Bottom-Up or Top-Down Influence? Determinants of Issue-Attention in State Politics

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Abstract

Who shapes the issue-attention cycle of state legislators? Although state governments make critical policy decisions, data and methodological constraints have limited researchers' ability to study state-level agenda setting. For this paper, we collect nearly 105 million Twitter messages sent by state and national actors in 2018 and 2021. We then employ supervised machine learning and time series techniques to study how the issue-attention of state lawmakers evolves vis-à-vis a series of local- and national-level actors. Our findings suggest that state legislators operate at the confluence of national and local influences. In line with arguments highlighting the nationalization of state politics, we find that state legislators are consistently responsive to policy debates among members of Congress. However, despite growing nationalization concerns, we also find strong evidence of issue responsiveness by legislators to the public in their states. In both years, shifts in attention by partisan members of the public within states had the strongest influence on the public agenda of state legislators. Local and state media had a moderate influence on state legislators while the President and the national media had little direct effect.

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1 Introduction

Why do US state legislators publicly discuss some policy issues, but not others? Classic theories of agenda setting argue that attention to an issue is a necessary precondition for policy change (e.g., Schattschneider 1960; Kingdon 1984; Baumgartner and Jones 2010): policymakers first need to perceive an issue as relevant before deciding to do something about it. Issue-attention cycles are therefore crucial for understanding whose interests are represented and when policies will change (Edwards and Wood 1999; Jones and Baumgartner 2004; Sulkin 2005; Lowery, Gray, and Baumgartner 2011; Neundorf and Adams 2018). While there is a long-standing literature exploring issue-attention cycles at the national level in the US, we know little about the conditions under which state legislators decide to focus on some issues rather than others, let alone the extent to which this emphasis affects other actors. Addressing this question is perhaps more relevant than ever, given that amid increasing gridlock and polarization in D.C., many of today's most important policy battles are taking place at the state rather than the national level. This includes debates over minimum wage laws, civil rights legislation, and responses to public health crises like the COVID-19 pandemic.

While we know that, on average, state policies tend to reflect 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), there are few established insights into the dynamics of state legislators' broader issue agendas. Largely due to data and methodological limitations, research on this topic at the state level remains limited (Tausanovitch 2019; Pritchard and Berkowitz 1993), with no studies to date systematically assessing whether and how different actors influence state legislators' issue-attention. The difficulty here arises from the fact that making robust inferences about agenda setting on the state level requires collecting time-stamped issue-attention data from legislators within a sufficient number of states, but also from the groups that potentially influence said agendas within these different states.

In this article, we provide what we believe to be the first large-scale, multi-state analysis of agenda setting dynamics in state politics. Specifically, we assess the explanatory power of two broad perspectives on state politics with regard to issue-attention. First, classic theories of federalism suggest that state legislators should be particularly attentive to the issue priorities of local-level actors (Madison 1961; Erikson et al. 1993). States are often viewed as being "closer to the people" because geographic proximity leads legislators to have greater knowledge of local priorities and closer connections to their constituents than would be possible for national politicians. However, research has also shown that in many respects, state and local politics have become increasingly nationalized over the past few years (Hopkins 2018). According to this perspective, the public communications of state legislators should emphasize the issues that are currently discussed on the national level by actors such as members of Congress, the national media, or the President.

To assess the influence of local and national-level actors on the issues state legislators emphasize in their public communications, we make use of the fact that most state legislators today actively use social media platforms such as Twitter to address issues they consider relevant (Payson et al. 2022). Moreover, the general public, various media outlets, and national legislators talk about policy issues on the same platform and in the same standardized format—which makes it possible to assess issue agenda setting dynamics between these groups (Barbera et al. 2019). For our study, we collected the universe of Twitter messages sent by: (a) state legislators from 13 states, (b) members of Congress, (c) four prominent national media outlets, (d) Presidents Trump and Biden, (e) the most consumed newspapers in each state, and (f) a sample of members of the public who closely follow state politics in each state. Using transformer models, we measure the topics of each tweet, classifying them into the policy areas of the Comparative Agendas Project. Finally, we use vector auto regressive models (VAR) to study who leads and who follows shifts in issue-attention by state legislators. We collected data and ran models for two separate time periods (2018 and 2021), identifying the handles and tracking the activity of state legislators serving in these two terms. This allows us to compare findings across political contexts and presidencies, notably increasing the robustness of the results.

Our findings indicate that both local and national level actors influence the agenda of state legislators albeit to different extents. First, despite concerns that politicians at all levels of government are increasingly beholden to national policy debates, we find strong evidence of local democratic issue responsiveness. Our results show that state legislators engage in policy debates specific to their own states. In particular, state legislators shift their issue-attention most dramatically in response to the policy discourse put forward by partisan members of the public within their states. State media outlets exert moderate influence on state lawmakers' issue-attention. Second, we show that members of Congress exert top-down influence on the issue agenda of state legislators. This is true even when the issues being discussed are those typically handled by the states, such as education and healthcare. At the same time, national media outlets and Presidents Trump and Biden have little to no impact on the issue discourse of state lawmakers. These findings add to – and add nuance to – a growing body of research documenting the nationalization of politics.

2 Bottom-Up or Top-Down Influence?

Who leads the issue-attention of state legislators? A core principle of representative democracy holds that elected officials are incentivized to represent the interests and policy priorities of their constituents (Dexter 1957; Miller and Stokes 1963; Erikson 1971; Achen 1977). Attention is a precondition for policy change, and empirical research on agenda setting at the national level has uncovered a strong correlation between public attention to particular issues and political action by elected officials. For example, members of Congress are more likely to debate, introduce bills, and hold hearings on issues that are salient in the public discourse (Sulkin 2005; Brayden, Bentele, and Soule 2007; Jones, Larsen-Price, and Wilkerson 2009; Baumgartner and Jones 2010). In a recent study, Barbera et al. (2019) found that the issue-attention of members of Congress is highly predictable by the issues discussed by members of the public—especially those that are attentive to politics.

While most evidence documenting constituents' capacity to influence legislators stems from the national level, there is good reason to believe that this dynamic extends to state legislators. In fact, classic theories of federalism suggest that state legislators should be particularly attentive to the issue priorities of local-level actors and maintain closer connections to their constituents than would be possible for national politicians (Madison 1961; Erikson et al. 1993). In line with this, a strand of literature in state politics portrays states as "closer to the people" in which legislators are more immediately concerned with local priorities rather than the federal agenda (Songer 1984; Krane 2007) – emphasizing a bottom-up dynamic when it comes to setting the agenda of state legislators.

Beyond the direct influence of constituents, media outlets from each state can also play a key role in channeling local issue priorities and in making this bottom-up dynamic possible. A long-standing literature on media effects has documented the agenda-setting capacity of the media on the national level (Berkowitz 1992; Baumgartner, De Boef, and Boydstun 2008; McCombs and Shaw 1972; Zaller 1992; Boydstun 2013). The media highlights issues that are then seen as more relevant by the public, and in turn politicians feel the need to address them in order to not be perceived as being inattentive. For example, in a study of the symbolic agenda of legislators from seven large US cities in regards to crime, Pritchard and Berkowitz (1993) discuss how an increase in crime coverage by local press can lead to an increase in attention to the issue by local policymakers. In a study of the policy (not issue or symbolic) agenda in eighteen US states between 1989 and 2006, Tan and Weaver (2009) find a strong positive relationship between shifts in attention by state media outlets and shifts in the issues being addressed in the state legislatures.

In this study, we study the impact of local issue priorities by focusing on these two state level groups. First, we assess the role of what we refer to as *state-* or *mass public partisans*, that is, members of the public within each state that are attentive to politics;[1] second, we examine the *state media outlets* that may provide important channels through which local priorities emerge in public discourse and reach politicians. Building off the literature described in the preceding paragraphs, we begin by testing the following two hypotheses:

> $\mathbf{H}_{1A}$: Changes in issue-attention by mass public partisans in each state will lead to an increase in issue-attention by state legislators.
>
> $\mathbf{H}_{1B}$: Changes in issue-attention by state media outlets will lead to an increase in issue-attention by state legislators.

Another strand of literature in state politics suggests a top-down explanation for the issues state legislators emphasize in their public communications. Especially in light of recent research on the nationalization of politics, including Hopkins (2018)'s *The Increasingly United States*, we might expect state legislators to cue off of the national political debate. With the rise of party unity and polarization, voters increasingly identify with the two national parties, and the proportion of voters who vote for the same party in state and national elections is on the rise. As a result, state representatives have strong incentives to publicly address issues that are already being discussed by national party elites, such as members of Congress and the President.

Furthermore, a well documented trend that plays into the nationalization of US politics is the decline of local news outlets (Hayes and Lawless 2018; Hopkins 2018; Martin and McCrain 2019). The decrease in the number and quality of local media outlets in recent years means that the public more often consumes and is exposed to news from national outlets.

[1] We classify members of the public as partisans if they follow at least 2 state legislators form a given state of either the Democratic or Republican party, and do not follow any members of the opposing party.

