for the CAP minor topic codes assigned to each of our topics). In Figure A7 we compare the original results in the paper (top six panels) to the results that originate from mapping our issues to the CAP minor issue codes (six bottom panels). The results are essentially the same. Politicians

[3] `http://comparativeagendas.net/`

FIGURE A7. A comparison between the VAR results in the paper and the VAR results of a model exploring attention to the minor issue codes of the Comparative Policy Agendas classification.



Note: The coefficients indicate (in percentage points) how much more attention the groups in the facet titles pay to a given issue 15 days after the groups in the y-axis increased the attention to the same issue by 10 percentage points.

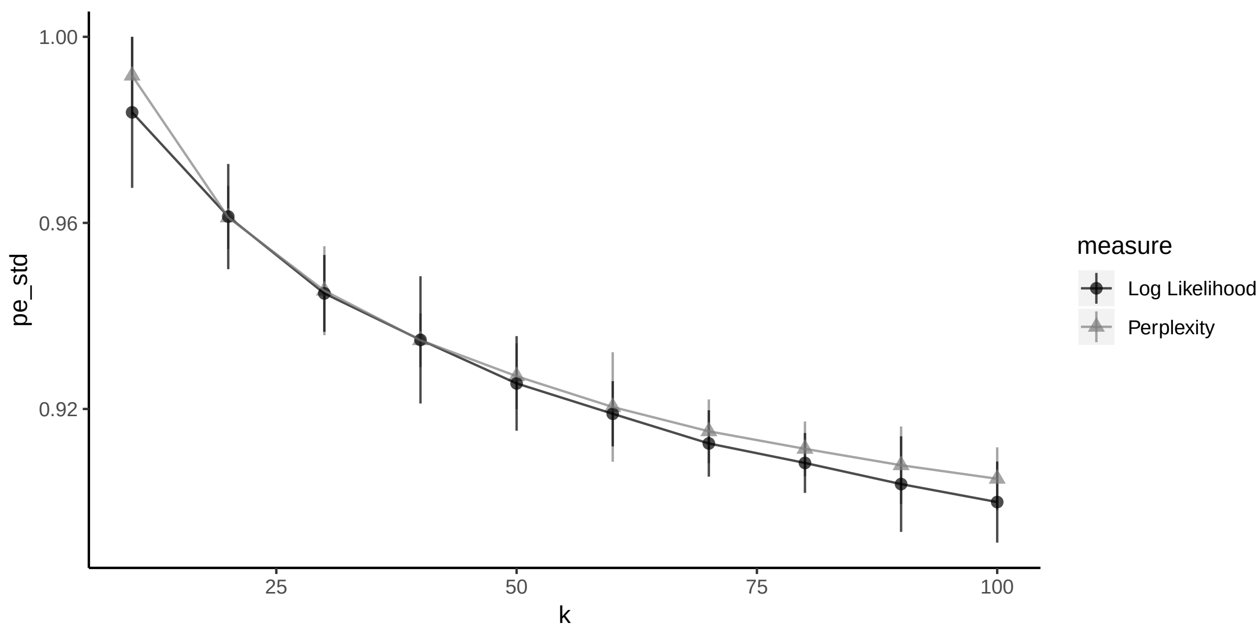
have the ability to influence the attention that the public pays to different political issues, and *vice versa*. However, the ability of the public to influence the issue attention of politicians is slightly greater. Politicians are particularly responsive to changes in issue attention by their party supporters and attentive publics.

E.4. Modeling Topics Discovered in All Tweets

In the paper we select the set of political issues to study by fitting an LDA model to the tweets of members of Congress. We then assess the extent to which the attention that politicians, the public, and the media pay to the resulting issues can be explained by an increase or decrease in attention by the other groups; indicating the presence of issue-responsiveness dynamics.

The advantage of fitting the LDA model only to the tweets of members of Congress is that we are more likely to discover political (rather than non-political) topics: research clearly shows that the mass public pays little attention to politics (Carpini and Keeter 1996; Hibbing and Theiss-Morse 2002) and

FIGURE A8. Goodness of fit statistics for several LDA models (with different number of topics) fit to all tweets from politicians, the media, and the public.



