Who Influences The Public Agenda in State Politics? Evidence From 45 Million Twitter Messages*

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Abstract

Who shapes the agenda of state legislators? Although state governments make critical policy decisions, data and methodological constraints have limited researchers' ability to study state-level agenda setting. We collect 45 million Twitter messages sent by state and national actors in 2018 and employ topic modeling and time series techniques to study how the issue attention of state lawmakers evolves vis-à-vis their constituents, members of Congress, and state and national media outlets. We find that national policy debates strongly influence the public agenda of state legislators, but that state lawmakers shape the national agenda on issues typically handled by the states. State legislators are also responsive to the general public and to regional media, and simultaneously influence the issue attention of these actors. These results suggest that state representatives are generally responsive to the public but influenced by the national agenda in a manner that differs substantially across issues and regions.

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1 Introduction

Classic theories of agenda setting suggest that attention to an area is a necessary precondition for policy change (e.g. Schattschneider 1960; Kingdon 1984; Baumgartner and Jones 2010). In the U.S., many critical policies are increasingly being crafted at the state level, including minimum wage laws, civil rights legislation, and responses to public health crises like the COVID-19 pandemic. Despite the importance of state policies on people's day-to-day lives, we still know little about when and why state legislators in the United States choose to pay attention to different policy areas in their public communications.

Existing theoretical frameworks offer competing predictions as to which political actors influence the policy discussions of state legislators. In this paper, we empirically assess the explanatory power of several prominent theoretical models. First, we test the argument that state and local politics have increasingly become nationalized. A growing literature argues that party unity, affective polarization, and the decline in local media have contributed to a political environment in which voters identify more strongly than ever with the two national parties and pay much more attention to (and know more about) national rather than state politics (Abramowitz and Webster 2016; Rogers 2016; Moskowitz 2019; Hopkins 2018). If this is true, state legislators might improve their electoral prospects by engaging in national policy debates (such as Obamacare or Trump's immigration plan) rather than by discussing policies specific to the state (such as education reform). According to this theoretical perspective, we should see the public communications of state legislators emphasizing the issues that are being discussed by national representatives, such as members of the U.S. Congress.

However, a long-standing literature on political responsiveness (Achen 1977; Weissberg 1978; Edwards and Wood 1999; Jones and Baumgartner 2004; Sulkin 2005) argues that politicians should mostly respond to the issue demands of their own constituents. Politicians are elected to represent the interests of those who voted for them, and in order to increase their chances of reelection, they need to listen and respond to the issue and policy priorities of their core supporters. According to this line of thought, we should see state legislators react to the issue priorities of the public in their state, and especially to changes in issue attention by the supporters of each party (Barbera et al. 2019).

Finally, the literature on media effects puts the emphasis on the ability of the mass media to influence the issues to which politicians pay attention. Numerous studies have found this to be the case in a wide range of political contexts (see Walgrave and Van Aelst 2016: for an overview). Media outlets highlight and publicize political problems, drawing public attention and pushing legislators to address those issues. This line of work predicts that state legislators will be particularly responsive to shifts in issue attention by the mass media.

Studying the validity of these competing theoretical claims—that is, to whose issue priorities state legislators are responding—is crucial for assessing the state of representative democracy and understanding the policymaking process in the U.S. states. However, research on this topic remains limited in large part due to data and methodological limitations. While we know that state policies tend to be responsive to the ideological preferences of state residents (e.g Erikson et al. 1993; Caughey and Warshaw 2016; Gray et al. 2004; Caughey and Warshaw 2018; Lax and Phillips 2009), we don't know if state legislators are following or leading the public in terms of issue attention and public opinion.

We also don't know if these aggregate correlations extend beyond legislated policies to the more general issue agenda. While the policies that actually pass at the state-level often roughly mirror the preferences of constituents, is there attention congruence on the larger set of possible policies being discussed? To date, researchers have lacked more fine-grained data on issue attention that would allow them to compare the behavior of state legislators with other political actors or the public. This is in large part because collecting data on which issues legislators from different states pay attention to is an extremely arduous task—for example, it would take a great deal of effort to collect and manually annotate press releases or newsletters from thousands of state and national legislators and to combine these with comparative state-level opinion polls reflecting the issue priorities of the public and news stories published by the mass media during the same time period.

However, a vast number of state and national legislators today are active on social media platforms such as Twitter, where they frequently express opinions on the issues that are important to them (Casas et al. 2020). Moreover, the public and media outlets also present their views on various topics on the same platform and in the same standardized format. Building on the methodological framework used by Barbera et al. (2019) to study issue responsiveness at the national level, from January 1st to December 31st 2018 we collected all Twitter messages sent by: (a) state legislators from 13 states, (b) members of Congress, (c) four prominent national media outlets, (d) President Trump, (e) the most consumed newspapers in each state, and (f) a sample of strong Democrats and Republicans who closely follow state politics in each state. Using a convolutional neural network, we predict the topic of each tweet, classifying them into the policy topics of the Comparative Agendas Project; and finally, we use vector auto regressive models (VAR) to study who leads and who follows shifts in issue attention by state legislators.

Our findings reveal a more nuanced view than either of the three broad theoretical approaches on which our analysis is based would suggest. We find indeed that the issues discussed by national actors (national media but especially members of Congress) strongly influence the issue agenda of state legislators; nevertheless, state lawmakers are also able to lead shifts in attention by these national actors on issues typically handled by the states, such as education and healthcare. Additionally, after controlling for these multi-level dynamics, we find very interesting responsive dynamics at the state level: lawmakers respond to shifts in issue attention by state media, and even more strongly to shifts by their constituents, and in turn, they are also able to influence the issue agenda of both groups (particularly of state media).

2 Leading the Issue Attention of State Legislators

2.1 A Nationalized Issue Agenda

Who leads the issue attention of state legislators? Recent work on the nationalization of politics, including Hopkins (2018)'s *The Increasingly United States*, offers one possible answer to this question: national political actors. This work argues that in the last few decades, local and state politics have become increasingly nationalized. Two main trends reflect this nationalization process. First, voters are increasingly using the same criteria for choosing representatives across the different levels of government. Voters also increasingly engage with and know more about national political affairs at the expense of regional ones (Rogers 2017; Moskowitz 2019). Different drivers are to blame for this nationalization process. In particular, Hopkins (2018) points to parties increasingly using the same (national) cues when running in elections across different levels of government, place-based identities rarely being politicized, media audiences shifting away from local newspapers and television, and regional media outlets increasingly discussing more national politics at the expense of regional policy issues.

Given that voters are more likely to pay attention to, be informed about, and identify with national rather than regional political issues, it seems logical for state legislators to also emphasize policy issues discussed by national legislators - as we believe that national legislators are defining the national agenda. Based on this theoretical argument, we hypothesize:

> $\mathbf{H}_1$: Changes in issue attention by members of Congress will influence changes in issue attention by state legislators.

2.2 Political Responsiveness

The core theoretical principle of representative democracies is that elected official represent the interests and policy priorities of those who elect them (Dexter 1957; Miller and Stokes 1963; Erikson 1971). Empirical research assessing the correlation between the issue priorities of the public and *national* politicians in the United States finds a strong correlation between the two: members of Congress are, for example, more likely to discuss, introduce more bills, and hold more hearings on issues the public deem relevant (Sulkin 2005; Brayden, Bentele, and Soule 2007; Jones, Larsen-Price, and Wilkerson 2009; Baumgartner and Jones 2010).

In line with long-standing theoretical models (Downs 1957; Arnold 1990; Aldrich 1995), public representatives seem to respond to the issue priorities of the public in order to achieve their reelection and policy-oriented goals. Early studies, however, were not able to clearly disentangle whether this correlation was due to politicians responding to the issue priorities of the public or *vice versa* (Lenz 2013). Recent studies, however, have taken advantage of time series analysis to show that members of Congress do indeed respond to shifts in attention by the mass public. (Barbera et al. 2019).

However, amid increasing gridlock and polarization in D.C., many of the most important policy battles today are taking place at the state level rather than the national level. At the same time, there is much less research on who leads and who follows in terms of issue attention at the state level (Tausanovitch 2019). We know that in the aggregate, state policies tend to be responsive to public opinion (Erikson et al. 1993; Caughey and Warshaw 2016; Simonovits, Guess, and Nagler 2019). And in a study of 18 states, Tan and Weaver (2009) examine the correlations between public opinion, the newspaper agenda, and the policy agenda of state legislatures. But again, it is unclear if these correlations indicate that state legislators are following the issue priorities of constituents or if the public is adopting the policy platform of state lawmakers. A growing number of field experiments show that state legislators do appear to respond to public opinion and update their beliefs when provided with information about constituent beliefs (e.g. Butler, Nickerson et al. 2011; Butler and Dynes 2016), so there are good theoretical and empirical reasons to believe that state lawmakers are indeed responsive to shifts in attention by their constituents. Recent literature on (national) political responsiveness however points to legislators being particularly responsive to those constituents that are more politically engaged, specially those who closely follow party elites (Barbera et al. 2019), rather than the public at large. For this reason we focus on studying responsiveness dynamics between state legislators and those constituents who closely follow Democrat and Republican lawmakers in their states. We put forward the following hypothesis:

> $\mathbf{H}_2$: Changes in issue attention by mass public partisans in each state will influence changes in issue attention by state legislators.

2.3 Media Effects

The media is often seen as the fourth state or branch of government (Schultz 1998). Mass media reports on and informs the public about ongoing political issues and debates, and in doing so, journalists and media outlets choose to emphasize some issues while paying less attention to others. The media often responds to public demands and the political agenda when deciding which issues to cover. Market pressure means that media outlets often try to cover the issues that they detect as being of interest to the public (Anand and Peterson 2000; Webster and Ksiazek 2012), and political institutions (e.g., Congress and the White House) and events (e.g., political speeches or the introduction of a new relevant bill) are an important source of newsworthy material.

But the media does not only respond to public and political shifts in attention. Sometimes, they are the ones leading the shift in issue attention. Research on media effects shows that sometimes the media successfully increases the salience of a particular policy issue (e.g., wrongful death convictions, (Baumgartner, De Boef, and Boydstun 2008)) which translates into greater public scrutiny followed by attention from politicians (McCombs and Shaw 1972; Zaller 1992; Boydstun 2013). An extensive literature based on data from multiple countries shows that shifts in issue attention by the media can lead to shifts in issue attention by public representatives (see Walgrave and Van Aelst (2016) for an overview). Based on this literature, as well as the nationalized agenda argument previously introduced (Hopkins 2018), we test the following two hypotheses:

> $\mathbf{H}_{3_a}$: Changes in issue attention by the national media will influence changes in issue attention by state legislators.

> $\mathbf{H}_{3_b}$: Changes in issue attention by the state media outlets will influence changes in issue attention by state legislators.

2.4 Heterogeneous Effects by Issue Type

Finally, we examine whether the type of policy being discussed dictates whether state legislators are leading or following in terms of issue attention. Given the federal structure of the U.S., certain policy areas fall primarily to state governments in terms of legislation and administration. These areas include education, healthcare, law and crime, and transportation, which comprise the bulk of legislation passed at the state level (Jewell 1982). At the same time, state governments have significantly less power to legislate on issues related to foreign trade, defense, and international affairs (Kollman 2017).