(Martin and McCrain 2019) also show that the acquisition of local television channels by large telecommunication conglomerates groups (e.g. Sinclair Broadcast Group) has led to an increase in the coverage of national political news in detriment of local affairs. When voters are more likely to pay attention to and be informed about national rather than regional political issues, state legislators have obvious incentives to shift their attention to issues according to what is being discussed in national media.

We represent the national political discourse and assess the degree to which it governs state legislators' issue agenda by studying three of its core actors: members of Congress, the President, and the national media. Specifically, we test the following hypotheses:

> $\mathbf{H}_{2A}$: Changes in issue-attention by members of congress will lead to an increase in issue-attention by state legislators.
>
> $\mathbf{H}_{2B}$: Changes in issue-attention by the President will lead to an increase in issue-attention by state legislators.
>
> $\mathbf{H}_{2C}$: Changes in issue-attention by national media outlets will lead to an increase in issue-attention by state legislators.

These two strands of literature provide clear predictions. According to the former, which we subsequently refer to as *bottom-up*, state legislators should shift their public communications in response to local level actors; the latter, which we call *top-down*, asserts that state legislators' issue priorities will follow those of national level actors. We note that these predictions are not mutually exclusive. Rather, it is their relative explanatory power that we aim to assess. The current state of the literature does not provide any indication as to whether we should expect *bottom-up* or *top-down* influences to prevail. In this paper we aim to close this gap by providing descriptive evidence about the relationships between the issue agenda of state legislators and those of the different state and national actors discussed above. We believe that this evidence will be crucial for future theorizing in this area and close with a Discussion of how further research can explore these relationships further.

3 Data to Measure Issue-Attention

We use Twitter data to identify what issues state legislators emphasize in their public communications and to examine how their issue-attention evolves *vis a vis* other groups. Twitter is widely and frequently used by both national (Barbera et al. 2019) and state-level (Payson et al. 2022) political elites. In addition, media outlets are active on Twitter (Eady et al. 2019), frequently posting about their most relevant stories. Moreover, the mass public also uses Twitter as a platform for expressing political views (Barbera et al. 2019) and for mobilizing on political issues (Freelon, McIlwain, and Clark 2018). Other research has shown that the topics Americans discuss on social media platforms like Twitter are highly correlated with survey-based measures of issue salience (O'Connor et al. 2010). As a result, Twitter data provide an opportunity to study the political issues publicly emphasized by different groups, on one single platform and in the same format.

There are alternative data one can draw on to study issue-attention but we note that these have their own limitations. Documents emerging from legislative settings (e.g., roll call votes, bill introduction, etc.) are perhaps the most bare representation of the legislative process. Yet, they are heavily constrained by an institutionalized process that comes with it's own logic as well as the agenda-setting power of the party leadership in the chamber. In comparison, Twitter is a medium where individual legislators can by and large choose freely what to communicate about. Other public communications by legislators that share this quality such as media interviews or press releases tend to be less frequent, and would, as will be shown below, not allow for the kind of temporally fine-grained analyses we conduct. Given this, we believe that tweets provide an excellent proxy for attention being paid to various policy topics. They allow us to assess agenda-setting dynamics at the state level in an unprecedentedly granular and detailed manner and thus to make theoretical (as well as descriptive) contributions to the literature on state politics that would be difficult to achieve otherwise.

Below we present a brief description of how we created the list of Twitter users belonging to each group in our analysis. We used the Twitter REST API to collect all tweets sent by the users in each group for two full years, 2018 and 2021. Given the computational intensity of collecting and analyzing hundreds of millions of tweets, most similar work in this area only examines a single legislative session (e.g. Barbera et al. 2019; Guess et al. 2021). We collected data for two different years in order to be able to generalize beyond one particular context (e.g. the Trump presidency) and to assess whether results are similar in years when state legislatures are or are not in session.[2] In Table 1, we report the total number of messages collected for each group, as well as the number of unique users responsible for them.

- **State Legislators**. We study the issue-attention distribution of state legislators from 13 states: Arizona, California, Florida, Illinois, Massachusetts, Montana, New Jersey, Nevada, New York, Ohio, Texas, Utah, and Virginia.[3] We first obtained a list and the Twitter handles of the state legislators serving in 2018, and then in 2021, in the lower and upper chambers of these state legislatures by using the Google Civic API. Then we manually checked to see if an account actually existed when the Google Civic API

[2]Some U.S. state legislatures meet only in odd numbered years. In our sample, Montana, Nevada, and Texas met only in 2021 and not in 2018. Other recent work, however, finds that being in session is not predictive of being less active on Twitter nor discussing policy-relevant issues less often (Payson et al. 2022). While state legislators remain politically active on the social media platform regardless of whether they are in the state capitol or not, including both an even and an odd year of data help us to allay this concern even further. Due to the intense effort (both computationally and qualitatively) that such data collection requires, we limit our analysis to one year of both the Trump and Biden presidencies.

[3]Collecting, processing, and analyzing tweets from state legislators, newspapers, and partisans from all 50 states was computationally and qualitatively unfeasible. Instead, we focused on a subset of states, which we selected to maximize variation across several key features, such as population, geographic region, levels of legislative professionalization, partisan composition of the chambers, and whether the legislature was in versus out of session in 2018. 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.

did not return an account for a policymaker, manually adding them to the list of state legislator Twitter accounts to track.

- **Members of Congress**. We used several public sources to collect the Twitter handles of members of Congress serving during the 115th and 117th Congress.[4]

- **President**. We collected all tweets sent by President Trump in 2018 and by President Biden in 2021.

- **National Media**. We tracked four of the main national media organizations in the United States: Huffington Post, CNN, Associated Press, and Fox News. We followed two main rationales when selecting them. First, these are major news organizations each with more than 10 million Twitter followers. Second, these outlets are roughly 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.

- **State Partisans**. We used the Twitter REST API to access the followers of all state legislators in our sample. Next, we created a group of state partisans for each of the 13 states by selecting those who followed at least 2 Democratic and no Republican state legislators from that state, and *vice versa*. Barbera et al. (2019) have shown that this method reliably identifies Twitter users from these states who are supportive of each party.[5] Appendix B contains some additional validation.

- **State Media**. We track the tweets of the most relevant news outlets from each of the

[4] We collected the handles of the official accounts via this collaborative github account with a variety 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.

[5] E.g., validated by matching Twitter users with their voter registration records for states that make it available for research, see SI.F2 in Barbera et al. (2019)

13 states.[6]

Table 1: Number of tweets and unique accounts by group

	2018		2021	
Group	Unique accounts	Tweets collected	Unique accounts	Tweets collected
Democrat State Legislators	672	375,791	802	468,308
Republican State Legislators	583	207,547	514	161,658
Democrats in Congress	393	331,558	448	397,530
Republicans in Congress	454	225,462	353	242,421
National Media	4	192,383	4	100,561
President	1	3,416	1	3,012
Democrat State Partisans	70,152	26,098,321	79,648	41,338,348
Republican State Partisans	32,809	15,136,002	29,938	15,621,228
State Media	130	1,100,320	1,070	3,226,880
Total	105,198	43,670,800	112,778	61,559,946

3.1 Classifying policy issues

At the heart of our analytical strategy is an assessment of when different actors discuss different topics on Twitter, so we now turn to how we identify the topics of discussion. We rely on the comprehensive list of policy issues defined by the Comparative Agendas Project (CAP)[7]. This classification schema has been widely adopted and allows scholars to study issue-attention, agenda setting, framing, and political responsiveness in a systematic and comparative fashion across contexts and time periods. We adopted this 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 below). Second, because this classification is used by a large community of scholars, it ensures that our results speak to existing and future work on the

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, foo1d 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, ...

topic.

Table 2 shows the 20 macro policy issue categories defined by the CAP codebook (such as the *Economy*) and several sub-issue categories (e.g., taxes and unemployment are subcategories of the *Economy*).[8] 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). Although these are broad categories, we are still able to accurately trace issue responsiveness between groups, as dis-

[6] For 2018, we tracked the top 10 newspapers in each state, based on circulation data from https://www.agilitypr.com/. For the 2021 data collection, we substantially complemented the number of state media accounts to ensure we accounted for a more comprehensive list of media outlets in each state. In this data, we include a total of 1,070 media Twitter accounts from the 13 states under analysis.

[7] https://www.comparativeagendas.net/codebook

[8] We excluded the CAP topic category *Culture*, as early analyses revealed that it was rarely discussed.

cussions around two sub-issue domains of the same topic category are unlikely to correspond in time (see Appendix E). For our analysis, we decided to add an additional macro issue category: *Gun Control*. Shootings and the regulation of gun ownership, carriage, and usage have been a very salient topic in the United States. Currently, the CAP codebook subsumes these discussions under *Law & Crime*, but due to the increased salience and number of tweets on this topic, we capture gun control as a separate policy category.

Finally, to assess whether state legislators are more likely to respond to or lead the public agenda on particular issues, we categorize the policy areas we study into those over which state governments have legislative 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. 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. In contrast, policies like health, education, and welfare are typically considered to be the realm of state government and comprise the largest number of bills passed by state legislatures.[9]. The states and federal governments also share responsibility for certain policy areas like the economy. For the sharpest comparisons possible, we focus on examining differences across the more clearly defined policy areas described in Table 3 rather than these shared areas.