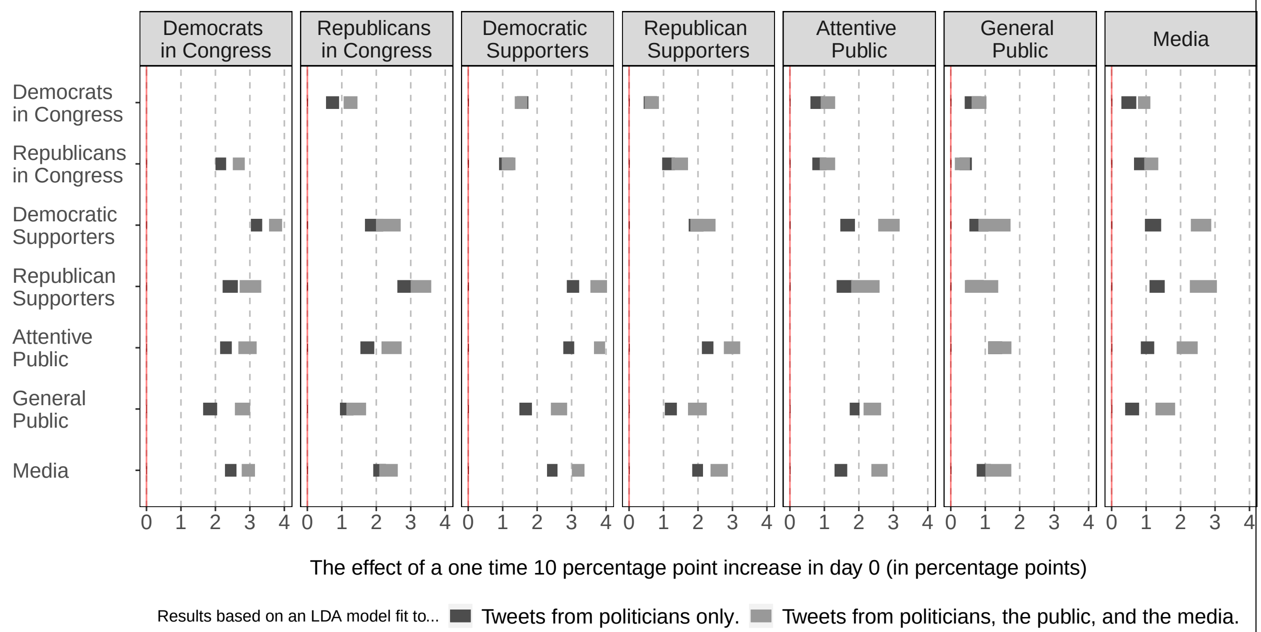
that when it does, it tends to focus on a small set of issues (Jones and Baumgartner 2004). Fitting an LDA model to all tweets from politicians, the media, and the mass public would hence lead to missing some political topics in detriment of non-political issues; which we clearly wanted to avoid.

A disadvantage of the approach used in the paper is that we could be potentially missing political topics discussed by the public but not by members of Congress. Although research indicates that this scenario is rare Carpini and Keeter (1996); Hibbing and Theiss-Morse (2002); Jones and Baumgartner (2004), in this section we examine whether we would have reached similar conclusions if we had initially fit an LDA model to the combined tweets of politicians, the media, and the public, instead of to the tweets of only politicians.

First, we fix the number of topics of the new LDA model by running several LDAs with a different number of topics k to all tweets of the study and examining the log likelihood and perplexity on holdout samples using 5-fold cross-validation. Similar to Figure A12 in the paper, Figure A8 shows these goodness of fit measures as the number of topics in the x-axis increases from 10 to 100. Similar to the original LDA model, we observe convergence for values of k as these get close to 100 and so we chose to fit another 100-topic LDA model to avoid over-fitting.

Table A4 illustrates the 100 topics discovered by this new LDA model. Few general traits stand out. First, as expected (and as indicated in the *Political* column of the table), we discover fewer political topics in this model than in the model used in the paper: 34 v. 53, respectively (27 v. 46 after merging the topics in each model that are very similar). Second, we observe that 20 of the 27 political topics in this new model are also present in the original topic model used in the paper. There are however 7 topics that were not discovered in the original LDA model, indicating that the mass public or the media

FIGURE A9. A comparison between the VAR results in the paper (in black) and the VAR results based on a 100-topic LDA model fit to the combined tweets of politicians, the media, and the public (in gray).



Note: The coefficients (with 95% confidence intervals) indicate (in percentage points) how much more attention the groups in the facet titles pay to a given issue 15 days after the groups in the y-axis increased the attention to the same issue by 10 percentage points.

paid a larger attention to them than politicians did: 2 topics related to the Black Lives Matter (BLM) movement (one about the incidents in Ferguson and another one about police brutality more generally), 3 foreign affairs topics (on Bowe Bergdahl, the Israel-Palestine conflict, and on defense and foreign policy generally), and two topics on national politics (one on Chris Christie and another one about local economies).

We fit the same VAR model (Equation 1) to the time series generated by these new 27 political topics, and present the results in Figure A9, where the original results are shown in black and the new results are shown in gray. The key inferences from the new estimates are generally consistent with the inferences from the original estimates: both Democratic and Republican members of Congress are primarily responsive to changes in attention by their party supporters and attentive voters, and their ability to influence changes in attention by these groups is lower than the *vice versa* effect.

There are some differences worth noticing when we compared to the original results. First, we observe in the new results that the ability of the public and the media to influence the agenda of members of Congress is slightly higher (the gray coefficients in the left two facets are higher than the black ones). Second, we observed that the ability of the media and the different groups of the public to influence the issue agenda of other groups of the public is also higher (the gray coefficients for party supporters, attentive public, general public, and the media are higher in the three middle facets). And finally, in the same way we observed the media to have a larger issue agenda setting role, we also observe the public to have a higher ability to set the issue agenda of the media (the gray coefficients for party supporters, attentive public, and general public are higher in the panel on the right). These two final points suggest that, by not fitting the original model to the tweets of the public and the media, in the original results we might have slightly underestimated the intermediate agenda setting role of the media. Nevertheless, the core findings of the study remain the same, and by focusing only on the topics discovered in the tweets of members of Congress, we were able to provide more detailed information about a larger number of political topics legislators discussed during the 113^{th} Congress.