Research on federalism typically finds that candidates for different levels of office tend to focus on the policy areas that are most directly tied to that office (e.g. Jacob and Vines 1965; Laumann and Knoke 1987). An extension of this logic would suggest that state legislators should pay more attention to issue areas that are primarily in the domain of state government as opposed to the federal government. We therefore expect that state legislators will be most attentive to shifts in issue attention by other actors when those groups are discussing policy issues that are primarily the domain of state government. At the same time, the literature on policy diffusion suggests that the federal government is often likely to look to the states for innovation in certain policy areas—especially when those policies are traditionally in the domain of state government Karch (2007). We therefore see reason to expect that this effect could go in either direction, but that in both cases the size of the effect is likely to be larger when the issues in question are in the traditional domain of state government; with that logic in mind, we test the following two additional hypotheses:

> $\mathbf{H}_{4_a}$: Changes in issue attention by other actors on *state issues* will be more likely to influence changes in issue attention by state legislators than will changes in issue attention on issues that are not traditionally in the domain of state politics.

> $\mathbf{H}_{4_b}$: Changes in issue attention by state lawmakers on *state issues* will be more likely to influence changes in issue attention by other actors than will changes in issue attention on issues that are not traditionally in the domain of state politics.

3 Data to Measure Issue Attention

We use Twitter data to identify the issues state legislators decide to emphasize in their public communications and to examine how their issue attention evolves *vis a vis* other groups. Research shows that Twitter is widely and frequently used by both national (Barbera et al. 2019) and state-level (Casas et al. 2020) political elites. In addition, media outlets are also very active on Twitter (Eady et al. 2019), frequently posting about their most relevant pieces of the day. Moreover, the mass public also often uses Twitter as a platform for expressing their political views (Barbera et al. 2019) and to mobilize on political issues (Freelon, McIlwain, and Clark 2018). In sum, Twitter data facilitates measuring in a standardized fashion the political issues publicly emphasized by the groups we study. Below we present a brief description of how we created the list of Twitter users belonging to each group of analysis. We collected all tweets sent by the users in each group between January 1st and December 31st 2018 using the Twitter REST API. In Table 1 we report the total number of messages we collected for each group, as well as the unique number of users responsible for those tweets.

- **State Legislators**. We study the issue attention distribution of state legislators from 13 states:[1] Arizona, California, Florida, Illinois, Massachusetts, Montana, New Jersey, Nevada, New York, Ohio, Texas, Utah, and Virginia. We first obtained a list and the Twitter handles of the state legislators serving in the lower and upper chambers of these state legislatures by using the Google Civic API.[2] We distinguish between **Democrat State Legislators** and **Republican State Legislators** from each state.

- **Members of Congress**. We used several public sources to collect the Twitter handles of members of Congress serving during the 115th Congress.[3]. We distinguish between **Democrats in Congress** and **Republicans in Congress**.

- **President Donald Trump**. We collected all tweets sent by the President between January 1 and December 31st, 2018.

[1]Collecting, processing, and analyzing tweets from state legislators, newspapers, and partisans from all 50 states turned out to be unfeasible; so we had to focus on a smaller set of states. We selected these 13 states to maximize variation across several key features, such as geographic region, levels of legislative professionalization, partisan composition of the chambers, whether the legislature was in session versus out of session, and population size. We based our selection criteria on data from a variety of sources, including the Census Bureau, the Correlates of State Policy Database, and the National Conference of State Legislatures.

[2]We manually checked to see if an account actually existed when the source (Google Civic API) that we used for obtaining the initial set of Twitter handles of state legislators did not return an account for a policymaker.

[3]We collected the handles of the official accounts via this collaborative github account with plenty of individual level information about members of Congress: `https://github.com/unitedstates/congress-legislators`. Additionally, we also collected and included the handles for the personal accounts of members of Congress.

- **National Media**. We collected all tweets sent in 2018 by four of the main national media organizations in the United States: Huffington Post, CNN, Associated Press, and FoxNews. We used two criteria for selecting them. First, these are major and relevant news organizations, and they are all followed on Twitter by more than 10 million users (11,401,075; 40,852,516; 13,056,706; 18,324,367 respectively).[4] And second, these are representative of the ideological media space, with FoxNews on the right, Huffington Post on the left, and CNN and the Associated Press representing a more moderate position in the ideological space.

- **State Partisans**. We then used the Twitter REST API to pull the list of followers of all state legislators in our sample. Next, we created a group of **Democrat State Partisans** and **Republican State Partisans** for each of the 13 states by selecting those who followed at least 2 Democrat and no Republican state legislators from that state, and vice versa.

- **State Media**. We track the tweets of the social media accounts of the top 10 newspapers from each of the 13 states.[5]

3.1 Classifying policy issues

At the heart of our empirical strategy is an assessment of when different actors discuss different topics on Twitter, so we now to turn to the question of how we identify topics of discussion. To do so, we rely on the comprehensive list of policy issues defined by the Comparative Agendas Project (CAP) (`https://www.comparativeagendas.net/codebook`). This classification approach has been widely adopted and allows scholars to study issue attention, agenda setting, framing, and political responsiveness in a systematic and comparative fashion

[4]These were the follower counts for these organization accounts around January 2020.
[5]We obtained the circulation and top-10 lists from `https://www.agilitypr.com/`

Table 1: Number of tweets and unique accounts by group

Group	Unique accounts	Numbers tweets collected
Democrat State Legislators	672	376,026
Republican State Legislators	583	207,547
Democrats in Congress	393	326,125
Republicans in Congress	453	220,790
National Media	4	191,855
President Trump	1	3,416
Democrat State Partisans	70,155	26,099,154
Republican State Partisans	32,809	15,134,372
State Media	130	1,100,407
Total	105,200	43,569,692

(across contexts and time periods). We adopted this particular issue categorization for two main reasons. First, the codebook provides a comprehensive list that allows us to classify virtually all policy-relevant tweets into one of the issue categories (with a minor exception that we discuss in the following paragraph). And second, given that this classification is used by a large community of scholars, it ensures that our results can more easily speak to existing and future work on the topic.

Table 2 shows the 20 macro policy issue categories defined by the CAP codebook (such as the *Economy*) and several sub-issue categories (for example, taxes and unemployment are subcategories of the *Economy*).[6] Because we use machine learning classifiers to predict the policy issues discussed in tweets and need many examples of annotated tweets within each category to build sufficiently accurate classifiers, we focus on shifts in attention across the 20 macro issue categories (rather than the numerous sub-issue ones). For the purpose of this analysis, however, we decided to add an additional macro issue category: *Gun Control*. Shootings and discussions around regulating gun ownership, carriage, and usage have been a very salient topic in the last few years in the United States. Currently in the CAP codebook these discussions are part of a *Law & Crime* category, but due to the increased salience and

[6]We excluded the CAP topic category *Culture* from the analysis, as a preliminary analysis revealed that it was rarely discussed.

Table 2: Policy areas included in the analysis, plus examples of sub-issues that are part of each policy area.

Policy area	Examples
Economy	Interest rates, unemployment, monetary policy, tax code, ...
Civil Rights	Minority and gender discrimination, voting rights, ...
Healthcare	Insurance, drug industry, medical facilities, reform, ...
Agriculture	Subsidies to farmers, food inspection and safety, ...
Labor	Workers safety, benefits and training, labor unions, ...
Education	Preliminary, secondary and higher education, ...
Environment	Water, air pollution, recycling, conservation, ...
Energy	Nuclear, electricity, natural gas and oil, coal, renewable, ...
Immigration	Immigrants, refugees, citizenship, ...
Transportation	Highways, air travel, railroad, maritime, ...
Law and Crime	Crime control, police, court administration, criminal and civil code, ...
Social Welfare	Assistance for low-income and elderly, child care, ...
Housing	Urban development, rural housing, low-income and veteran assistance, ...
Domestic Commerce	Banking, securities and commodities, small businesses, ...
Defense	Alliances, intelligence, personnel issues, foreign operations, ...
Technology	Space, science transfer, telecommunications, broadcast, ...
Foreign Trade	Trade agreements, exports, tariffs, exchange rates, ...
International Affairs	Foreign aid, human rights, international organizations, ...
Gov. Operations	Appointments, scandals, bureaucratic oversight, branch relations, ...
Public Lands	National parks, native American affairs, water resources, ...
Gun Control	Gun carriage, gun production, gun control/rights groups, ...

number of tweets on this topic we classified gun control as a separate policy category.

Finally, in order to test whether state legislators are more likely to lead the public agenda on particular issues, we categorize the policy areas we study into those over which state governments have substantial power ("state issues") and those that are primarily the domain of the federal government ("federal issues"). The policy areas that are traditionally the focus of the federal government are finance and domestic commerce, defense, science, technology and communications, foreign trade, and international affairs and aid (Kollman 2017). Most state legislatures do not have standing committees on these issues (Fouirnaies and Hall 2018), and the federal government has sole power to conduct foreign affairs and regulate interstate commerce. On the other hand, other policy areas are typically considered to be the realm of state government (Jewell 1982) and comprise the largest number of bills passed by state legislatures.[7] These areas include health, education, labor and employment, transportation, law and crime, social welfare, and housing. It is worth noting that the states and the federal governments also share responsibility for certain policy areas like the economy. For the sharpest comparisons possible, when studying issue-level differences however ($\mathbf{H}_{4_a}$ and $\mathbf{H}_{4_b}$), we have elected to focus on examining differences across the more clearly defined policy areas described in Table 3 rather than these shared areas.

Table 3: State vs. Federal Issues in the Comparative Agendas Project

State Issues	Federal Issues
Education	Domestic Commerce
Healthcare	Defense
Law & Crime	International Affairs
Transportation	Technology
Labor	Foreign Trade
Social Welfare	
Housing	
Gun Control	

4 Methods

4.1 Modeling the Issues Discussed on Twitter

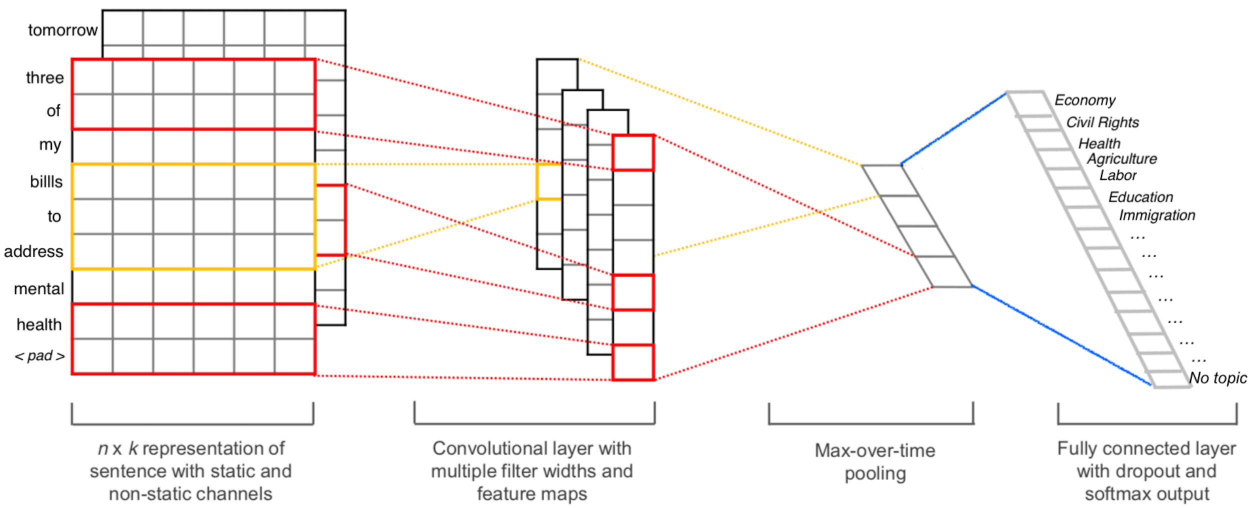
We use three convolutional neural networks (CNNs) to classify the tweets sent by the groups we study into one of the policy areas presented in Table 2: one CNN to classify the tweets sent by politicians, another one to classify the tweets sent by the mass public, and another one to classify the messages sent by the media. We use three separate supervised CNN models to account for the fact that politicians, the mass public and the media often use different style language to talk about the same issues.