4 Methods

4.1 Modeling the Issues Discussed on Twitter

We fine-tune a BERT model to classify the tweets sent by the groups we study into one of the 21 policy areas presented in Table 2, plus a non-policy category for those tweets

[9] https://openstates.org/

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	

not related to politics (22 classes in total). BERT (Devlin et al. 2018) is a transformer-based neural language model that has been trained to solve generic tasks such as predicting a randomly masked word within a text sequence. From this, the model obtains general knowledge about the English language. Subsequently, the model can be fine-tuned to solve downstream tasks. Transformer-based language models currently define the state-of-the-art for supervised classification and are thus well-suited to our task (see Terechshenko et al. (2020) for a social science-oriented introduction to these models).

We fine-tuned three version of the same BERT model (`bert-base-uncased`): one model to classify the tweets by politicians; another for the tweets by the mass public; and a final model for the media messages. We use separate models to account for the fact that these actors often use different language to discuss the same issue.

We trained each of the models with various datasets, assessed the out-of-sample accuracy of each model-dataset pair based on an annotated sample of the tweets we collected for this analysis, and selected the best performing model-data pairing to generate topic predictions for all tweets sent in 2018 and 2021 by the actors under study. In Appendix A, we explain the training process in detail, and we also show how BERT models outperform an ngram-based machine learning model.

In Table 4, we report the accuracy of the final classifiers that we use in the paper. We split the labeled data into three sets during training: a training set used for model estimation and to update the model weights at each training iteration, a test set used for calculating the model loss and deciding when to stop the training, and a validation set that remained unseen during training and that we used to perform a final accuracy test. In Table 4, we report the validation accuracy for each model, which provides the best estimate for the model's performance when predicting the remaining unlabeled tweets. These accuracy measures are based on 3-fold cross-validations, where we used different random seeds to split the training and test sets (the fully unseen validation set remained the same across folds).

Table 4: Accuracy of three BERT models fine-tuned to predict the policy areas discussed by politicians, mass media, and the mass public (state partisans).

Model	Max. Class Prop.	Accuracy	Policy F1
Politicians BERT	0.13	0.65	0.62
Media BERT	0.06	0.77	0.67
Partisans BERT	0.06	0.83	0.65

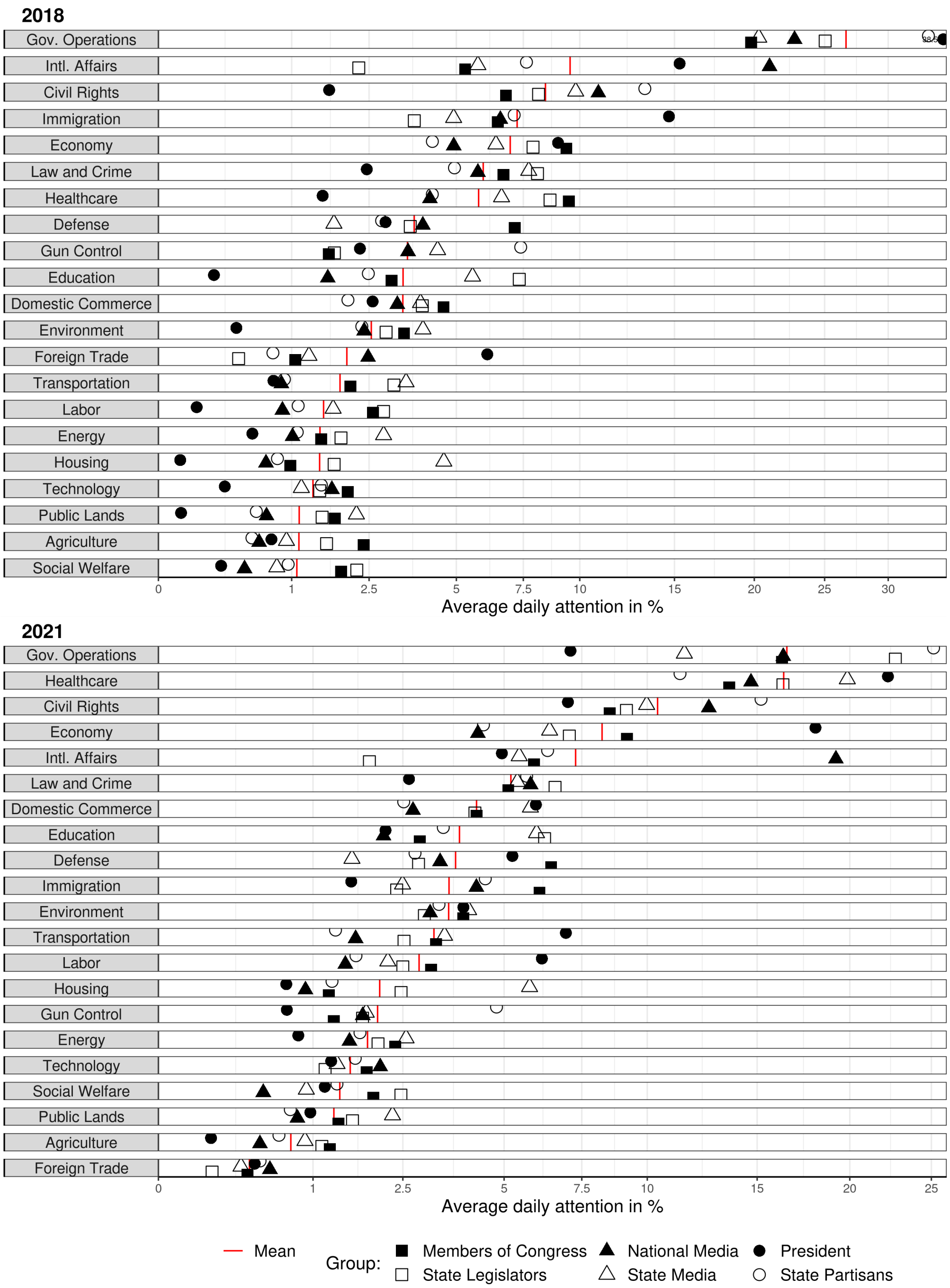
We also provide information about the proportion of tweets classified into the largest topic class in the labeled data (after excluding the non-topic category). This *Maximum Class Proportion* serves as a baseline to judge the performance of each model, as it indicates how well we would do by simply classifying all tweets into the modal topic category. We report the model's *Accuracy* (how often the model makes correct predictions) as well as the *Policy F1 score* after removing the non-policy category (the average of how well the model makes correct predictions for each of the 21 topic categories). The accuracy allows us to assess overall model performance, while the policy F1 score allows us to judge whether the model is doing a good job across all the different topic categories. This is necessary because we want to make sure that the model does a good job at distinguishing policy-relevant tweets from non-policy ones as well as discerning between policy issue categories.

Overall, the three models perform well at both of these tasks and prove to be useful for the objective at hand. Accuracy is high for all classifiers (66% for the Politician Model, 74% for the Media Model, and 82% for the Partisans Model), especially given that the model is generating predictions for a large number of (unbalanced) topic classes, which is a very difficult task. In addition, the policy F1 scores for the three models are between 62 and 67%. This means that when classifying policy-relevant tweets, our BERT model for Politicians performs 4.8 times better than a model classifying tweets naively (into the modal policy category referenced in the *Max. Class Prop.* column), and our Media and Partisans BERT models perform 11.2 and 10.8 times better, respectively. In Appendix A, we provide additional analyses to document the satisfactory accuracy of these classifiers. Of course, we cannot classify each tweet correctly by topic. However, the quantities used in our analysis are aggregates of tweet-classifications (i.e., topic predictions) over many tweets. We are thus confident that the high level of accuracy we have achieved in addition to the many validation tests presented in this section and in Appendix A show that these models perform well for the task at hand and are appropriate for the analysis conducted in the rest of the paper.

Finally, we use the BERT model trained on politicians to generate topic predictions for the tweets sent by state legislators and members of Congress in 2018 and 2021, the BERT model trained on the media for tweets sent by state and national media accounts both years, and the BERT model trained on tweets from the mass public to for the tweets sent by the followers of state legislators in both years. In Figure 1, we show the average daily attention paid to each policy area by each of these groups in 2018 and 2021. 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, topics such as *Agriculture* or *Public Lands* received relatively little attention, which makes sense given that agriculture is a relevant sector for some states but not others.

We observe some key differences between issue prevalence in 2018 and 2021. In 2018, for example, *Immigration* was among the most discussed issues, as the Trump administration

Figure 1: 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 and 2021. 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 the average of all groups. Note that the X-axis is compressed in the figure.