E.5. Rulling out a Media-Collider Bias

In our VAR models we control for the attention that media outlets pay to the issues under study in order to control for potential media effects and the alternative explanation that media outlets may be the actors leading changes in political and public issue attention. However, since we observe both politicians and the public to lead media attention, there is room for a potential collider bias, and so for the observed relationship between groups of the public and politicians to be a simple artifact of controlling for media effects. Here we rule out this possibility by fitting the main VAR model of the paper without controlling for media effects. In Figure A10 we compare the IRFs of two models, one in which we control for media effects (in blue), and another one in which we do not (in orange). We observe that the predicted relationships between the different groups of the public and politicians do not vary.

FIGURE A10. Comparing the results for the main VAR model of the paper when controlling, and not controlling, for media effects.

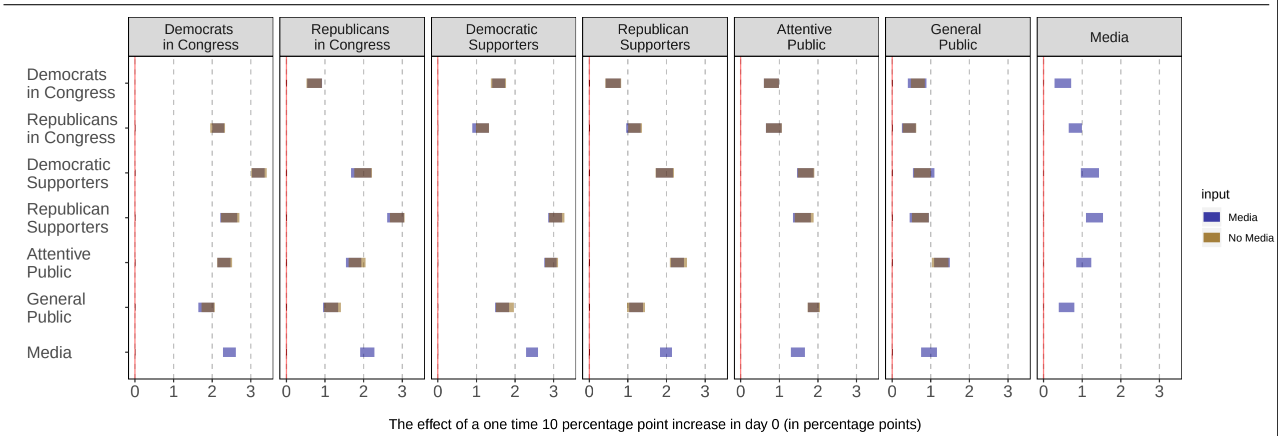


TABLE A4. Description of the topics in the alternative 100-topic LDA model fit to all tweets from politicians, the media, and the public. The *Political* column indicates whether we considered to topic to be a political issue, and the *Match* column indicates whether the same (or a very similar) topic exists in the LDA model used in the paper

#	Most Predictive Features	Label	Political	Match
8	#obamacare, hearing, meeting, #tcot, passed, icymi, rep, obamacare, budget, staff	Obamacare	Yes	Yes
9	gop, tax, republicans, budget, party, voted, rep, votes, pay, republican	Government Budget	Yes	Yes
11	@sentedcruz, #makedclisten, cruz, obamacare, #defundobamacare, @senrandpaul, #standwithrand, ted, ted cruz, rand	Government Shutdown	Yes	Yes
17	nsa, father's, father's day, #nsa, snowden, june, immigration, happy father's, fathers, surveillance	NSA Surveillance Scandal	Yes	Yes
18	marriage, court, gay, samesex, gay marriage, supreme, equality, supreme court, samesex marriage, marriage equality	Marriage Equality	Yes	Yes
20	zimmerman, trayvon, black, martin, george, trayvon martin, george zimmerman, justice, verdict, white	Police Brutality - BLM	Yes	No
24	climate, isis, march, change, #peoplesclimate, scotland, nfl, climate change, sept, #indyref	Climate Change	Yes	Yes
30	city, business, million, free, post, county, high, latest, tomorrow, stay	Local Economy	Yes	No
31	christie, 2014, snow, cold, jan, unemployment, chris, january, winter, weather	Chris Christie	Yes	No
35	ukraine, march, putin, russia, #ukraine, russian, crimea, flight, patrick's, spring	Protests in Ukraine	Yes	Yes
38	israel, gaza, hamas, #gaza, border, israeli, #israel, children, war, killed	Israel-Palestine	Yes	No
40	#tcot, gun, god, #tgdn, control, guns, media, follow, 2013, gun control	Gun Violence	Yes	Yes
41	isis, 9/11, labor, #neverforget, #isis, joan, labor day, strategy, rivers, september	Islamic State	Yes	Yes
42	bergdahl, cantor, june, taliban, #bergdahl, eric, bowe, california, campaign, bring	Bowe Bergdahl	Yes	No
46	election, gop, voting, voters, republican, republicans, polls, win, voted, race	Election Day 2014	Yes	Yes
51	rep, #raisethewage, let's, #renewui, economy, reform, community, million, #aca, pay	Minimum Wage	Yes	Yes
54	syria, #syria, war, chemical, weapons, syrian, attack, labor, chemical weapons, kerry	Use of Military Force in Syria	Yes	Yes
59	pope, sequester, march, budget, cuts, white, #sequester, paul, francis, sequestration	2013 Budget Sequestration	Yes	Yes
60	irs, #irs, scandal, holder, benghazi, #benghazi, targeting, groups, tea, party	IRS Scandal	Yes	Yes
63	#ferguson, ferguson, police, black, brown, grand, wilson, jury, grand jury, darren	Freguson - BLM	Yes	No
65	gun, guns, gun control, control, violence, nra, sandy, 2013, gun violence, debt	Gun Violence	Yes	Yes