These supervised machine learning models work as follows. First, we represent each

[7] https://openstates.org/

word in a given tweet as a 300-dimension word-embedding (a vector that ideally represents an integration of each word's meaning and context/position in the text as dense features for further analysis).[8] This results in a tensor ($n \times k \times d$) that is used as our primary model input, where n is the maximum word length for all training documents, k is the size of the embedding (300), and d is the number of documents to pass through to the CNN.

Figure 1: Architecture of the Convolutional Neural Net predicting the policy topics discussed in tweets.



The three CNNs have the same exact architecture. They are comprised of three convolutional layers of different sizes, each processing 3-, 4-, and 5-word embeddings at a time, and so producing hidden layers of different sizes. These hidden layers are joined into a single vector for each tweet by max-pooling the weights in each word-vector. The last stage of each of the CNNs is comprised of a fully connected layer mapping the previous max-pooled vector to the 22 issue classes (the 21 policy areas plus the "non-policy/not-relevant" class).[9]

[8] We generate the word-embeddings by finetuning a pretrained Word2Vec model for an additional 10 epochs (Mikolov et al. 2013), to which we had first added all unique new vocabulary present in our training datsets as well as in the tweets to which we wanted to apply the resulting model. We used the python `Gensim` word2vec model and methods, and GloVe pretrained embeddings: Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download).

[9] We employ a cross-entropy loss function and gradient optimization is performed via adaptive moment estimation (Kingma and Ba 2015). We use a batch size of 64 for training the model.

We trained each of the three CNN with various datasets, assessed the out-of-sample accuracy of each model-dataset pair, and selected the best performing model-data pairing to generate topic predictions for all tweets sent in 2018 by the actors under study. In Appendix A we explain the training process in more detail and we also show how this CNN model outperforms, and so is more suitable than, a baseline ngram-based machine learning model. Figure 1 provides a visual overview of our methodological approach.

In Table 4 we report the accuracy of the final classifiers that we use in the paper to predict the topics discussed in tweets sent by politicians, media, and partisans. We split the labeled data into three sets during training: a training set used for model estimation, a test set used for calculating the model loss and updating the model weights at each epoch/iteration, and a validation set that remained unseen during training and that we used to perform a final accuracy/generalizability test. In Table 4 we report the final test and validation accuracy for each model. Given that the validation set was not involved in the training at all, the validation accuracy is the one that provides a more clear judgement of how well the model performs at predicting the remaining unlabeled tweets.

Table 4: Accuracy of three Convolutional Neural Networks predicting the policy areas discussed by politicians, mass media, and the mass public (state partisans).

		Test Accuracy		Validation Accuracy	
Model	Max. Class Prop.	All	Policy	All	Policy
Politicians CNN	0.13	0.78	0.79	0.59	0.55
Media CNN	0.06	0.78	0.78	0.69	0.52
Partisans CNN	0.06	0.77	0.51	0.72	0.44

We also provide information about the proportion of tweets classified into the largest topic class in the labeled data (after excluding the non-topic category). This *Maximum Class Proportion* (column 2) serves as a baseline to judge the performance of each model, as it indicates how well we would do by simply classifying all tweets into the modal topic category.[10] We report two types of validation (and test) accuracy: when taking into account *All* tweets (those labeled as belonging to a topic category as well as the non-topic one), and when taking only into account those tweets labeled into one of the *Policy* issue categories. We do so because we want to make sure the model does a good job at distinguishing policy-relevant tweets from non-policy ones, but also at discerning between policy issue categories.

Overall, the three models do a good job at both of these tasks and prove to be useful for the objective at hand. When classifying tweets into issue categories as well as the non-policy one, the validation accuracy is very high for the three models (59% for the Politician Model, 69% for the Media Model, and 72% for the Partisans Model). Then, predicting a large number of (unbalanced) topic classes is a very complicated task. A model classifying tweets naively (i.e., into the modal category) would only get it right 13% of the time for the Politicians Model, and 6% of the time for the Media and Partisans one (as indicated by the *Maximum Class Proportion* column); whereas a model predicting at random a perfectly balanced dataset with only 2 outcome classes would already get it right 50% of the time. When excluding the non-policy tweets, the validation accuracy is greater than 50% for the Politician and Media Models, and 44% for the Partisan one. This means that when classifying policy-relevant tweets, our Politicians-CNN performs 4.2 times better than a model classifying tweets naively, and our Media and Partisans CNNs perform 8.6 and 7.3 times better, respectively. The *Policy* validation accuracy for the Partisans Model is slightly lower probably because ordinary users are likely to discuss policy issues using less technical (and harder to leverage) language. To emphasize the satisfactory accuracy and validity of these classifiers, we show in Appendix A that our CNN model architecture outperform the n-gram based models used in the past to automatically classify text into CAP topics. Moreover, in Tables A.5 to A.9 of the same Appendix we show that the most distinctive features of the tweets classified into each topic (and for each group of analysis) are words that one

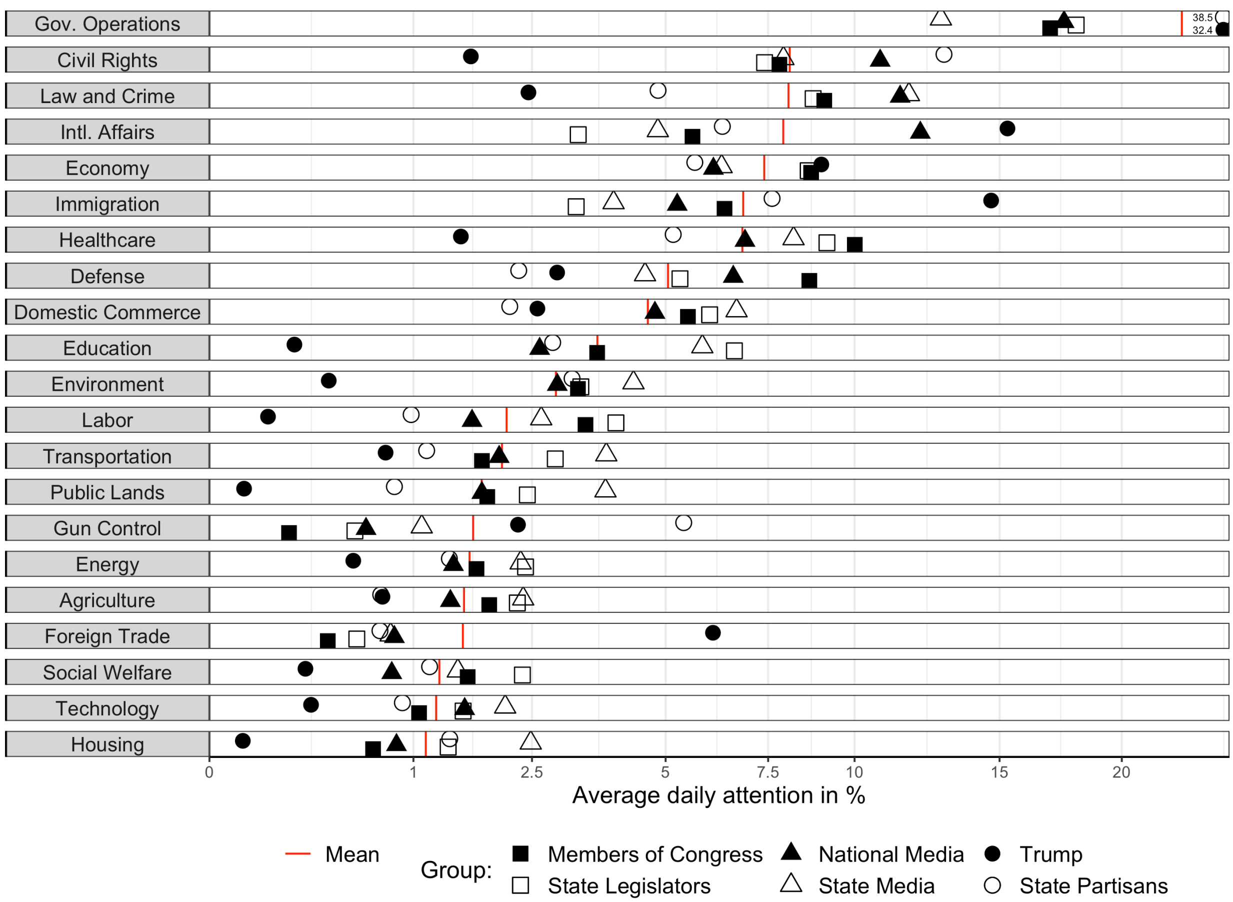
[10] Note that as this is a multi-label classifier, maximum accuracy is *not* 1 minus the modal category.

would clearly associate to each of the topics. Finally, we note that less than perfect accuracy suggests that we are measuring our variables of interest with measurement error. But, as will be seen in the analysis, we are aggregating over many tweets, and thus any stochastic measurement error becomes smaller. However, any remaining measurement error does of course mean we are conducting conservative tests of our hypotheses.

Finally, we use the Politician Model to generate topic predictions for the tweets sent by state legislators and members of Congress, the Media Model for tweets sent by state and national media accounts, and the Partisans Model for the tweets sent by our partisan followers of state legislators. In Figure 2, we show the average daily attention paid to each policy area by each of these groups. Across groups, *Government Operations* dominate the agenda. This broad category includes discussions related to political campaigns, government appointments, state and federal agencies, procurement, and political scandals. At the other end of the spectrum, *Housing* received the least amount of relative attention, which makes sense given that housing is a local issue primarily dealt with by city governments rather than by state and federal officials.

Note that, across issue areas, the groups under study display quite a bit of variation in the relative attention paid to each topic. For some issues, like education, state legislators appear to pay quite a bit more attention to the policy area than members of Congress. On others, like defense, members of Congress are more active. President Trump actively tweeted about many topics, including international affairs and immigration, while paying less attention to the issue of civil rights. These initial patterns help to validate the policy classifications of the tweets in our sample and suggest some interesting possible differences in the communication behavior of state legislators relative to other groups.

Figure 2: Average daily issue attention by group.