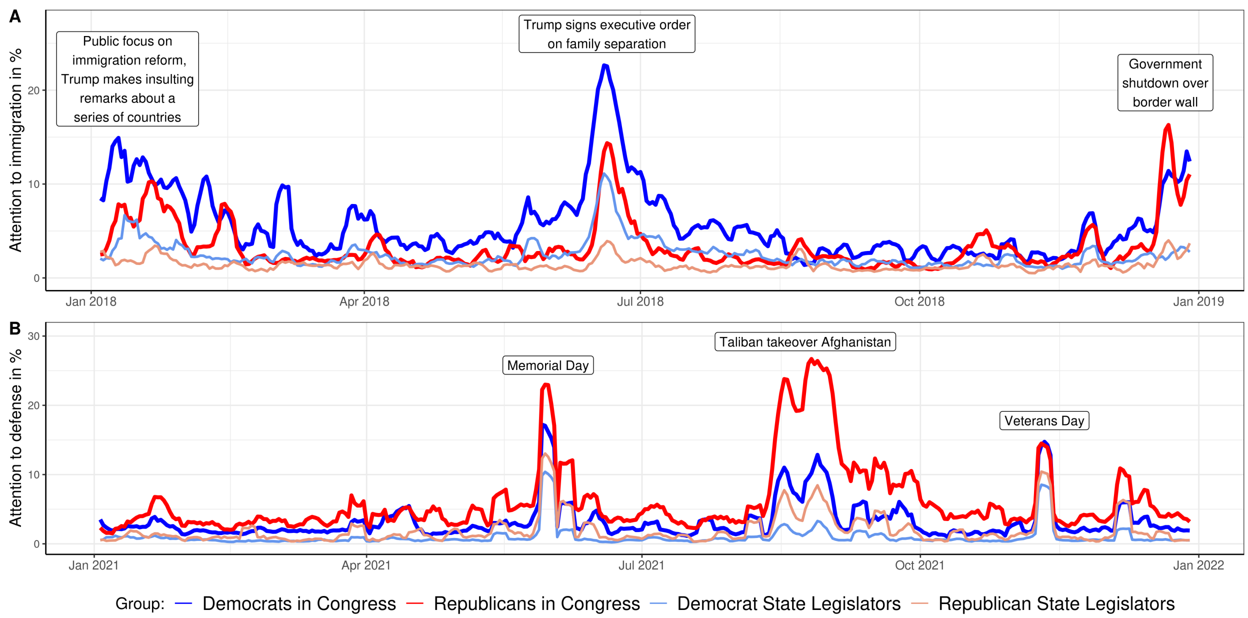
took a strong anti-immigration stance with discussion around building a wall on the Mexican border and the practice of separating migrant families. Unsurprisingly given the COVID pandemic that began in 2020, topics such as *Healthcare* and the *Economy* were considerably more prevalent in 2021, comprising a large share of the overall issue-attention that year. 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. These initial patterns add face validity to the policy classifications of the tweets in our sample and suggest some interesting differences in the communication behavior of state legislators relative to other groups.

4.2 Vector Auto Regressive Models

To see whether shifts in attention by one group are predictive of subsequent shifts in attention by other groups, we leverage the temporal dimension of our data and model these in a vector autoregression (VAR). VAR models help 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 been used to study political responsiveness (Barbera et al. 2019; Edwards and Wood 1999; Wood and Peake 1998). To illustrate the logic of this approach, consider Figure 2, which shows the attention paid to immigration and defense, broken down by party and level of government over the years 2018 and 2021 respectively. Spikes in attention generally correspond to salient events, such as Trump signing an executive order on family separation or the takeover of Afghanistan by the Taliban. Often, state legislators and national legislators appear to move in tandem on issues. But in some instances, it appears that one group starts to discuss an issue before another group then follows suit.

While the raw data are suggestive, it is difficult to ascertain whether systematic political

Figure 2: Example issue-attention time series.



Note: The displayed time series capture the share of attention that was paid to the issues immigration and defense 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.

responsiveness exists between state legislators and other actors in terms of the policy issues emphasized. To uncover how these groups interact with each other over time across the total range of policy issues, we need to model their 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 at 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 BERT 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 attention to a given issue usually happens around a few particular points in time, 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).[10] 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, thereby modeling the assumption that groups today only respond directly to tweets by other groups posted within the previous 5 days.[11] Formally, the model can be expressed as follows:

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

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

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 groups are constant across state and issue. While this assumption is inaccurate to some extent, it drastically reduces the complexity of our data and makes the analysis more tractable. Within this framework, we can express the degree to which changes in issue-attention by one group are

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

[11] Partial auto-correlation analyses conducted on these time series indicated the inclusion of up to 5 lags in our models.

predictive of changes in issue-attention by another group.

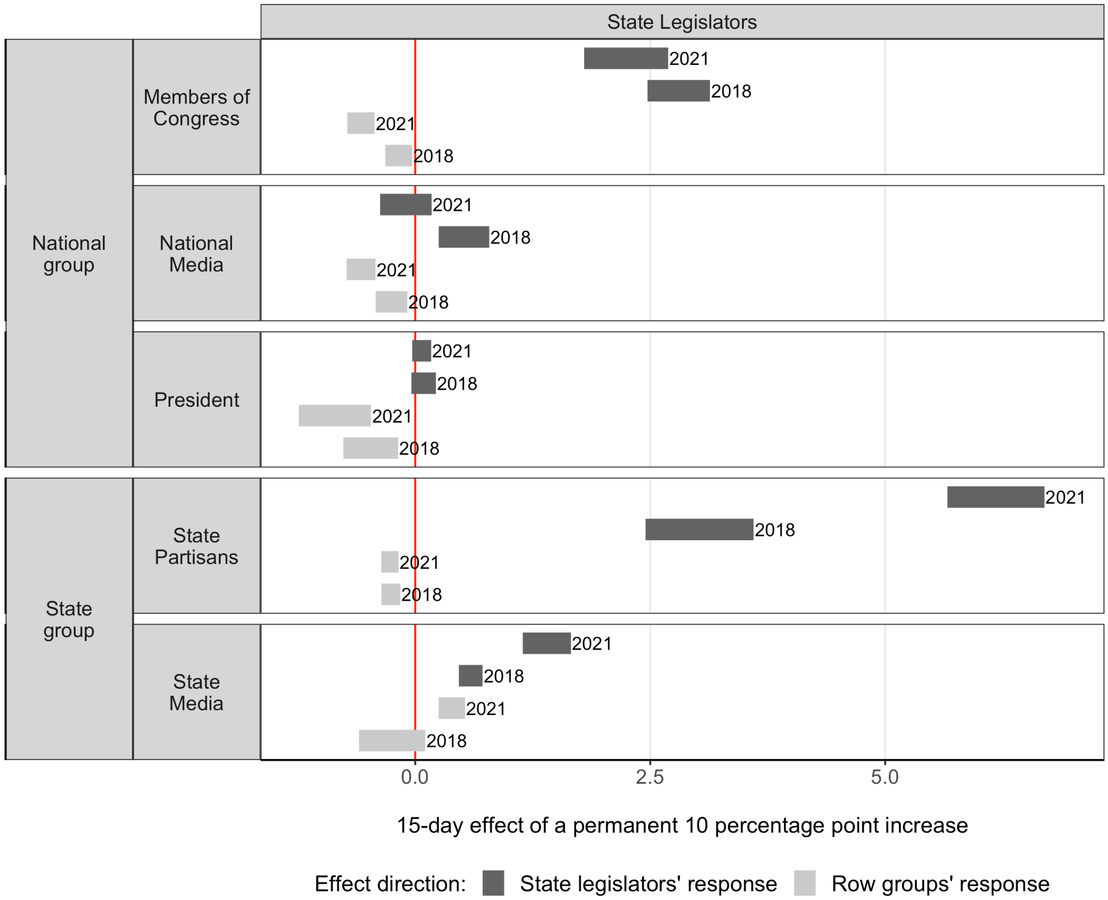
5 Results

5.1 Bottom-Up: State Level Actors

VAR coefficients are difficult to interpret, so we use cumulative impulse response functions (IRFs) to display the results of our models. IRFs trace the effect of simulated shocks to the VAR system of equations.[12] In our case, we simulate a sudden increase in attention to an issue by one group to observe the resulting changes in 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 may 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%.[13]

Intuitively, to interpret these effects assume that on a given day none of the groups are paying attention to an issue j. We then introduce a 10 percentage point increase in attention in the time series of one group (day 0) 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

Figure 3: Cumulative 15 day effect of a permanent 10 percentage point increase



Note: The dark gray estimates 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 gray estimates show the row groups' responses to changes in issue-attention by state legislators. The bands represent 95% confidence intervals.

13 days, we would observe a cumulative 15-day effect of 1.5 percentage points.

In all models reported in this study we control for the influence of each group (state and

[12]When estimating the IRFs we assume no contemporaneous effects between the different groups under analysis.