67	border, #tcot, illegal, irs, emails, iraq, illegals, #bringbackourmarine, lost, #pjnet	Immigration	Yes	Yes
68	#benghazi, benghazi, mother's, mother's day, mothers, mom, happy mother's, hillary, moms, draft	Investigation of Attack on American Embassy in Benghazi	Yes	Yes
74	obamacare, navy, yard, #breakingbad, navy yard, shooting, #obamacare, gun, ios, @andi_sloan	Obamacare	Yes	Yes
77	shutdown, government, gop, #shutdown, obamacare, debt, republicans, shut, government shutdown, #gopshutdown	Government Shutdown	Yes	Yes
79	ebola, #ebola, cdc, patient, dallas, africa, texas, travel, october, hospital	Ebola	Yes	Yes
83	war, bush, party, john, deal, win, obama's, gop, attack, say	Defense and Foreign Policy	Yes	No
85	hobby, lobby, hobby lobby, #hobbylobby, court, supreme, #scotus, supreme court, control, decision	Hobby Lobby Supreme Court Decision	Yes	Yes
86	#tcot, isis, #pjnet, god, islamic, obama's, 2014, #isis, @jjauthor, muslim	Islamic State	Yes	Yes
87	immigration, obama's, executive, #immigration, action, #immigrationaction, amnesty, @barackobama, immigrants, keystone	Executive Action on Immigration	Yes	Yes
88	#ericgarner, police, #icantbreathe, #blacklivesmatter, torture, eric, garner, black, cia, eric garner	Police Brutality - BLM	Yes	No
92	obamacare, #obamacare, insurance, website, plans, health care, iran, sebelius, healthcare, health insurance	Obamacare	Yes	Yes
95	texas, #txlege, #standwithwendy, #sb5, rights, #scotus, wendy, court, @wendydavistexas, #doma	Abortion	Yes	Yes
98	#ferguson, police, ferguson, black, brown, #mikebrown, cops, michael, officer, michael brown	Freguson - BLM	Yes	No
14	#tcot, obamacare, god, 2014, follow, gun, #obamacare, #pjnet, government, life	Party Talk	No	No
15	#uniteblue, 2014, #p2, gop, #tcot, #renewui, black, republicans, htt ..., wage	Party Talk	No	No
25	#tcot, #pjnet, gruber, amnesty, obama's, obamacare, @foxnews, stupid, #gruber, black	Party Talk	No	No
50	gun, #p2, 2013, #uniteblue, gop, #getglue, stories today, social, gay, background	Party Talk	No	No
55	#tcot, 2014, #pjnet, gun, god, free, #teaparty, reid, harry, government	Party Talk	No	No
69	#uniteblue, #p2, gop, 2014, htt ..., #tcot, republicans, @dailykos, gun, htt	Party Talk	No	No
75	gop, #p2, 2013, #uniteblue, republicans, food, #tcot, party, media, #gop	Party Talk	No	No
81	#tcot, obamacare, god, @sentedcruz, obama's, #benghazi, follow, @breitbartnews, media, @foxnews	Party Talk	No	No
93	august, obamacare, nsa, weiner, aug, black, baby, egypt, royal, stories today	Party Talk	No	No
97	2014, #uniteblue, black, gop, htt ..., #p2, @dailykos, republicans, white, 2015	Party Talk	No	No

1	memorial, memorial day, #yesallwomen, #memorialday, maya, angelou, maya angelou, men, veterans, remember	Memorial Day	No	Yes
2	#gameinsight, i've, #androidgames, #android, #androidgames #gameinsight, #gameinsight i've, #android #androidgames, collected, coins, gold	Entertainment	No	No
3	2014, photo, foto, follow, 2013, htt ..., haha, ang, @estucrudaverdad, snow	Entertainment	No	No
4	follow, #iphone, #iphonegames #gameinsight, #iphonegames, haha, #iphone #iphonegames, followers, love, #gameinsight, stats	Entertainment	No	No
5	halloween, #halloween, #worldseries, series, costume, world series, happy halloween, game, nov, candy	Halloween	No	No
6	think, can't, did, say, really, that's, man, got, you're, does	Boilerplate	No	No
7	super, bowl, valentine's, super bowl, valentine's day, valentines, #superbowl, valentines day, love, power	Super Bowl and Valentine's Day	No	1
10	follow, @camerondallas, love, bae, summer, #callmecam, birthday, #mtvhottest, 2014, mean	Entertainment	No	No
12	follow, love, bae, birthday, happy birthday, life, mean, 2014, game, boys	Entertainment	No	No
13	follow, haha, love, thirsty, lol, 2013, thirsty thirsty, followers, spring, snow	Entertainment	No	No
16	photo, posted, facebook, photo facebook, new photo, posted new, facebook posted, love, weekend, photos	Photos Posted on Facebook	No	Yes
19	bowl, super, super bowl, #superbowl, broncos, game, seahawks, peyton, #sb48, seattle	Super Bowl XLVIII	No	No
21	boston, marathon, suspect, bombing, police, boston marathon, #boston, #bostonmarathon, gun, explosion	Boston Marathon	No	Yes
22	spring, march, #marchmadness, bracket, win, ncaa, game, april, basketball, michigan	March Madness	No	No
23	#oscars, #goldenglobes, oscar, @theellenshow, oscars, photo, longer, arm, #oscars2014, best photo	Oscars	No	No
26	que, los, por, para, las, del, una, mas, como, esta	Spanish Twittershpere	No	No
27	snow, #sochi2014, olympics, usa, feb, sochi, winter, olympic, #wearethepeople, gold	2014 Winter Olympics	No	Yes
28	cup, world cup, #worldcup, usa, #usa, game, #worldcup2014, iraq, #usmnt, soccer	World Cup	No	Yes
29	follow, love, followers, birthday, stats, unfollowers, today stats, followed, mean, snow	Entertainment	No	No
32	change, love, tell, community, rights, climate, we're, public, education, action	Community	No	No
33	man, say, police, #edshow, white, photos, here's, breaking, death, photo	Breaking News	No	No
34	game, football, team, win, play, auburn, alabama, sec, college, fans	College Football	No	No
36	jeter, holder, october, derek, eric, oct, game, secret, derek jeter, hong	Baseball	No	No