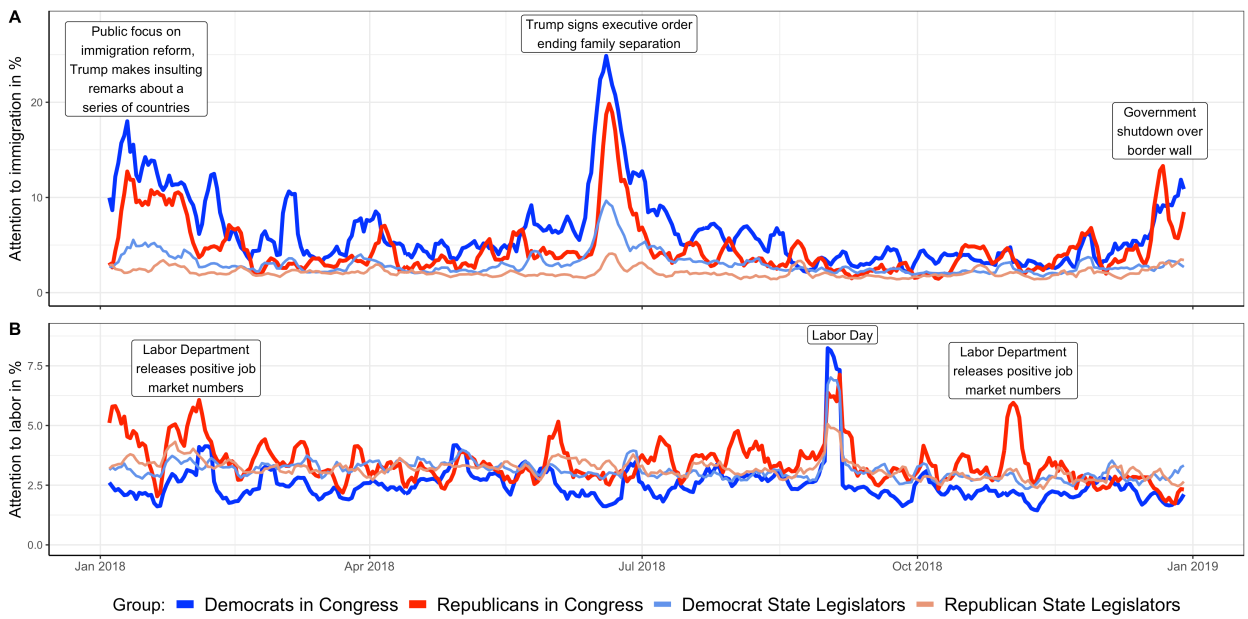
Note: The symbols represent the average daily amount of attention that a group paid to an issue during 2018. These were generated by first averaging the issue distributions of all tweets sent by a group on a given day and then averaging over all days. For political groups, both parties were weighted equally. The lines represent 7-day averages. The spacing of the x axis was square root transformed.

4.2 Vector Auto Regressive Models

In order to adjudicate who puts issues on whose agenda (the direction of influence) we leverage the temporal aspect of our data and model these in a vector autoregression (VAR). VAR models make it possible to identify dependencies among multiple time series (Freeman, Williams, and Lin 1989; Sims 1980). While most commonly applied to economic time series data, these models have also successfully been used to study agenda setting (Barbera et al.

2019; Edwards and Wood 1999; Wood and Peake 1998). For example, Figure 3 shows issues attention over time to two different policy areas—immigration and labor—broken down by party and level of government over the entire year being studied. Spikes in attention generally correspond to salient events, such as Trump signing an executive order to end family separation or the release of new employment data by the Labor Department. Often, state legislators and national legislators appear to move in tandem on issues. But it also appears that sometimes one group will start to discuss an issue before another group then increases its Twitter activity.

Figure 3: Exemplary issue attention time series.



Note: The displayed time series capture the share of attention that was paid to the issues immigration and labor by each of the four groups on Twitter. These were generated by averaging the issue distributions of all tweets sent by a group on a given day. The lines represent 5-day averages. For state legislators, each state was weighted equally.

While the raw data are suggestive, it is difficult to ascertain whether there is a systematic pattern in terms of how state legislators are using Twitter to discuss policy issues vis a vis members of Congress, particularly when visualizing the entire time series. Furthermore, we have data on 20 policy areas and tweets from additional actors, including the media and partisan constituents of each state in our sample. In order to uncover how these groups interact with each other over time across the total range of policy issues, we need to model this behavior statistically.

For the analysis, we transform the data into a set of time series Y, where $Y_{i,s,j,t}$ captures the amount of attention that group i, in state s paid to issue j on day t of the observed time period. For groups or actors on the national level, the time series are constant across states. The values of the time series were generated by averaging the issue distributions (the predicted tweet-level topic probabilities from the CNN models) of all tweets sent by a given group from a given state on a given day. These values vary between 0 and 1, with 0 implying that no attention was paid to an issue at all and 1 implying that attention was exclusively devoted to this issue. Because issues only receive attention on a few days but are undiscussed for most of the year, these distributions are heavily right-skewed. For the models, we transform our data to log odds $Z_{i,j,s,t}$, as is common when analyzing time-series with proportional values (Wallis 1987)[11]. Our VAR model comprises a system of equations, in which every time series $Z_{i,s,j,t}$ is modeled as a function of its lagged values plus the lagged values of the other time series. We use five lags (1, 2, 3, 4, and 5 days), thereby modeling the assumption that groups today only respond directly to tweets by other groups posted within the previous 5 days. While our models indicate that issue responsiveness usually decays after the first day, this allows for longer-term decay. Formally, the model can be expressed as follows:

$$Z = log(\frac{Y}{1-Y}) \tag{1}$$

[11] We impute values of .01 and .99 for 0 and 1 values respectively.

$$Z_{i,s,j,t} = \alpha_{s,j} + \sum_{i} \sum_{p=1}^{5} \beta_{i,p} Z_{i,s,j,t-p} + \varepsilon_{i,s,j,t} \tag{2}$$

In our first model, we use fixed effects $a_{s,j}$ for each combination of state and issue. We thereby make the simplifying assumption that dependencies between our nine groups are constant across state and issue. While this assumption is inaccurate to some extent, it drastically reduces the complexity of our data, thereby allowing us to test our first set of general hypotheses (**H1** to **H4**). Within this framework, we can express the degree to which changes in issue attention by one group are predictive of changes in issue attention by another group. To test the set of hypotheses relating to issue domain (**H5** and **H6**), we loosen this assumption and estimate separate models for each type of issue.

5 Results: A Mixed Picture of Responsiveness

VAR coefficients are difficult to interpret, so we use cumulative impulse response functions (IRFs) to display the results of our models: we simulate shocks to the VAR system of equations by simulating the effects of a sudden increase in attention to an issue by one group to then observe the resulting cumulative attention devoted to that issue by another group over time. We estimate cumulative IRFs for a 15-day period. As Barbera et al. (2019) have pointed out, it maybe be more realistic for changes in political issue attention to last longer than a day. We follow their approach and present our results as responses to a permanent attention change to a given issue from 0% to 10%.[12]

[12] To estimate responses to permanent changes in issue attention, we repeatedly insert an increase in attention to the respective time series until it reaches 10%. Formally these increases $\phi_{i,t}$ for group i in day t can be expressed as

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

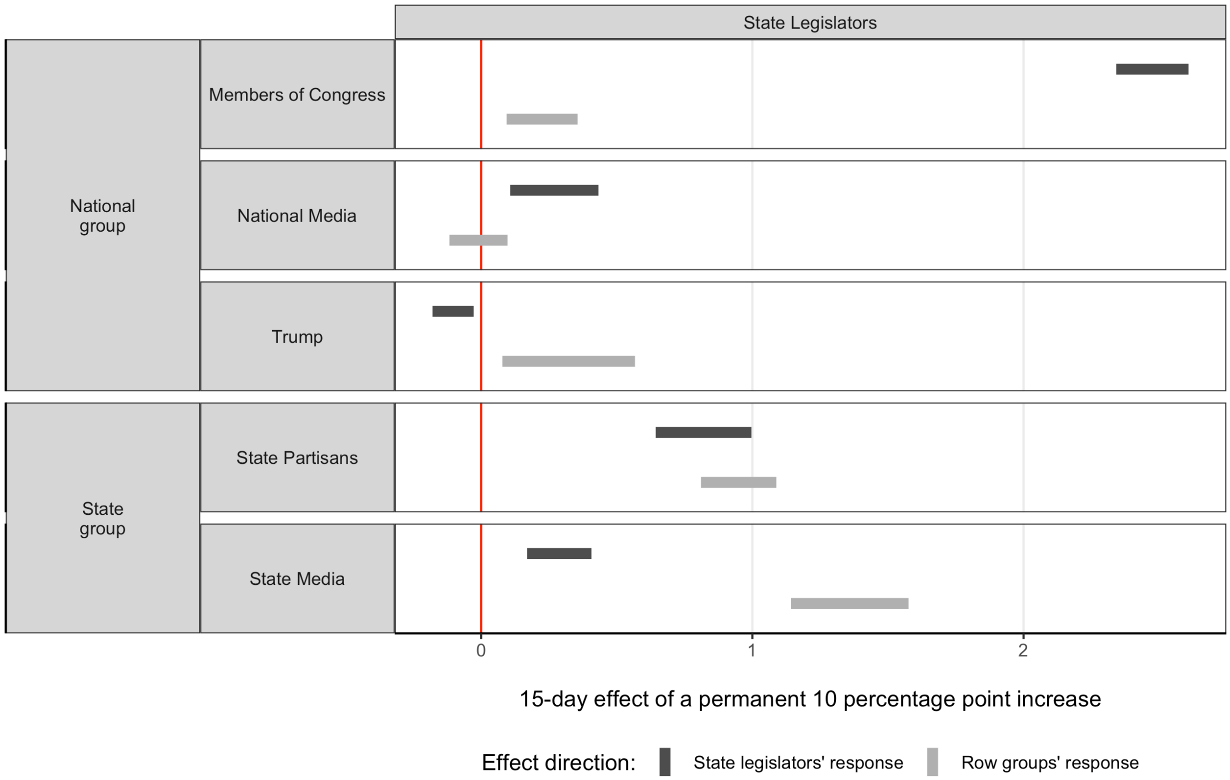
To get an intuitive understanding of these coefficients, assume that on day 0, none of the groups is paying attention to an issue j. We then introduce a 10 percentage point increase in attention in the time series of one group on day 1 and keep it fixed at 10% over the subsequent 15 days. We then use the parameters of our VAR model to calculate the resulting cumulative change in issue attention by each of the other groups over the next 15 days. So if a group reacted by discussing the topic in 1% of the tweets in day 1, 0.5% in day 2, and 0% the remaining 13 days, we would observe a cumulative 15-day effect of 1.5 percentage points.

Figure 4 shows the 15-day response coefficients of the general model with which we test **Hypotheses 1, 2, $\mathbf{3}_a$** and **$\mathbf{3}_b$**, with 95% confidence intervals. The coefficients are expressed in percentage points. The dark grey bands represent responses by state legislators to increases in issue attention by each of the five groups (members of Congress, the national media, President Trump, state partisans, and state media), while the light grey ones stand for responses of these five groups to increases in state legislators' issue attention. The coefficients range between 0 and 2.5 and are similar in size to those found by Barbera et al. (2019) using a similar methodological framework. We believe that these responses are substantively meaningful in magnitude. Getting issues onto the agenda of other groups is extremely difficult (Jones and Baumgartner 2005; Schattschneider 1975) and attention dynamics tend to follow nonlinear functions with tipping points, so that small changes in attention have potentially large consequences (Baumgartner and Jones 1993; Kingdon 2013).