[13]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

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

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

national legislators, state and national media, the President, and state partisans) on the issues discussed by every other group. To simplify the presentation of the results, we only report the effects that include state legislators. Figure 3 shows the 15-day effects from the main model for both national and state actors (and associated 95% confidence intervals). The effects are expressed in percentage points. The dark gray bands represent responses by state legislators to increases in issue-attention by each of the five groups on the left side of the figure, while the light gray ones stand for responses of these five groups to increases in state legislators' issue-attention. To the right of the estimates we indicate whether they are based on the 2018 or 2021 data. The effects range from about 0 to 6.4 and are substantively meaningful in magnitude as shifting the agenda of other groups is extremely difficult (Jones and Baumgartner 2005; Schattschneider 1975). Attention dynamics tend to follow nonlinear functions with tipping points, so even small changes in attention have potentially large consequences (Baumgartner and Jones 1993; Kingdon 2013).

When assessing the results of our main model, we particularly care about whether state legislators are responsive to other groups or not (dark bars), but we also show whether other groups are in turn responsive to the issue-attention of state legislators (light bars). Despite some differences between the 2018 and 2021 estimates, the patterns are remarkably robust across years.

Arguably the most striking takeaway from Figure 3 is that state legislators are strongly influenced by changes in issue-attention of mass public partisans. The corresponding effects are shown in Figure 3 row 4 (State Partisans). In both 2018 and 2021, state legislators increased the attention they paid to an issue following a spike in attention by partisan twitter users in their state by 3.2 percentage points in 2018 and 6.4 percentage points in 2021. This supports $\mathbf{H}_{1A}$ and the theoretical expectation that public discussions around relevant policy issues at the state level follow a bottom-up dynamic, with state legislators reacting to the issue demands of their constituents.

While state partisans' influence on state legislators is the strongest among the different groups in both years, it is noteworthy that state legislators vary in how attentive they are (with higher responsiveness in 2021 than in 2018). While beyond the scope of this paper, the observation that state legislators' responsiveness fluctuates from year to year suggests that there are conditions under which state lawmakers are more attuned to public discourse, which will be an important area for further research.

We also find mild support for $\mathbf{H}_{1B}$. State legislators are moderately influenced by the state media (row 5). However, these effects are considerably weaker than those for state partisans (1.4 percentage points in 2021 and 0.6 percentage points in 2018). Still, this suggests that state legislators are attuned to the media of their state.

5.2 Top-down: National Level Actors

Turning to the national level actors in our main model, we also find that state legislators are responsive to members of Congress, as indicated by the dark gray bands in the first row. The estimated effects indicate that a permanent 10-point increase in attention to an issue by members of Congress is predicted to increase the cumulative attention of state legislators by 2.9 (2018) and 2.3 (2021) percentage points. These results document a top-down dynamic and give support to $\mathbf{H}_{2A}$. State politics is nationalized (Hopkins 2018) in the sense that state legislators evidently cue off of the the policy discourse of members of Congress.

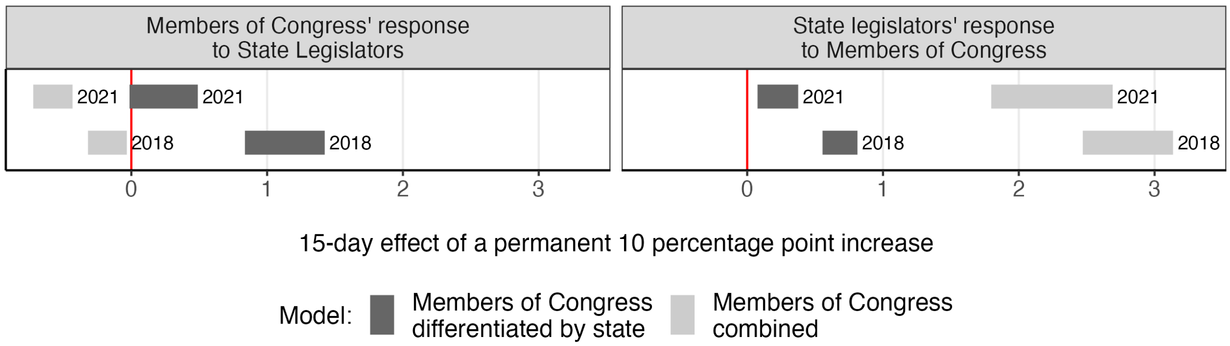
In contrast, regarding $\mathbf{H}_{2C}$, we find that the national media has only modest, if any influence on state legislators, with no effect in 2021 and a substantively small effect (0.5) in 2018. Furthermore, contrary to the idea that President Trump had a strong influence on the political agenda (see Wells et al. (2016) for an overview), we observe that neither he nor President Biden had any influence on the issues that state legislators discussed (after adjusting for the influence of other groups). This means that we find no support for $\mathbf{H}_{2B}$ Although Trump sent over 11,000 tweets during his time in office and often used the platform to attack his opponents (Shear et al. 2019), the public policy discussions at the state-level appeared to be largely immune from presidential influence in both 2018 and 2021.

Together, these results show that U.S. state legislators react most strongly to the discourse of the partisan public in their state, as well as to that of members of Congress. In other words, both top-down and bottom-up dynamics shape the public issue agenda of state legislators. While the primary focus of our paper lies on the question of who influences state legislators, our analytical framework also allows us also assess whether state legislators impact the issue agendas of any of the other groups. We find virtually no evidence indicating that this is the case. For some actors (the President and the national media) this is not surprising, but the unidirectional dynamic between state legislators and their counterparts on the national level warrants further investigation. In the next section, we take a closer look at agenda setting dynamics between national and state legislators.

5.3 Differentiating National Legislators by State

In Figure 3 we observe that members of Congress strongly influence the issue agenda of state legislators but uncover null effects in the opposite direction. But this dynamic might be due to the fact that we pool national lawmakers. In Figure 4, we replicate the main results but decompose the time series of members of Congress by state in order to look only at dynamics between legislators from the same state (e.g., state legislators form NY and members of Congress from NY). The model controls for each group included in the main model in Figure 3, but in Figure 4 report only the effects for members of Congress.

Figure 4: Issue Responsiveness with Members of Congress Differentiated by State



Note: Unlike in the previous figure, colors differentiate models for different dynamics. Dark gray estimates represent how much more cumulative attention (in percentage points) legislators pay to an issue as a result of a permanent 10 percentage-point increase in issue-attention by legislators of the respectively other political level from their state 15 days ago. For comparison, light gray estimates show responses in the model where members of Congress are combined in a single time series. The bands represent 95% confidence intervals.

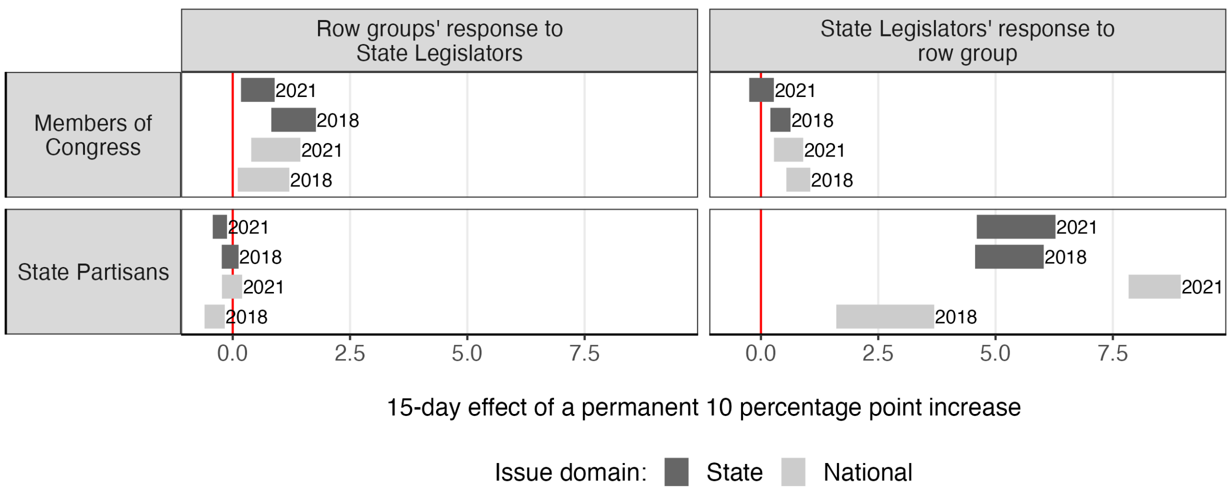
In Figure 4, the dark gray bars represent issue responsiveness between state legislators and members of Congress from the same state. For comparison, we include the estimates of the previous model where all members of Congress are combined in a single time series shown in Figure 3 (lighter gray estimates). State legislators are considerably more likely to respond to spikes in issue-attention by Congress as a whole than they are to spikes in attention by the representatives of only their state (Figure 4 column 2).

Perhaps more interestingly, however, column 1 of Figure 4 shows that members of Congress do at times respond to the issue agenda of state legislators *from the state they represent*. For 2018, we find that members of Congress are responsive to changes in issue-attention by lawmakers of their state. The estimated effect for 2021 points in the same direction but just barely misses statistical significance at the 95% level. While the top-down influence still outweighs these effects, these results suggest that state legislators can influence the issue-attention of those members of Congress that are from their respective state.