37	police, cops, nypd, officers, #nypd, cuba, sony, cop, mayor, black	Unclear	No	No
39	game, football, nfl, win, team, season, play, cowboys, sunday, fans	Football	No	No
43	night, game, love, weekend, come, saturday, photo, win, birthday, fun	Entertainment	No	No
44	love, lol, got, can't, really, you're, shit, life, think, fuck	Entertainment	No	No
45	class, tomorrow, come, game, friday, thursday, birthday, win, excited, #tbt	Entertainment	No	No
47	sunday, church, win, god, #nerdland, #uppers, race, watching, #nascar, life	Religion	No	No
48	monday, weekend, #thewalkingdead, tomorrow, happy monday, sunday, dead, win, mondays, #rhoa	Entertainment	No	No
49	thanksgiving, happy thanksgiving, thankful, black, black friday, friday, #thanksgiving, turkey, holiday, #blackfriday	Thanksgiving	No	Yes
52	robin, williams, robin williams, rip, suicide, #robinwilliams, sad, iraq, #riprobinwilliams, rip robin	Robin Williams's Death	No	No
53	2013, follow, #getglue, haha, love, photo, que, lol, hahaha, yang	Entertainment	No	No
56	love, life, @youtube, free, lol, you're, music, favorite, things, think	Entertainment	No	No
57	mandela, nelson, nelson mandela, #peopleschoice, #bethanymotagiveaway, #bethanymotagiveaway #bethanymotagiveaway, holiday, snow, jensen, 2013	Nelson Mandel's Death	No	Yes
58	2014, photo, @tm2000back, @myriammontecruz, men's, htt ..., dan, shi, update, following	Entertainment	No	No
61	lebron, heat, game, spurs, nba, james, miami, summer, june, finals	Basketball	No	No
62	sterling, donald, #bringbackourgirls, donald sterling, clippers, game, nba, bundy, girls, racist	Basketball	No	No
64	added, added video, video @youtube, @youtube playlist, playlist, @youtube, hot, historic, stock, hot new	Entertainment	No	No
66	rice, ray, ray rice, nfl, apple, iphone, violence, goodell, domestic, @nfl	Entertainment	No	No
70	4th, veterans, july, 4th july, independence, #veteransday, happy 4th, veterans day, fireworks, freedom	4th July	No	No
71	phil, duck, dynasty, duck dynasty, robertson, #duckdynasty, phil robertson, 2013, @aetv, free	Entertainment	No	No
72	#ff, friday, weekend, #scandal, happy friday, #tgif, @scandalabc, it's friday, #followfriday, sunday	Follow Friday Tweets (#FF)	No	Yes
73	#voicesave, #givingtuesday, paul, december, walker, kat, @nbcthevoice, #voicesave kat, paul walker, holiday	Entertainment	No	No
76	#grammys, king, luther, martin luther, martin, luther king, mlk, #inaug2013, dream, march	Martin Luther King	No	No
78	april, easter, happy easter, spring, game, jesus, fools, season, thatcher, april fools	Eastern	No	No