Members of Congress exert the strongest influence on the agenda of state legislators, as indicated by the dark grey band in the first row. The sizable effect indicates that a permanent 10-point increase in attention to an issue by members of Congress is predicted to increase the cumulative attention by state legislators by 2.5 percentage points. These results

where $\hat{y}_{i,t}$ is the predicted value of attention for the respective group on a given day.

Figure 4: 15 Day Cumulative Predicted Issue Responsiveness



Note: The dark grey coefficients represent how much more cumulative attention (in percentage points) state legislators pay to an issue as a result of a permanent 10 percentage-point increase in issue attention by the groups in the rows 15 days ago. The light grey coefficients stand for the other groups' responses to changes in issue attention by state legislators. The bands represent 95% confidence intervals.

give unambiguous support to **Hypothesis 1**. In contrast, we find that state legislators have little influence on the agenda of national legislators.

We also find evidence for **Hypothesis 2** (political responsiveness): that changes in issue attention by mass public partisans will influence state legislators. The effects shown in Figure 4 row 4 (for state partisans) indicate that the public influences the policy areas to which state legislators pay attention. These light grey bar shown in row 4 further suggest that, in contrast to findings with regard to members of Congress, the relationship between state legislators and constituent attention is bidirectional: not only are state legislators responsive to partisans in their states, but these constituents are equally responsive to state legislators. If either group begins discussing a particular policy area on Twitter, the other group also shifts their attention toward that topic over the next fifteen days.

The model also supports our hypotheses regarding media effects ($\mathbf{H3}_a$ and $\mathbf{H3}_b$). Both the national media (row 2) and the state media (row 5), have a modest influence on the issues that state legislators discuss on Twitter. And these effects are estimated to be approximately equal in magnitude. Notably, state media outlets are also very responsive to state legislators (much more so than state legislators are to media). And, as might be expected, the topics discussed by state legislators appear to have no effect on the topics discussed by national media.

The results in Figure 4 show the overall responses of state legislators to all members of Congress (and vice versa). But perhaps that relationship might look different if we restrict the analyses to lawmakers from the same state at both the state and federal levels. In Figure B1 in Appendix B, we replicate the main results but look only at legislators from the same states (e.g., how do state legislators in California respond to shifts in issue attention by members of Congress generally vs. shifts by congressional representatives from California). The results indicate the same general dynamic between Members of Congress and state legislators: the former continue to exert a strong influence on the public agenda of state legislators while the latter have little to no chance to influence the agenda of members of Congress.

We include President Trump only as a control in the model, we did not put forward any clear directional hypothesis as there are mixed findings in the literature regarding whether the sitting President is able to influence other political agendas (Wells et al. 2016; Lawrence and Boydstun 2017) or not (Edwards and Wood 1999). This control variable however yields very interesting findings. Contrary to the idea that President Trump had a very strong influence on the political agenda of other groups (see Wells et al. (2016) for an overview), we observe the President to have no influence on the issues state legislators discuss. If anything, the President seems to react to issues put on the agenda by state legislators.

Together, these results suggest that U.S. state legislators are positioned at the crossroad of national and state level politics. On the one hand, the strongest influence on their public agenda comes from member of Congress, although state legislators have little if any impact on the agenda of these national level actors. On the other hand, state legislators are embedded in a local discourse. Both partisan members of the public within each state and state-level media help shape the issues to which state legislators pay attention. This state level discourse, however, reverberates, with state legislators also having an impact on the agenda of these other state level actors.

5.1 Exploring Partisan Differences

Although we did not put forward any hypotheses about potential party differences, in this section we break down our analyses by party to examine how Democratic and Republican state lawmakers, members of Congress, and constituents influence each other in terms of issue attention. To do this, we generate independent time series for Democratic and Republican legislators and partisans. The goal is to have a better understanding of which party has a stronger influence on the aggregate patterns seen in Figure 4 as well as to provide some descriptive results that can inform future research on the topic. In Figure 5, the panel on the left shows the results for Democratic state legislators, and the panel on the right shows the results for Republicans. As before, the dark bars indicate the response by state legislators to the group in each row, while the light grey bars reflect the group's response to a change in attention by state legislators.

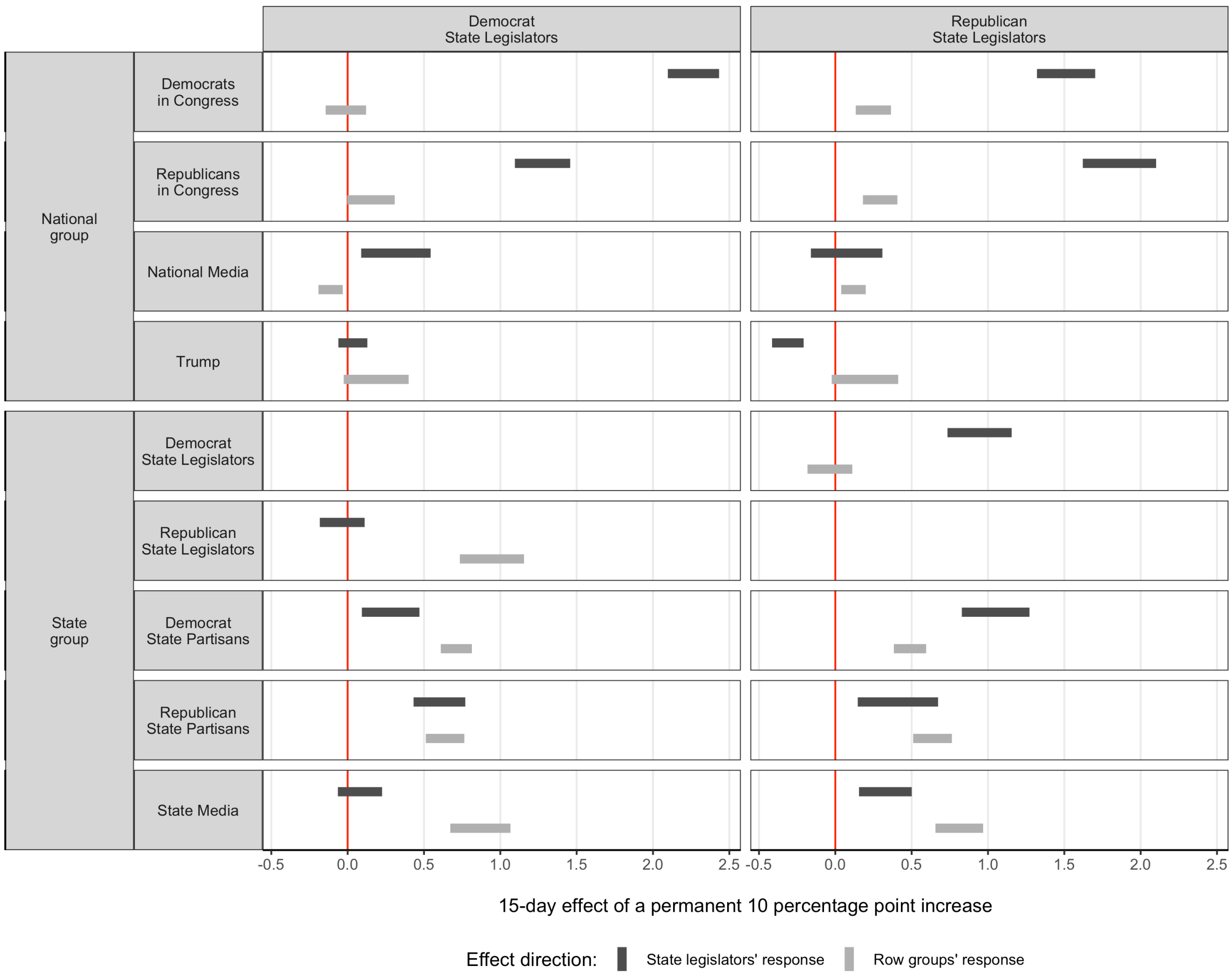
The main results provided strong evidence that state legislators adjust their public communication in response to the issues dominating the agenda of national lawmakers in Congress. Interestingly, both Republican and Democratic state lawmakers become more likely to discuss not only the issues being focused on by their Congressional co-partisans, but also those being discussed by the other party. For example, a permanent 10-percent increase in issue attention by Republican members of Congress is associated with a 1.3 percentage point increase in issue attention by Democratic state legislators. Of course, in practice the issues being discussed on Twitter by both parties are likely highly correlated with each other, making it difficult to isolate marginal effects. It is also likely that members of both parties are discussing policy areas in very different terms. For example, while lawmakers from both parties were more likely to discuss immigration after President Trump signed the executive order ending family separation, the tone and content of tweets from Republicans were almost certainly distinct from those of Democrats.

Democratic state law makers also appear to exert greater influence over the public agenda of Republican state legislators than vice versa. When Democrats in a state begin tweeting about an issue, Republicans often follow suit, but the reverse doesn't seem to happen as often.

Also of note is the fact that both Democratic and Republican state legislators appear to shift their attention in response to the twitter discussions of both co-partisan and non co-partisan constituents in their states. If anything, state lawmakers appear to be slightly *more* responsive to shifts in issue focus by constituents from the other party. Again, this could simply reflect the fact that partisans from both sides often are discussing the same issues in different terms, making it difficult to credibly isolate an independent increase in attention by one group. At the state level, a rich and reciprocal dialogue appears to happen between the public and state lawmakers, regardless of party.

In Figure 4 we observed state legislators to react to changes in issue attention by the state and national media, and to have a strong influence on the issues that state media outlets discuss. In Figure 5 we observe Democrat but not Republican state legislators to react to national media, and we observe Republican but not Democrat state legislators to

Figure 5: Issue Responsiveness by Party



Note: The coefficients represent how much more cumulative attention (in percentage points) a group pays to an issue as a result of a permanent 10 percentage-point increase in issue attention by another group 15 days ago. The bands represent 95% confidence intervals.

react to shifts in issue attention by state media. About the *viceversa* effect, we observe state representatives from both parties to influence the agenda of state media, but only Republicans to influence shifts on issue attention by national media outlets.

Finally, the null effects observed for President Trump in Figure 4 are seen again in this new Figure 5, as we see no statistically significant impact on Democratic issue-attention, and Republican state legislators appearing to pay less attention to issues in response to changes in issue attention by the President.