5.4 Different Patterns for State *vs.* National Issues?

Thus far, we have analyzed agenda setting dynamics considering all 21 CAP policy areas. However, as discussed above, state legislators have legislative power over some policy areas while others are the domain of national politics. We expect state legislators to be particularly responsive — and also influential — on issues that are primarily the domain of the state rather than the federal government.

Figure 5: Issue Responsiveness by Issue Domain



Note: In this figure, the columns differentiate the direction of the effect whereas band colors represent each of the two sets of issues as listed in Table 3. Dark gray bands represent the estimates for state owned issues and light gray bands represent the estimates for nationally owned issues with 95% confidence intervals. As in the previous figures, these estimates 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.

To assess whether agenda setting dynamics differ according to issue domain, we break down the analysis and estimate two distinct models: one for state owned issues and one for federally owned issues (both listed in Table 3). Figure 5 shows the results. Note that now, dark gray bands reflect issues that are the domain of state governments (such as education and transportation), and the light gray bands represent issues where the federal government holds legislative power (such as defense and foreign trade). The panel on the left shows how members of Congress and state partisans respond to state legislators' attention on the two sets of issues, while the panel on the right shows how state legislators respond to shifts in attention by each of these two groups. Because we only observed members of Congress to respond to shifts in issue-attention by state legislators of the same state, we continue to distinguish members of Congress by their state for this analysis (as we did in the analyses presented in Figure 4). To avoid overcrowding the figure we only report the results for the three main groups of interest.

We observe that, contrary to our expectation, state legislators are not necessarily more likely to react to shifts in attention by members of Congress or state partisans when the topic being discussed is a policy area traditionally delegated to the states such as education and housing. If anything, we see some evidence to the contrary, suggesting that state legislators may be more responsive to national legislators on nationally owned issues (column 2, row 1). This difference is not particularly salient, however, and should be read as suggestive evidence. In the same vein, we do not see the two other groups reacting differently when state legislators increase their attention to state issues, with members of Congress being somewhat responsive on both kinds of issues and state partisans being responsive on neither. With some minor differences, the findings are very similar for the two years we study.

6 Discussion

Amid growing gridlock and partisan polarization in the federal government (Binder 1999; Theriault 2008), state legislatures are increasingly the locus of key policy decisions. The issues politicians discuss in their public communications can have a substantive effect on politics and policy (Schattschneider 1960; Kingdon 1984; Baumgartner and Jones 2010), as attention to an issue is often seen as a precondition for policy change. However, data limitations have constrained the ability of scholars to study issue responsiveness and agenda setting at the state-level, and to clearly test existing claims regarding which actors can influence what policy issues state legislators emphasize in public. Some theoretical accounts focus on a bottom-up dynamic (Madison 1961; Erikson et al. 1993), with state legislators being particularly responsive to the issue demands of their constituents, while others stress a top-down dynamic (Hopkins 2018), by which state legislators are likely to shift issue-attention in reaction to issues discussed at the national-level.

In this paper we take advantage of novel computational methods. Using comprehensive Twitter data from two full calendar years under two different presidential administrations (2018 and 2021 – strengthening the robustness of our findings), and machine learning and time series models, we study which issues state legislators discuss in their public communications and how these correspond to the issues being discussed by members of Congress, the President, state constituents, and national and state media outlets. This allows us to generate dynamic estimates of agenda setting activity for these different groups and draw conclusions about who leads and who follows in the world of state politics issue-attention.

The contribution of the paper is four-fold. First, despite concerns that state politicians are increasingly beholden to national policy debates (Hopkins 2018; Hayes and Lawless 2018), we find strong evidence of state legislators responding to their constituents. In line with a bottom-up perspectives on government, state lawmakers are highly responsive to the political discourse of partisans and, to a lesser extent, media outlets in their states. In fact, we find the influence of state partisan to be the strongest among the groups we considered. This suggests that state policymakers are highly responsive to the issue preferences of their constituency.

Second, in line with top-down arguments, we find that state legislators are strongly responsive to the public communications of members of Congress and frequently shift their attention to issues being discussed at the national level. This finding adds to the literature on agenda setting and the nationalization of politics in the U.S. While we obviously cannot make any claims about historical shifts in the responsiveness of state legislators to national elites, our results establish *that* there is a sizable top-down influence when it comes to issue agendas. Furthermore, we were able to provide insights into *how* this top-down dynamic unfolds, namely by state legislators being primarily attuned to members of Congress, but considerably less, if at all, to the President or the national media. In our analysis we account for and estimate how shifts in issue-attention by President Trump and Biden, and by popular national outlets such as CNN and Fox News, predict shifts in issue-attention by state legislators, and find little to no effects.

Third, building on the two previous points, although there is a growing concern about the issue agenda at the state level being today dominated by national politics (Hopkins 2018; Hayes and Lawless 2018), we find state legislators to respond to shifts in issue-attention by national actors but also by constituents and local media outlets in their states. In other words, we find a confluence of bottom-up and top-down agenda-setting dynamics, indicating that state legislators are tuned and aim to be responsive to issue demands coming from different sources and levels.

Finally, we uncover many additional findings regarding the agenda setting process at the state level. For example, we find no meaningful difference in the ability of state legislators to respond to or influence conversations on issues delegated to the state (e.g. education, housing) *v.* federal government (e.g. defense, foreign trade); we find some relevant national actors (e.g. national media, the President) to exert little-to-no influence on the issues discussed by state legislators; and the presence of a bottom-up dynamic to be stronger in 2021 compared to 2018.

Hence, in this paper we do not only put forward crucial tests showing that issue-attention in state politics can follow both a bottom-up and top-down dynamic, but we also reveal a rich set of descriptives that can help further theorizing and move the field forward. For example, an important unanswered question that emerges from the analysis is the conditions under which constituents in each state can influence the issue-attention of policymakers in their states more strongly. We see a relevant variation between the two years we studied in the paper, 2018 and 2021. We hope that future research can address whether this can be a function of some state legislatures not meeting in odd years, a higher need to responding to the constituents needs due to new problems that require higher levels of state power and intervention (e.g. COVID crisis), or other underlying circumstances. Overall, we believe this is the first paper to provide a very fine-grained picture of issue-attention dynamics at the state level and that the evidence uncovered here will inform many new research moving forward.

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Online Appendix

Bottom-Up or Top-Down Influence? Determinants of Issue-Attention in State Politics

Contents

Appendix A Training of the topic classifiers

We fine-tuned three times the same BERT model (`bert-base-uncased`) 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, plus an additional non-policy category for those tweets that are not about politics: 22 classes in total. The training process worked as follows.

Table A1: Datasets coded using the CAP issue classification, used for fine-tuning the BERT 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).[14]

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

We fine-tuned each of the three BERT models (the politicians, the media, and the partisans one) seven 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 BERT 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 set B, (6) set C.n and a small sample of set B (1,300 tweets), and (7) set C.n and the other C sets. For fine-tuning the original BERT model, we use an Adam optimizer (with a learning rate of 5e-5, and an epsilon of 1e-8), and in each occasion (model-data pair) we fine-tune the model for several epochs, until the test loss does not improve for three consecutive epochs. In addition, we fine-tune each model-data pair three times/folds, using a different random seed each time (1234, 54321, 123).

To assess the performance of these seven 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 30% 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 3-fold cross-validated accuracy of the models (based only on the untouched validation sets, not on the training nor test sets involved in the actual training). We report the model's overall accuracy (*Acc.*: how often the model makes correct predictions) as well as the *Policy F1* weighted score after removing the non-policy category (so the average of how well the model makes correct predictions for each of the 21 topic categories). The accuracy allows us to assess overall model performance, while the policy F1 score allows us to judge whether the model is doing a good job across all the different topic categories. We particularly care about this F1 score, as we want to make sure the model does a good job at distinguishing policy-relevant tweets from non-policy ones, but especially at discerning between policy issue categories.

Different data combinations performed best for the different classifiers. For example, combining our own coded Tweets with Russell (2018)'s set leveraged the best results (highest Policy F1 weighted score) for the Politicians BERT model; whereas combining our own coded Tweets with the full set of CAP-labeled data leveraged the best results for the Media BERT model. As we show in Table A2, these BERT models outperform an n-gram based model (SVM) that previous research has found to perform well at classifying text into the CAP topic categories (Collingwood and Wilkerson 2012). Something that is very important to highlight is that transfer learning contributed to substantially improve accuracy across the board. In all cases, the models trained only with our own coded data performed worse than when we added additional data that had been coded following the same topic classification but for other projects. This indicates that further research on how transfer learning can improve classification tasks in the social science is crucial moving forward (see the work of

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.

Terechshenko et al. (2020) for further details on this). We hence chose the best performing model in each case (highlighted in gray) to then generate predictions for the rest of unlabeled tweets in our dataset. We used the best performing Politican BERT model to generate predictions for the tweets sent by state legislators, members of Congress, and the President; the best performing Media BERT model to generate predictions for the tweets sent by state and national media accounts; and the best performing Partisans BERT model to generate predictions for the tweets sent by the state partisans.

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.