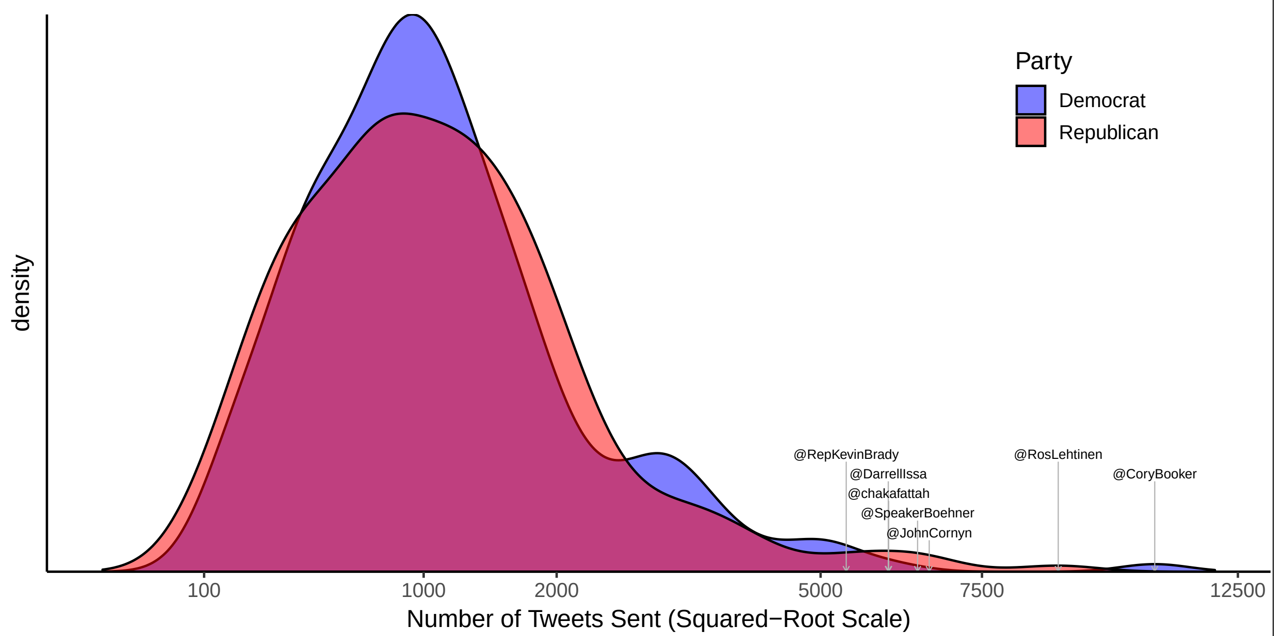
80	follow, summer, love, 2014, birthday, bae, followers, retweet, happy birthday, mean	Entertainment	No	No
82	tornado, cdt, issued, nws, oklahoma, warning, severe, june, cdt nws, april	Severe Wheather in Oklahoma	No	No
84	sen, senator, mcconnell, bipartisan, hearing, floor, sexual, assault, murray, reform	General Vocabulary (Senate)	No	Yes
89	christmas, merry, merry christmas, holiday, santa, holidays, eve, gift, #christmas, christmas eve	Christmas Holidays	No	Yes
90	#vote5sos, #votefifthharmony, #vmas, challenge, ice, bucket, ice bucket, 5sos, #votedemilovato, bucket challenge	Entertainment	No	Yes
91	christmas, follow, love, birthday, bae, 2014, 2015, #mtvstars, life, happy birthday	Entertainment	No	No
94	#sotu, state union, union, @barackobama, speech, rubio, wage, president obama, sotu, address	State of the Union Adress	No	Yes
96	new year, happy new, 2014, 2013, new years, year's, new year's, eve, cliff, resolution	New Year's Eve	No	No
99	summer, july, photo, beach, park, hot, weekend, camp, june, follow	Entertainment	No	No
100	2014, 2015, photo, christmas, holiday, @youtube, htt ..., win, snow, direction	Entertainment	No	No

F. ADDITIONAL DESCRIPTIVE STATISTICS

F.1. Members of Congress on Twitter

This Appendix offers additional details regarding the data collection process. Our list of Twitter accounts of Members of Congress was collected through the New York Times Congress API and then revised for errors. We included only active Twitter accounts, which we consider to be those that sent at least one tweet during our period of analysis, although as shown in Figure A11, most legislators sent between 200 and 2,000 tweets during this period.

FIGURE A11. Distribution of number of tweets sent by Members of Congress during period of study



As noted in the main text, our data comprises all legislators that served during the 113th Congress. Multiple House representatives served in a few congressional districts: 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. We also observe similar cases in the Senate: 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 Booker; and John Walsh, who substituted Max Baucus after his appointment as U.S. Ambassador in China. We include in our dataset the tweets by legislators while they were in office.

F.2. Party Supporters on Twitter

Two of our citizen samples correspond to party supporters, which we identified as those that follow three or more members of Congress of one party and no legislators of the opposite party. In order to validate that this operationalization properly captures the notion of party supporters, we used data collected as part of a previous study (Barberá et al. 2015), where we matched geolocated Twitter accounts with voter registration records in five states (Arkansas, California, Florida, Ohio, and Pennsylvania) that make them publicly available for academic research purposes. From each of these datasets, we extracted party affiliation (Democratic or Republican party), turnout in the 2012 presidential election, and turnout in the 2010 congressional election; as well as the number of Members of Congress from each party that the voters follow on Twitter as of July 2018. Even if the data is more recent compared to our period of study, we believe it can provide useful evidence regarding the validity of our measurement strategy.

We find that our choice to identify party supporters as those who follow 3 or more members of Congress from one party and 0 from the opposite party is adequate. First, this threshold is able to classify party affiliation with approximately 90% accuracy: 87% (92%) of Twitter accounts in our sample who meet our criteria to be classified as a Republican (Democratic) supporter is affiliated with that party according to the voter files. Second, a large proportion (61%) of those who we identified as supporters turned out to vote in both elections (2010 and 2012). In contrast, turnout among voters affiliated with a party in our dataset was 51%. Finally, although this metric does not capture all party supporters, we find that 18% of voters who are affiliated with a party and voted in both 2010 and 2012 meet this definition.