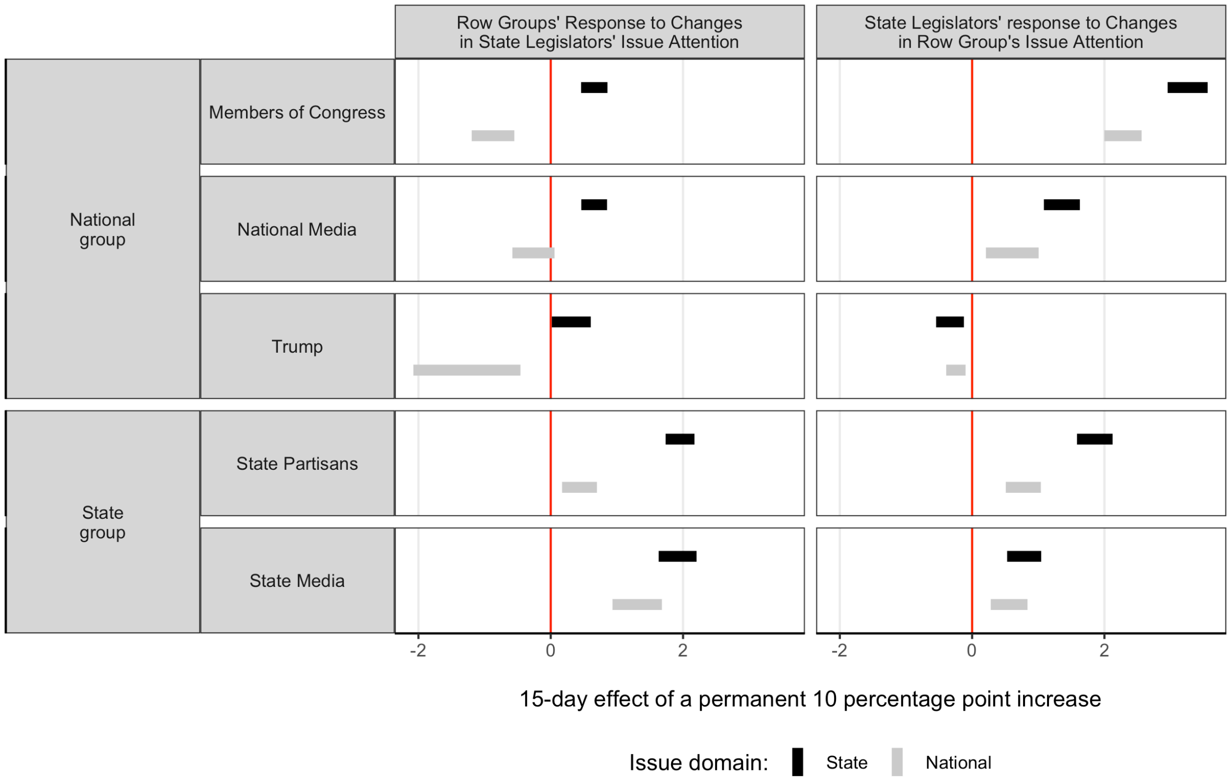
5.2 Heterogeneity by Issue Domain

Next, we break down the analysis by issue domain and estimate two distinct models: one for the state policies listed in Table 3 and one for the federal policies also listed in Table3. Figure 6 shows the results. Note that now, dark bars reflect issues that are the domain of the state government (such as education and transportation), and the light bars represent issues where the federal government is more powerful (such as defense and foreign trade). The panel on the left shows how each of the five groups under study responds to state legislators' attention vis a vis these issues, while the panel on the right shows how state legislators respond to shifts in attention by each group.

Notably, the dark bars are consistently to the right of the light grey bars *in both panels* of Figure 6. In other words, for topics that are particularly germane to state government, state legislators are both more likely to shift their focus to that topic in response to other groups discussing that topic, and to influence the agenda of other groups, than they are for topics more germane to the federal government. These results are consistent with both $\mathbf{H4}_a$ and $\mathbf{H4}_b$. In fact, even though the main results indicated that members of Congress have a strong overall effect over the twitter discussions of state lawmakers, here we see that state legislators do have the capacity to lead the agenda when it comes to state-level issues. When state legislators increase their discussion of policy topics like education, health, transportation, or law and crime, congressional representatives follow suit (row one, left-hand panel). At the same time, state legislators continue to follow the issue agenda being put forth by members of Congress (row one, right-hand panel)—and they seem even more responsive when the policy being discussed is a state issue.

State partisans are also substantially more likely to shift their attention to an issue being discussed by state legislators if that policy area is one that is primarily the domain of

Figure 6: Issue Responsiveness by Issue Domain



Note: Unlike in the previous figures, the columns differentiate the direction of the effect whereas band colors represent the set of issues as listed in Table 3. Dark grey bands represent the coefficients for state owned and light grey bands represent the coefficients for nationally owned issues with with 95% confidence intervals. Like in the previous figures, these coefficients represent how much more cumulative attention (in percentage points) a group pays to an issue as a result of a permanent 10 percentage-point increase in issue attention by another group 15 days ago.

state government (compared to issues that are more national in scope). This same pattern holds for the national media and state media outlets. Overall, after controlling for the fact that these groups also have an influence on the issues state legislators discuss, when the policy agenda consists of issues that are particularly important to state governments, state legislators appear to have substantially more influence over the public discourse surrounding those topics.

6 Discussion

Amid growing gridlock and partisan polarization in the federal government, state legislatures are increasingly becoming the locus of key policy decisions. While research on state politics has historically lagged behind that on national politics, over the past few decades the field has undergone a transformation, with scholars discovering (or rediscovering) the theoretical utility of focusing on state and local political dynamics. After early work in this area uncovered a strong correlation between state-level policy and state-level ideology (e.g. Erikson et al. 1993), scholars have continued to explore how political representation and policy-making operate in state government.

However, this work has often been constrained by data limitations, with the majority of research relying on roll-call votes and public opinion surveys to measure responsiveness. As a result, we still know relatively little about areas such as issue attention and agenda setting at the state level. In this paper we take advantage of recent data and computational advances and use Twitter to study which issues state legislators discuss in their public communications and how these correspond to the issues being discussed by members of Congress, state constituents, and by national and state media outlets. This allows us to generate dynamic estimates of agenda setting activity for these different groups on the same set of issues, enabling us to draw conclusions about who leads and who follows in the world of state politics issue attention.

We find that state legislators are particularly responsive to the public communications of Members of Congress and frequently shift their attention to issues being discussed at the national level. This is true for both Democratic and Republican state legislators and suggests that the increasing nationalization of politics in the U.S. has implications for the agenda stetting process in state legislatures. At the same time, state lawmakers are both responsive to and influence the political discourse of both partisans and media outlets in their states, suggesting a bidirectional relationship in terms of agenda setting influence.

While state legislators have little ability to drive issue attention at the national level overall, we find evidence that they are able to lead the agenda on issues that are traditionally associated with state government, such as education and public safety. In these areas, state legislators appear to influence the discourse of national actors, importantly including members of congress, and strongly influence the discourse of state partisans. While state lawmakers might be constrained in important ways by the national environment when it comes to their public communications on many issues, they are still able to play an important role in setting the state and national agenda when it comes to state-focused issues.

These results paint a more nuanced portrait of state politics than recent research would suggest. While some scholars argue that we are in an age where "all politics is national" (e.g. Hopkins 2018) and others find little evidence of accountability in state legislative politics (e.g. Rogers 2017), we find that state lawmakers play an important role in linking their constituents to national policy conversations. While we uncover substantial evidence that state legislators follow the discussions of Members of Congress in terms of the topics they discuss on Twitter, we also find that state lawmakers are quite responsive to members of the public in their states and in turn shape the public discourse of state partisans. Moreover, on issues that are traditionally the domain of state government, state legislators do appear able to move the needle on national policy conversations.

States are often described as "laboratories of democracy" where policy innovation can take root. If attention is a necessary condition for policy change, then a full understanding of the state-level policymaking process must take agenda setting and issue attention into account. This research represents the first effort that we know of to study the policy discourse of state legislators, national actors, the public, and the media on the same platform. It is our hope that the methodological approach and evidence offered in this paper can spearhead a research agenda focused on the intersection of agenda setting, policy-making, and public communication in state politics.

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Appendix A Training of the topic classifiers

We trained three convolutional neural networks (CNNs) to predict the topics discussed in tweets sent by politicians, media accounts, and partisans (followers of state legislators). We relied on 20 topic categories from the Comparative Agendas Project (CAP) plus an additional *Gun Control* one, 21 in total. The training process worked as follows.

Table A1: Datasets coded using the CAP 21-issue classification, used for training and testing the classifiers predicting the policy areas discussed by politicians, the media, and the mass public.

Set	Dataset	Time	N
A	Congressional Quarterly Almanac	1948-2015	14,444
	New York Times Front Page	1996-2006	31,034
	New York Times Index	1946-2014	54,578
	Congressional Bills	1947-2016	463,762
	Congressional Hearings	1946-2015	97,593
	Public Law Titles	1948-2011	33,644
	Public Laws	1948-2017	20,928
	Executive Orders	1945-2017	4,294
	Presidential Veto Rhetoric	1985-2016	1,618
	State of the Union Speeches	1946-2018	22,289
	Democratic Party Platform	1948-2016	15,953
	Republican Party Platform	1948-2016	19,836
	Supreme Court Cases	1944-2009	9,031
B	Tweets sent by Senators 113th Congress	2013-2015	45,394
C	1. Tweets sent by media accounts	2018	8,802
	2. Tweets sent by followers of state legislators	2018	9,286
	3. Tweets sent by state legislators	2018	3,368
	Total	1944-2018	855,854

In our training datasets, each observation (document or tweet) has been coded as belonging to one (mutually exclusive) topic category or the no-topic one, 22 classes in total. We used three datasets to train the models, described in Table A1. In the first dataset (A) we combined all available CAP-labeled datasets for the United States available in the CAP website (789,004 observations in total). The second dataset (B) is comprised of 45,394 tweets from Senators who served during the 113th Congress and that were labeled by Russell (2018). The third set (C) consists of random samples of the tweets we collected and that we annotated for the purpose of this paper: (C.1) state legislators (N = 3,368), (C.2) state media accounts (N = 8,802), and (C.3) state partisans (N = 9,286).[13]

[13]The inter rater reliability for the tweets we coded is the following. (C.1) Tweets sent by media accounts:

We trained each of the three CNNs (the politicians, the media, and the partisans one) nine times using the following data combinations, with the goal of taking advantage of transfer learning and training more accurate models than simply training the model with the tweets from each group (politicians, media and partisans) that we had coded: (1) only set A, (2) only set C.n (so only training the politicians/media/partisans CNN with the tweets we coded from politicians/media/partisans) , (3) set A and set C.n, (4) set C.n and a small sample of set A (1,300 observations), (5) set C.n and a smaller sample of set A (650 observations), (6) set C.n and set B, (7) set C.N and a small sample of set B (1,300 tweets), (8) set C.n and a smaller sample of set B (650 tweets), (9) set C.n and the other C sets.

To assess the performance of these nine versions of each model we split the data used in each case into a train, test, and validation set. The validation set is composed of 20% of our own labeled tweets in the C.n set. The train and test sets are composed of 80 and 20% (respectively) of *all* labeled cases used for training (after excluding those tweets in the validation set when applicable – so when set C.n involved in the training).

In Tables A2, A3, and A4 we report the accuracy of the models . We assess the test accuracy when predicting tweets in the test (*Test Set*) and validation splits (*Validation Set*), and also when predicting *All* tweets (so those coded as being about a policy area as well as those coded as not being about a policy topic) and also when only predicting the tweets coded as being about one of the *Policy* areas, so after excluding the no-policy tweets. The tweets not related to any policy area represented a large part of the tweets we coded from each group (set C) and we wanted to make sure that our model did well at both distinguishing overall policy relevance and at distinguishing between policy areas.