Table A2: Out of sample accuracy of the nine versions of the BERT model we fine-tuned to predict the political topics of the Comparative Agendas Project in tweets sent by **POLITICIANS** (state legislators).

	BERT		SVM	
Model version	Acc.	Policy F1	Acc	Policy F1
(5) set C.3 and B	**0.65**	**0.62**	0.38	0.40
(4) set C.3 and small A	0.66	0.62	0.58	0.27
(6) set C.3 and small B	0.66	0.61	0.59	0.27
(7) set C.3 and C.1&C.2	0.65	0.60	0.61	0.31
(3) set C.3 and A	0.64	0.58	0.44	0.45
(1) set A	0.28	0.55	0.23	0.47
(2) set C.3	0.64	0.53	0.57	0.19

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

Model version	Acc.	Policy F1
(3) set C.1 and A	**0.77**	**0.67**
(7) set C.1 and C.2&C.3	0.78	0.66
(5) set C.1 and B	0.77	0.64
(4) set C.1 and small A	0.78	0.63
(6) set C.1 and smmall B	0.78	0.61
(1) set A	0.21	0.60
(2) set C.1	0.78	0.57

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

Model version	Acc.	Policy F1
(4) set C.2 and small A	**0.83**	**0.65**
(6) set C.2 and small B	0.81	0.63
(3) set C.2 and A	0.74	0.62
(7) set C.2 and C.1&C.3	0.81	0.61
(5) set C.2 and B	0.79	0.60
(2) set C.2	0.81	0.59
(1) set A	0.12	0.46

Table A5: Top topic features in tweets by MEMBERS OF CONGRESS

Topic	Top Features
No policy issue	day, happy, me, thanks, family, time, honor, county, congratulations, morning, see, work, office, first, good, join, year, community, proud, service
Economy	tax, taxreform, taxcutsandjobsact, jobs, reform, economy, cuts, americans, thanks, employees, benefits, bonuses, families, news, because, taxes, see, american, money, act
Civil Rights	life, prolife, women, abortion, act, protect, people, fbi, house, american, unborn, right, protection, read, bill, government, memo, support, americans, day
Healthcare	health, opioid, help, care, bill, house, funding, chip, crisis, opioidcrisis, legislation, act, combat, cancer, patients, week, bipartisan, drug, epidemic, fight
Agriculture	farmers, bill, farm, ag, agriculture, house, 2018farmbill, farmbill, ranchers, work, committee, senate, support, food, across, help, rural, act, industry, hemp
Labor	jobs, job, work, workers, good, people, workforce, get, time, americans, employees, help, working, act, million, need, skills, training, american, find
Education	school, students, education, schools, high, service, children, help, young, academy, act, national, programs, work, college, meeting, support, week, many, thanks
Environment	water, epa, act, bipartisan, communities, work, earthday, release, community, introduced, lake, must, species, infrastructure, many, some, w, year, caucus, congress
Energy	energy, jobs, hearing, week, drilling, epa, nuclear, offshore, act, bill, help, read, bipartisan, committee, good, grid, housecommerce, important, live, meeting
Immigration	immigration, border, illegal, daca, security, bill, american, wall, secure, would, house, dreamers, children, immigrants, must, people, solution, borders, country, law
Transportation	infrastructure, act, state, transportation, economy, federal, house, law, nations, safety, traffic, week, critical, ensure, important, like, national, plan, projects, air
Law and Crime	law, enforcement, officers, protect, safe, families, day, keep, trafficking, work, children, communities, help, house, women, need, sex, support, act, bill
Social Welfare	help, food, snap, work, poverty, bank, need, bill, get, hunger, those, community, families, find, people, program, programs, service, children, continue
Housing	housing, bill, families, support, week, act, behind, last, local, opportunity, project, veterans, affordable, communities, hearing, home, house, hudgov, need, schumershutdown
Domestic Commerce	small, businesses, business, help, economy, bill, local, smallbusinessweek, community, disaster, relief, act, banks, week, communities, jobs, house, thanks, federal, financial
Defense	veterans, military, service, women, men, support, care, country, need, national, va, day, act, house, iran, defense, them, deal, honor, must
Technology	broadband, internet, rural, cyber, bill, access, security, congress, innovation, america, like, live, space, act, americans, federal, hearing, help, house, nation
Foreign Trade	trade, tariffs, american, steel, china, economy, nafta, workers, foreign, like, aluminum, imports, letter, need, other, see, companies, consumers, could, discuss
Intl. Affairs	north, must, korea, israel, russia, jerusalem, people, against, embassy, regime, kim, human, stand, support, world, continue, rights, american, iranian, syria
Gov. Operations	senate, government, house, vote, congress, support, state, time, work, shutdown, conservative, day, campaign, need, am, democrats, office, court, get, schumershutdown
Public Lands	national, bill, act, water, natresources, park, parks, week, help, infrastructure, interior, legislation, resources, wrda, land, secretaryzinke, bipartisan, critical, house, keep
Gun Control	violence, school, gun, would, act, bill, bipartisan, guns, schools, stop, house, laws, safety, support, teachers, working, enforcement, first, keep, law

Table A6: Top topic features in tweets by STATE LEGISLATORS

Topic	Top Features
No policy issue	day, community, happy, me, congratulations, thanks, annual, work, time, state, year, join, honor, morning, proud, school, students, city, ca
Economy	budget, tax, cabudget, state, funding, income, million, credit, jerrybrowngov, economy, earned, proud, help, bill, investments, passed, —
Civil Rights	women, proud, lgbt, rights, community, day, equality, womens, me, pride, work, support, sentoniatkins, vote, sexual, court, lgbtq, march
Healthcare	health, flu, care, people, get, day, disease, help, measles, healthcare, children, vaccine, state, bill, cases, need, medical, or, access
Agriculture	animal, food, animals, ag, ab, coast, day, fishing, large, protect, proud, support, week, adoption, asmgarcia, bill, did, diego
Labor	workers, job, working, jobs, proud, lorenasgonzalez, union, unions, childcare, support, work, workplace, bill, labor, thanks, workforce, californialabor, minimum
Education	students, education, college, school, student, schools, support,higher, state, important, teachers, public, early, funding, assembly, bill, join,
Environment	water, climate, clean, earthday, environmental, air, plastic, protect, change, environment, pollution, day, happy, community, need, bill, proud
Energy	energy, drilling, oil, offshore, clean, sb100, coast,future, gas, against, bill, decision, expand, proud, solar, trumps, assembly
Immigration	immigrants, immigration, immigrant, children, families, daca, dreamers, de, citizenship, proud, policy, border, administration, parents, san, back, question, trumps
Transportation	transportation, transit, bill, state, cars, funding, traffic, housing, near, projects, public, senate, committee, passed, road, san, million, ride
Law and Crime	sexual, bill, youth, help, senate, foster, harassment, police, support, violence, assembly, children, gun, end, committee, proud, victims, community
Social Welfare	food, nonprofit, meals, year, free, summer, kids, seniors, poverty, hunger, assembly, community, sacramento, thanks, work, state, million, nutrition
Housing	housing, homelessness, affordable, homeless, crisis, bill, support, home, need, people, help, working, build, city, community, state, thanks, communities
Domestic Commerce	county, business, evacuation, small, areas, disaster, businesses, please, area, calfire, help, evacuations, fire, recovery, state, bill, center, lake, sb
Defense	veterans, military, day, memorial, honored, remember, yountville, air, service, community, fallen, families, fire, forces, honor, members, annual, ceremony
Technology	netneutrality, net, neutrality, bill, internet, sb822, scottwiener, fcc, important, kdeleon, senate, industry, nasa, protect, discuss, fight, hard, law
Foreign Trade	arbitration, lorenasgonzalez, tomorrow, ab3080, agrees, any, asmaguiarcurry, assembly, assessment, awareness, billdoddca, cagobiz, camadegov, capitol, co, condition, consumer, dawniamarie
Intl. Affairs	armenian, assembly, million, state, children, genocide, honor, join, salvador, anniversary, armeniangenocide, celebrating, colleagues, day, must, russian, american, assemblydems
Gov. Operations	bill, senate, state, support, proud, assembly, vote, passed, day, me, san, election, year, governor, make, first, legislative, work
Public Lands	fire, state, wildfires, calfire, wildfire, community, county, water, parks, park, protect, senate, assembly, management, national, passed, bill
Gun Control	gun, violence, action, shooting, enoughisenough, guncontrolnow, guns, safety, students, against, call, notonemore, across, bill, join, joined, killed, like, lives, lost