We also considered alternative thresholds. If we increase the minimum number of accounts to 5, we see a minimal increase in the accuracy in predicting party affiliation (89% for Republicans; 93% for Democrats) and turnout among this group (63%), but the coverage of frequent voters by this metric drops by half (to 9%). If we lower the threshold to only one Member of Congress of a party and none of the other, we unsurprisingly see that around 55% of frequent voters meet this definition, but the metric now has high error rates when predicting party affiliation (with accuracy going down to 73% for Republicans and 86% for Democrats), and turnout is very similar to the entire population of voters who are affiliated with a party (54%). For these reasons, we think that our operationalization of party supporter is valid.

G. TOPIC MODELING OF TWEETS BY LEGISLATORS AND CITIZENS

G.1. Overview of Latent Dirichlet Allocation Model

Latent Dirichlet Allocation (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 et al. 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.

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.

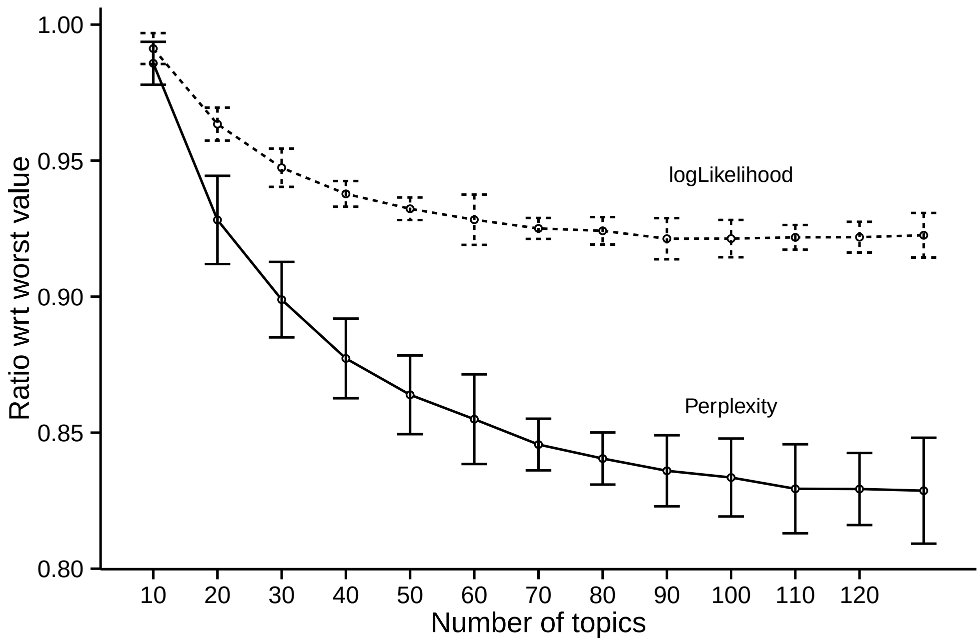
This model requires us to fix K, the number of possible topics. There are two main parameters of interest: β, a matrix of dimensions $K \times V$ indicating the distribution of tokens over topics; and θ, a matrix of dimensions $K \times N$ indicating the distribution of topics over documents.

In our application, we fit the model with a collapsed Gibbs sampler (Griffiths and Steyvers, 2004, *PNAS*), implemented in R (Grün and Hornik, 2011, *Journal of Statistical Software*). 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 and bigrams.

G.2. Choosing the Number of Topics of the LDA Model

To fix the number of topics, we ran our model multiple times with different values of the number of topics (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, see Chang et al, 2009, NIPS – where smaller values indicate a better model fit). Figure A12 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, *The Elements of Statistical Learning*).

FIGURE A12. LDA model fit with different number of topics



Note: This figure shows the cross-validated log likelihood and estimated perplexity after running our topic model with different numbers of topics. We find that 100 topics yields the best performance.

G.3. Validation of Discovered Topics

In this Appendix we demonstrate that the topics that are discovered by the Latent Dirichlet Allocation model are valid representations of the political issues that legislators and citizens discussed during the 113th Congress. 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: http://www.pablobarbera.com/congress-lda. A screenshot of one the topics is shown in Figure A13. 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.[4]

As we show in Figure A13, 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, consistently with the notion of predictive validity. 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.), as well as the sample of tweets, are also related to this issue, which demonstrates the semantic validity of this topic.

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 (see Footnote 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

[4]Note that although our topic model is fit using aggregated tweets, here the tweets were selected after computing the posterior probabilities at the tweet level.

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 A5). This yearly publication selects a series of key votes in the House and Senate that are considered the “major issues of the year”.[5] 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.

G.4. Attention to political issues by legislators and citizens

This Appendix complements the results shown in Figure 1, in which we can observe that the groups of the public do not pay an equal amount of attention to politics. These differences can be best appreciated in Table A6 below, where we show the average daily attention that each group dedicated to political topics during the 113th Congress. Members of Congress dedicated about 30% of their Twitter communications to discuss particular political issues. Party supporters also dedicated a substantive amount of their overall attention to discussing them: about 20%. Nevertheless, we observe the Attentive public, and particularly the General Public, to dedicate a much smaller fraction of their communications to discuss these political issues: 9% and 5% respectively.