Training the models with the tweets in set B and set C.N yielded the most satisfactory results: high accuracy when predicting *All* as well as only the tweets coded as being about a *Policy* area. In Table A3 we show that the accuracy in distinguishing between policy areas for the Media model was higher when only training the model with set A. However, that model did a poor job at distinguishing between policy and no-policy tweets. For this reason we decided to go with the model trained with set B and set C.N also for the Media model.

As additional validation exercise, in Tables 5-9 we show the more frequent words in tweets about each policy area, broken down by group (national and state legislators, national and state media, and state partisans). We pulled these by (a) first calculating, for each word in corpus, the proportion of tweets in which they appear, (b) then calculating the proportion of tweets about each issue in which each the same words appear, and (c) finally calculating the difference between (b) and (a), which indicates which words/features are more likely to show up in tweets about that topic than on tweets about other topics. From a face validity point of view, these top topic features make total sense, they are words one would expect to be used in tweets discussing these policy areas.

89% agreement and 0.7 Cohen's Kappa. (C.2) Tweets sent by followers of state legislators: 91% agreement and 0.77 Cohen's Kappa. (C.3) Tweets sent by state legislators: 87.1% agreement and 0.74 Cohen's Kappa.

Table A2: Out of sample accuracy of the nine versions of the CNN model we trained predicting the political topics of the Comparative Agendas Project in tweets sent by **POLITICIANS** (state legislators).

	Test Set		Validation Set			
	CNN		CNN		SVM	
Model version	All	Policy	All	Policy	All	Policy
(6) set C.3 and B	0.78	0.79	**0.59**	**0.55**	0.38	0.40
(1) set A	0.73	0.73	0.27	0.53	0.23	0.47
(3) set C.3 and A	0.73	0.73	0.36	0.52	0.44	0.45
(9) set C.3 and C.1&C.2	0.77	0.49	0.66	0.43	0.61	0.31
(7) set C.3 and small B	0.56	0.36	0.61	0.32	0.59	0.27
(4) set C.3 and small A	0.55	0.32	0.60	0.28	0.58	0.27
(8) set C.3 and smaller B	0.57	0.29	0.61	0.29	0.58	0.23
(5) set C.3 and smaller A	0.56	0.28	0.60	0.27	0.59	0.22
(2) set C.3	0.60	0.26	0.59	0.22	0.57	0.19

Table A3: Out of sample accuracy of the nine versions of the CNN model we trained predicting the political topics of the Comparative Agendas Project in tweets sent by the **MEDIA** (state/regional media accounts).

	Test Set		Validation Set	
	CNN		CNN	
Model version	All	Policy	All	Policy
(1) set A	0.74	0.74	0.19	0.55
(6) set C.1 and B	0.78	0.78	**0.69**	**0.52**
(3) set C.1 and A	0.73	0.73	0.65	0.51
(9) set C.1 and C.2&C.3	0.77	0.49	0.71	0.49
(7) set C.1 and small B	0.70	0.40	0.74	0.39
(4) set C.1 and small A	0.71	0.40	0.74	0.38
(8) set C.1 and smaller B	0.72	0.38	0.75	0.38
(5) set C.1 and smaller A	0.72	0.37	0.74	0.36
(2) set C.1	0.74	0.33	0.73	0.29

Table A4: Out of sample accuracy of the nine versions of the CNN model we trained predicting the political topics of the Comparative Agendas Project in tweets sent by **PARTISANS** (followers of legislators from each state).

	Test Set		Validation Set	
	CNN		CNN	
Model version	All	Policy	All	Policy
(6) set C.2 and B	0.79	0.79	**0.72**	**0.44**
(1) set A	0.74	0.74	0.11	0.42
(9) set C.2 and C.1&C.3	0.75	0.44	0.81	0.42
(7) set C.2 and small B	0.77	0.43	0.80	0.40
(8) set C.2 and smaller B	0.78	0.38	0.81	0.38
(3) set C.2 and A	0.74	0.73	0.66	0.35
(4) set C.2 and small A	0.76	0.40	0.80	0.35
(5) set C.2 and smaller A	0.78	0.35	0.80	0.34
(2) set C.2	0.80	0.33	0.79	0.31

Table A5: Top topic features in tweets by NATIONAL MEDIA

Topic	Top Features
No policy issue	new,says, police, man, say, first, people, former, one, school, ___year___, shooting, woman, during, florida, breaking, like, over, found, house
Healthcare	health, says, new, people, care, medical, or, one, mental, opioid, work, get, your, cancer, patients, all, first, potus, could, drug
Gov. Operations	house, says, trumps, former, white, ___year___, fbi, think, democratic, potus, senate, court, democrats, special, donald, mueller, realdonaldtrump, campaign, new, director
Intl. Affairs	north, korea, says, un, kim, russia, potus, jong, summit, korean, latest, russian, south, world, breaking, syria, leader, putin, talks, apsports
Public Lands	apwestregion, national, aptravel, endangered, park, space, day, heat, historic, museum, native, near, new, part, wildfire, wildfires, wildlife, ___year___, africanamerican, american
Labor	jobs, wage, workers, employees, job, minimum, new, potus, wages, over, pay, report, created, economy, february, low, million, security, ai, american
Law and Crime	gun, police, shooting, sexual, says, florida, law, violence, apwestregion, apcentralregion, new, school, officers, people, say, victims, children, against, enforcement, parkland
Defense	military, nuclear, potus, missile, says, north, korea, deal, war, iran, national, breaking, veteran, air, our, alert, american, weapons, hawaii, syria
Immigration	immigration, border, daca, potus, illegal, immigrant, immigrants, children, says, wall, people, ice, democrats, policy, sanctuary, trumps, california, deal, families, over
Domestic Commerce	apwestregion, hurricane, volcano, billion, business, apsports, big, back, california, companies, new, potus, could, hawaii, hawaiis, kilauea, maria, says, sports, across
Civil Rights	women, people, court, rights, says, black, new, one, justice, or, our, potus, white, first, facebook, fisa, all, fbi, memo, supreme
Economy	tax, potus, foxbusiness, economy, going, realdonaldtrump, economic, house, spending, time, cuts, ___year___, new, our, people, tariffs, very, dow, reform, says
Environment	climate, scientists, water, apwestregion, epa, change, new, lava, pruitt, volcano, environmental, hawaiis, pollution, agency, air, gas, health, kilauea, most, officials
Transportation	airport, flight, airlines, cars, plane, bridge, passengers, southwest, say, florida, passenger, new, runway, apwestregion, carrying, engine, international, one, pedestrian, says
Energy	oil, coal, solar, could, drilling, energy, gas, says, say, industry, power, ___year___, administration, burning, china, east, florida, jobs, mine, missing
Agriculture	farm, apwestregion, chicken, food, salmonella, state, tied, agriculture, apeastregion, breaking, buzzards, bye, farmers, fish, flies, giant, hog, jurors, kfc, m
Social Welfare	welfare, reform, food, need, americans, growing, like, newtgingrich, require, right, security, social, stamp, states, together, –, 8year, afford, again, all
Gun Control	school, shooting, florida, action, heres, high, take, victims, 19th, anniversary, called, calls, chaotic, columbine, david, demand, expected, far, fear, first
Education	school, students, teachers, student, florida, teacher, college, schools, shooting, high, our, kids, make, parents, potus, public, shootings, apcentralregion, children, elementary
Technology	internet, nasa, nasas, company, launches, rocket, spacex, your, data, facebook, mars, net, neutrality, new, or, russian, satellite, successfully, which, access
Foreign Trade	trade, tariffs, china, aluminum, potus, steel, war, canada, goods, trumps, could, imports, allies, eu, free, mexico, new, says, some, states
Housing	housing, before, homeless, million, raise, rents, states, tax, —, across, acute, affect, affordable, americas, amused, average, avoided, belongings, ben, bezos

Table A6: Top topic features in tweets by PARTISANS

Topic	Top Features
No policy issue	your, my, all, our, so, me, one, like, realdonaldtrump, or, people, get, good, great, time, m, new, now, today
Healthcare	health, mental, our, care, insurance, medicaid, new, opioid, planned, get, healthcare, parenthood, states, work, your, all, defund, life, need, over
Gov. Operations	fbi, realdonaldtrump, our, comey, maga, mueller, vote, all, democrats, obama, so, hillary, state, clinton, now, why, gop, house
Intl. Affairs	iran, north, korea, syria, realdonaldtrump, israel, obama, russia, hamas, iranian, muslim, deal, nuclear, our, america, isis, islam, russian
Public Lands	indiana, carmel, draws, mosque, opposition, proposed, wthrcom
Labor	labor, 21st, administration, american, americans, anyway, buy, careers, century, cheep, departments, deserve, destroyed, does, education, elected, fdrlst, good, harm
Law and Crime	police, sex, justice, trafficking, crime, fbi, criminal, cops, illegal, our, people, human, law, should, system, california, child, drugs, realdonaldtrump, against
Defense	our, military, american, national, realdonaldtrump, security, veterans, any, great, need, or, war, would, action, citizens, country, democrats, deployed
Immigration	illegal, border, immigration, our, realdonaldtrump, daca, wall, all, immigrants, them, aliens, amnesty, ice, ms13, children, democrats, realjameswoods, american, country, should
Domestic Commerce	small, business, laws, over, realdonaldtrump, so, stop, used, using, ‘, 69magnitude, accurate, across, adigaskell, ai, aid, already, assets, bad, banks
Civil Rights	women, people, black, all, against, muslim, so, abortion, rights, or, why, media, would, should, speech, our, ‘, conservative, democrats, free
Economy	tax, our, realdonaldtrump, economy, cuts, jobs, taxes, democrats, so, budget, pay, unemployment, cut, new, potus, funding, spending, american, bill
Environment	climate, change, water, global, ca, environmental, warming, conservation, new, our, species, al, animals, arizona, california, congress, data, does, efforts, hillary
Transportation	program, project, ___year___, arizona, bu, came, capital, city, comment, construction, council, county, discussing, draft, effort, fiveyear, floor, focused, future, governors
Energy	energy, gas, oil, clean, arizona, coal, nuclear, production, ___year___, ‘, basin, cleanhealthyaz, could, fracking, fuel, green, last, money, natural, new
Agriculture	benefit, cattlemen, farm, our, program, raising, advertising, aecon, alarm, allison, asked, bill, builds, canada, ceding, children, company, concerns, control, cooke
Social Welfare	want, children, disabilities, our, support, thank, working, aappd, able, act, ada, adoption, americans, autism, azs, care, childrens, common, community
Gun Control	nra, gun, guns, 2a, my, so, school, all, dloesch, why, florida, parkland, people, shooting, did, new, our, fbi, tweetyournramembership, your
Education	schools, our, education, school, teachers, students, college, need, public, children, teacher, charter, student, arizona, parents, some, state, districts, dougducey, dvusd
Technology	netneutrality, act, arrested, call, congress, ended, energy, facebook, fcc, freedom, hours, industry, innovation, instagram, kamalaharris, kids, kill, less, meddling, media
Foreign Trade	trade, tariffs, realdonaldtrump, tariff, billion, china, trumps, against, all, american, attacking, barriers, breaking, business, center, chinese, companies, deficit, eu, europe
Housing	safety, building, county, housing, liberal, mesa, ordinance, pinal, pinalcounty, pool, rise, stresses, temperature, agency, alamitos, antisanctuary, ap, approves, asu, banking

Table A7: Top topic features in tweets by MEMBERS CONGRESS

Topic	Top Features
No policy issue	my, our, all, de, your, today, great, thank, happy, day, me, la, so, el, family, community, thanks, work, y
Healthcare	health, care, our, need, all, people, opioid, my, your, americans, access, act, families, help, should, work, bill, drug, must, so
Gov. Operations	our, my, so, people, house, help, your, one, today, back, campaign, time, all, should, m, now, or, vote, ___year___, get
Intl. Affairs	our, russia, ___year___, must, putin, russian, today, my, all, american, elections, or, sanctions, democracy, korea, world, election, foreign, people, should
Public Lands	national, our, park, parks, today, my, public, all, great, lands, fire, bill, forest, your, conservation, findyourpark, native, protect, state, tribal
Labor	workers, jobs, our, wages, working, my, work, families, american, family, leave, new, wage, act, unions, create, labor, need, one, today
Law and Crime	gun, our, violence, students, children, my, congress, must, today, families, these, neveragain, all, people, safety, school, act, need, action, should
Defense	our, veterans, military, my, nuclear, honor, service, national, iran, thank, today, security, war, your, day, work, all, should, country, great
Immigration	our, dreamers, daca, immigration, families, children, border, immigrants, my, de, now, these, country, must, policy, parents, dreamactnow, people, congress, immigrant
Domestic Commerce	our, help, small, puerto, businesses, hurricane, my, need, banks, business, disaster, new, rico, fema, must, great, local, these, all, bill
Civil Rights	our, women, rights, all, today, equality, fight, my, justice, people, country, every, right, must, vote, netneutrality, work, day, so, time
Economy	tax, our, goptaxscam, families, budget, americans, republicans, all, bill, cuts, working, now, american, corporations, plan, gop, today, year, need, realdonaldtrump
Environment	our, climate, water, change, epa, clean, environmental, environment, must, my, protect, earthday, communities, all, public, air, drilling, health, new, should
Transportation	our, infrastructure, my, safety, new, great, today, rail, train, all, must, need, public, transportation, congress, news, roads, bridges, bus, investment
Energy	our, energy, oil, drilling, offshore, clean, gas, coal, new, plan, renewable, administration, back, my, fuel, or, ___year___, economy, jobs, must
Agriculture	farmers, our, farm, bill, farmbill, food, my, support, agricultural, m, today, ag, agriculture, trade, bipartisan, ranchers, ___year___, economy, committee, great
Social Welfare	snap, food, families, children, meals, nutrition, program, kids, our, security, assistance, social, would, americans, benefits, cuts, house, bill, gopfarmbill, make
Education	students, our, school, education, all, teachers, student, today, college, my, schools, your, high, make, proud, these, thank, great, future, public
Technology	internet, netneutrality, open, free, access, fccs, repeal, fcc, vote, fight, my, today, your, broadband, need, our, all, americans, big, colleagues
Foreign Trade	trade, canada, tariffs, billion, chinese, continue, goods, here, jobs, m, my, our, so, state, trumps, war, worry, ___year___, ability, action
Housing	housing, affordable, families, our, make, need, act, community, development, homeless, my, one, today, working, access, all, assistance, crisis, great, improve

Table A8: Top topic features in tweets by STATE LEGISLATORS

Topic	Top Features
No policy issue	our, my, thank, your, great, all, today, so, day, me, one, happy, m, good, time, ___year___, thanks, join
Healthcare	health, care, our, maternal, mental, new, your, day, flu, healthcare, work, get, state, tx, medicaid, mortality, all, donnahowardtx
Gov. Operations	vote, our, election, today, your, day, state, voting, ___year___, primary, early, my, all, house, so, time, democratic, people
Intl. Affairs	russia, my, our, russian, putin, right, thehill, now, trumps, world, american, dead, peace, people, says, so, ___year___, again, am
Public Lands	our, park, state, fire, today, during, great, public, thank, wildlife, beautiful, city, confederate, contained, discussion, grand, heritage, history, land
Labor	job, workers, fair, jobs, our, great, today, alief, community, employees, need, todays, work, workforce, working, youth, according, all, better
Law and Crime	our, children, gun, all, violence, families, today, my, law, parents, sexual, separated, thank, guns, people, child, school, community
Defense	our, military, veterans, war, one, day, women, ___year___, state, today, my, families, honor, or, veteran, friend
Immigration	daca, children, border, immigration, immigrants, immigrant, malctx, families, dreamers, our, policy, parents, detention, migrant, family, today, stand, trumps
Domestic Commerce	harvey, flooding, our, community, business, small, city, need, local, w, businesses, hurricane, many, ___year___, disaster, state, thank, flood
Civil Rights	women, our, all, rights, scotus, malctx, today, redistricting, day, voter, case, every, ___year___, or, join, people, court, families
Economy	tax, taxes, our, ___year___, property, budget, economy, should, state, tariffs, m, my, now, your, need, spending, today, w
Environment	water, climate, our, change, earthday, right, air, cleanup, lake, nasa, san, so, today, all, brownsville, could, great, mars
Transportation	transportation, nasa, ___year___, houston, southwestair, without, txdot, airlines, future, hearing, like, ve, your, bus, get, glad, inst, now, texas
Energy	energy, gas, oil, solar, texasoilnews, oilandgas, one, our, texasoil, txenergy, back, coal, committee, cpsenergy, great, look, nasa, natural, next
Agriculture	food, farm, farmers, ___year___, agriculture, taking, accdistrict, agricultural, bureau, campus, elgin, farming, good, grande, hd50, learning, my, new
Social Welfare	food, safoodbank, snap, hunger, meals, thank, help, million, our, w, free, program, put, should, children, kids, nutritious, people, summer, texans
Education	school, students, our, education, public, schools, all, teachers, state, finance, your, college, ___year___, high, teacher, funding, great, kids
Technology	nasa, space, station, mission, astronaut, international, students, media, new, crew, launch, satellite, speak, astronauts, awards, ___year___, contract, earth, first, internet
Foreign Trade	trade, trumps, war, ___year___, abandons, bad, barrel, beijing, billion, breath, c, ca, canada, chinese, cover, currently, dallasnews, deals, economy
Housing	housing, affordable, hearing, association, austin, citys, gentrification, losaltos, meeting, neighborhood, policy, texashouse, txsenateigr, ___year___, 7th, aacogceo, access, aff, affairs

Table A9: Top topic features in tweets by STATE MEDIA

Topic	Top Features
No policy issue	wyoming, casper, photos, man, sheridan, county, high, free, basketball, state, new, story, gillette, first, police, gowyo, school, local, cheyenne, ___year___
Healthcare	health, wyoming, care, medical, opioid, bill, cancer, center, would, state, states, patients, medicaid, work, mental, county, hospital, crisis, new
Gov. Operations	wyoming, free, state, race, governor, county, run, city, republican, wyomings, election, story, court, cheyenne, candidate, announces, supreme, house, district, says
Intl. Affairs	korea, ___year___, new, election, south, wyomings, against, announces, compete, interference, jaelin, kauf, know, north, olympics, over, pics, pyeongchang, russians, sanctions
Public Lands	wyoming, county, bill, national, public, parks, yellowstone, near, federal, land, area, bones, committee, mammoth, park, wilderness, free, study, cheney, lands
Labor	jobs, new, county, workers, ___year___, assessor, assessors, casper, four, lawmakers, lose, meet, natrona, office, rate, reins, staffers, takes, address, aim
Law and Crime	wyoming, abuse, bill, man, sexual, casper, assault, county, child, katiekull1, story, crime, gun, police, our, sex, judge, prison, case, law
Defense	service, air, memorial, wyoming, army, free, marines, one, county, photos, veterans, casper, cemetery, council, drill, get, honored, jrotc, kelly, natrona
Immigration	border, immigration, need, state, county, ice, says, support, wyoming, children, daca, delegation, evanston, facility, faith, high, leaders, legal, migration, proposed
Domestic Commerce	wyoming, business, tourism, local, businesses, cheyenne, small, your, county, would, city, industry, support, best, casper, state, these, cities, flood, legislature
Civil Rights	wyoming, court, lgbtq, vote, voting, wygovdebate, casper, denies, law, new, state, ‘, athlete, council, week, laws, open, over, policy, public
Economy	tax, budget, wyoming, state, county, bill, percent, free, story, fiscal, next, would, optional, ___year___, year, economic, legislature, sales, cuts, senate
Environment	water, wyoming, river, wildlife, carbon, federal, grouse, sage, court, oil, fee, fish, game, some, wind, basin, big, breaking, community, company
Transportation	air, airport, cheyenne, would, city, regional, new, service, leaders, maintenance, all, bill, bridge, funds, mph, oks, or, photos, allegiant
Energy	wyoming, coal, oil, gas, energy, basin, work, mine, face, rule, river, wyomings, drilling, federal, judge, company, large, proposed, wind, firms
Agriculture	wyoming, give, bill, farm, northeast, bees, gillette, honey, ag, casper, fish, food, ice, new, work, would, animal, around, back, bee
Social Welfare	county, food, program, hunger, looks, money, nutrition, poverty, raise, thought, work, activities, assessment, care, center, conducts, inhome, offers, transportation, wyoming
Gun Control	gun, arrested, county, led, lockout, natrona, schools, student, theft, threats, school, district, high, shooting, anniversary, came, cody, columbine, evanston, firearms
Education	school, students, wyoming, schools, education, county, college, state, new, board, free, uw, story, natrona, district, high, year, lcsd1, student, trustees
Technology	broadband, internet, force, task, cheyenne, service, technology, wyoming, aim, collect, enzi, experienced, find, house, improve, law, looking, measures, online, recommendations
Foreign Trade	tariffs, could, across, check, column, country, economy, fact, guns, mean, new, newspapers, russia, trade, states, ag, announces, auto, bad, beef
Housing	council, city, cheyenne, historic, casper, code, district, homeless, downtown, north, planning, wo, approves, capitol, commission, neighborhood, parking, wyoming, add

Appendix B Differentiating national legislators by state

In our main analyses, we find a clear top-down pattern, with state legislators being much more responsive members of Congress than vice versa. We test whether these dynamics differ if we represent the agendas of national legislators not as a single time series but as 13 separate time series - taking only the subset of members of congress from each state. Figure B1 shows that the results of this model indicate the same general pattern we find in the main analyses: Members of Congress continue to exert a strong influence on the public agenda of state legislators while the latter have virtually no capacity to influence the public agenda of the former. However, we also find a decrease in responsiveness to the national legislators as well as an increase in responsiveness to the national media. We interpret this as indication that state legislators are generally responsive to members of Congress from their state, as well as to a broader national political discourse. Hence, when disaggregating the time series of national legislators by state, the estimated responsiveness to the national media likely increases because this time series becomes the best measure of the broader national discourse in the model.

Figure B1: Issue Responsiveness with national legislators differentiated by state