Figure 1 (and Table A6) also highlights that mass media potentially played a key issue agenda setting role, as media outlets dedicated a large amount of attention to all the political topics that emerged during the 113th Congress. Moreover, we observe that, compared to the issue attention distribution of members of Congress, mass media distributed their attention more equally across topics. This is not surprising given that we included both liberal and conservative leaning outlets into our sample. Nevertheless, it is important to notice that, similar to mass media, party supporters also distributed their agenda more equally across topics, signaling a potential stronger relationship between their issue agendas.

[5] 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.

FIGURE A13. Visualization of Topics with Online Dashboard

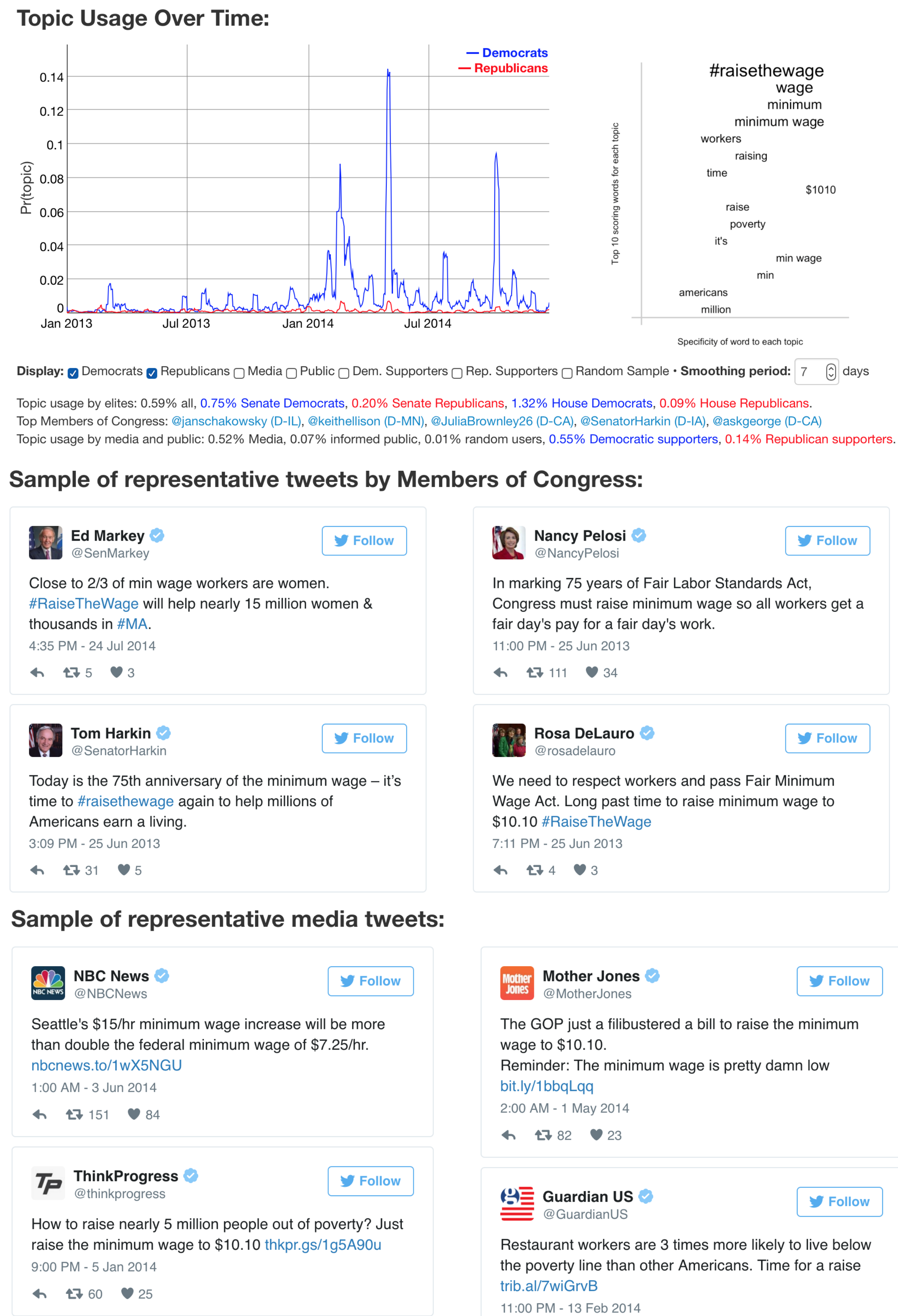


TABLE A5. Correspondence between key votes in Congress and our discovered political issues

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**

Note: This table shows the topics in our model (second column) that corresponds to key votes in Congress (first column), as selected by the Congressional Quarterly Almanac. **No** indicates that a matching topic could not be identified.

TABLE A6. Percentage of the expressed issue agenda of different groups that was devoted to 46 political issues during the 113th Congress.

Group	Average Daily Attention to Political Topics
Democrats in Congress	27.28%
Republicans in Congress	27.08%
Democratic Supporters	19.26%
Republican Supporters	21.47%
Attentive Public	8.95%
General Public	5.33%
Media	32.14%

Note: The percentages represent the average of the sum of daily posterior probabilities-percentages assigned to political topics.

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