Table A7: Top topic features in tweets by NATIONAL MEDIA

Topic	Top Features
No policy issue	man, police, state, cleveland, county, cincinnati, school, indians, cavs, day, game, high, shooting, dayton, first, breaking, fire, icymi, win
Economy	tax, budget, shutdown, levy, government, jobs, dow, percent, state, would, county, rate, down, dayton, latest, need, senate, voters, year
Civil Rights	court, state, metoo, racist, supreme, black, fight, police, abortion, case, woman, charged, federal, law, sex, voter, women, against, bill
Healthcare	opioid, health, drug, medical, marijuana, get, people, program, epidemic, pharmacy, breaking, crisis, medicaid, addiction, ban, blinfisherabj, care, akron, benefit
Agriculture	know, animal, before, county, foodservice, go, inspection, lucas, operations, products, recall, recently, released, reports, arizona, barbecued, beef, bill, cdc, coli
Labor	workers, labor, union, county, pension, program, summer, bill, dayton, employees, forced, job, jobs, law, pensions, retirement, take, ‘, 401k
Education	school, schools, students, state, board, education, threat, teachers, county, levy, children, city, officials, shooting, student, study, year, armed, community
Environment	water, toledo, lake, carp, plan, city, mayor, pollution, residents, advisory, akron, deer, erie, million, protect, trash, could, council, county
Energy	gas, power, davisbesse, energy, nuclear, oil, prices, city, leak, million, production, public, settlement, acres, arabia, boost, claims, companies, customers
Immigration	immigration, immigrant, border, bill, children, families, could, migrant, family, gop, help, ice, mexico, people, separation, agents, california, cities, coming, congress
Transportation	county, state, road, bridge, city, columbus, come, crash, million, streets, toledo, transit, would, council, downtown, keep, parking, part, plan
Law and Crime	police, marijuana, child, county, come, death, drug, breaking, jail, judge, man, federal, court, officers, pot, woman, car, cleveland, found
Social Welfare	food, make, america, awareness, b, box, breakfast, cardi, going, need, poor, really, rich, right, school, security, senio, senior, social, state
Housing	city, community, council, park, columbus, million, project, development, homeless, housing, county, plans, proposed, affordable, center, home, plan, purchase, residents, state
Domestic Commerce	sports, states, betting, amazon, bankruptcy, court, businesses, columbus, supreme, area, banks, bet, breaking, firstenergy, judge, latest, legalize, make, oppose
Defense	nuclear, north, korea, breaking, ap, baker, weapons, would, airstrikes, deal, dorsey, house, iran, jackson, korean, mayfield, military, missile, south, syria
Technology	facebook, americans, analytica, apnorc, apples, back, bankruptcy, call, cambridge, center, come, cook, could, data, debacle, declaring, down, facebooks, firm, ginni
Foreign Trade	tariffs, trade, chinese, china, steel, imports, announces, brown, ease, fight, heres, sensherrodbrown, stocks, administration, agree, aluminum, billion, cavs, deal, delivers
Intl. Affairs	north, summit, kim, korea, korean, un, jong, leader, russia, singapore, police, historic, latest, world, calls, south, syria, uk, arrive, breaking
Gov. Operations	election, house, primary, race, senate, state, county, gop, vote, republican, governor, candidate, may, breaking, candidates, rep, speaker, court, probe
Public Lands	indians, water, american, mayor, regional, advice, city, council, debate, enlist, indian, land, legal, may, memorial, museum, native, outside, remove, south
Gun Control	gun, shooting, school, violence, high, shootings, florida, guns, students, control, kasich, student, carry, house, mass, or, parkland, laws

Table A8: Top topic features in tweets by STATE MEDIA

Topic	Top Features
No policy issue	police, people, man, house, news, first, former, white, woman, killed, re, school, day, during, like, time, american, apcentralregion, apsports, home
Economy	shutdown, government, tax, economy, spending, dow, foxbusiness, house, bill, cuts, unemployment, budget, jobs, million, deal, people, plan, senate, breaking, during
Civil Rights	black, women, people, metoo, white, first, roseanne, woman, abortion, movement, rights, sex, students, racist, bias, gay, against, why, womens, breaking
Healthcare	health, opioid, aphealthscience, drug, people, flu, study, marijuana, cdc, first, medicaid, tells, could, finds, states, administration, apcentralregion, appolitics, apwestregion, babies
Agriculture	food, farm, meat, world, american, anim, aphealthscience, artificial, bakery, because, brands, bread, bureau, cafes, cheese, company, contamination, convention, cream, customers
Labor	workers, first, many, apwestregion, time, want, american, employees, strike, supreme, unions, could, court, get, help, job, jobs, kids, people, re
Education	school, florida, students, shooting, schools, teachers, teacher, student, high, apwestregion, college, oklahoma, pay, public, safety, texas, believe, california, education, funding
Environment	climate, epa, change, scientists, endangered, pruitt, found, help, scott, them, advisory, agency, apwestregion, boards, could, rhinos, somebody, water, white, actually
Energy	drilling, offshore, oil, power, coal, energy, general, administration, apcentralregion, attorney, could, electric, florida, gas, plan, ryan, solar, states, these, trumps
Immigration	immigration, border, illegal, daca, immigrant, immigrants, wall, sanctuary, children, house, people, families, trumps, california, democrats, government, caravan, country, migrant, migrants
Transportation	bridge, airport, breaking, infrastructure, people, air, carolina, florida, airline, coast, collapse, crash, injured, passenger, passengers, pedestrian, red, traffic, year, airlines
Law and Crime	border, breaking, fbi, marijuana, judge, police, law, security, federal, justice, child, florida, abuse, children, court, sessions, apcentralregion, during, people, state
Social Welfare	food, work, ambassador, amnesty, colin, conscience, does, go, international, kaepernick, named, people, poverty, reform, requirements, stamp, think, those, welfare, ablebodied
Housing	help, homeless, apcentralregion, autism, california, crisis, democratic, department, development, housing, kushner, people, those, travfed, urban, veterans, act, affecting, ago, allegations
Domestic Commerce	apwestregion, hurricane, maria, volcano, breaking, california, hawaiis, puerto, billion, kilauea, big, court, financial, hawaii, people, some, sports, still, business, businesses
Defense	nuclear, north, deal, iran, korea, military, nato, syria, weapons, breaking, defense, chemical, war, attack, fisa, house, summit, intelligence, memo, russia
Technology	zuckerberg, facebook, mark, data, first, space, ceo, facebooks, nasa, scandal, before, breaking, congress, mars, people, administration, aphealthscience, asks, company, did
Foreign Trade	trade, tariffs, china, steel, tariff, trumps, aluminum, world, countries, billion, united, war, deal, foxbusiness, going, states, american, canada, deficit, eu
Intl. Affairs	north, korea, kim, un, jong, korean, breaking, summit, south, leader, russian, meeting, russia, people, minister, state, first, latest, putin, between
Gov. Operations	house, senate, campaign, mueller, former, gop, fbi, trumps, white, special, breaking, primary, sen, russia, republican, investigation, state, court, democrats, election
Public Lands	american, apwestregion, native, indian, memorial, national, apeastregion, burial, public, state, court, dead, democrats, discovered, florida, land, mexico, park, pocahontas, puerto
Gun Control	gun, school, shooting, florida, guns, nra, students, control, high, parkland, violence, people, house, laws, mass, want, weapons, national, protest, shootings

Table A9: Top topic features in tweets by PARTISANS

Topic	Top Features
No policy issue	me, like, de, day, get, or, people, time, did, know, love, ve, go, good, see, some, am, why, re
Economy	tax, gop, shutdown, bill, government, down, trumpshutdown, republican, economy, jobs, last, budget, congress, cut, cuts, passed, republicans, spending, trillion, would
Civil Rights	women, white, people, black, rights, racist, children, or, them, against, racism, like, re, sexual, because, want, woman, america, house, lgbtq
Healthcare	health, care, healthcare, people, insurance, medicaid, need, or, medical, time, children, drug, kids, medicare, opioid, which, would, access, childrens
Agriculture	dairy, bill, canada, congress, farm, nations, water, —, 3rd, 4h, administration, afbf18, africa, afternoon, agriculture, approved, banning, billion, bo, bottled
Labor	workers, working, —, families, america, build, deserve, lets, work, address, american, better, broken, ca, demand, fight, hard, income, inequality, labor
Education	students, school, education, teachers, schools, public, texas, kids, student, them, , best, ca, like, teacher, work, act, charter, colleges, country
Environment	climate, water, change, because, environmental, flint, federal, still, against, air, big, clean, does, first, local, people, scott, work, world, year
Energy	energy, gas, oil, infrastructure, plan, solar, first, heres, lead, why, , administration, breaking, civilisation, companies, company, dakota, drilling, emissions, executives
Immigration	border, children, immigrant, immigration, immigrants, daca, families, parents, why, policy, trumps, dreamers, asylum, separated, separating, administration, people, illegal, or, wall
Transportation	transit, transportation, capmetroatx, public, also, always, because, credit, deaths, draft, funding, improve, like, offers, plan, since, take, texas, year, across
Law and Crime	police, justice, officer, people, marijuana, domestic, prison, because, department, violence, abuse, against, california, children, does, first, get, ice, officers, stop
Social Welfare	or, chip, food, against, children, contingency, fund, child, families, homeless, hr, million, plan, poverty, time, billion, childrens, conroy, coverage, cut
Housing	plan, city, housing, austin, enough, get, houstondon, imagine, income, infrastructure, local, low, lowincome, progress, residents, spent, 65xs
Domestic Commerce	hurricane, market, puerto, died, maria, people, rico, tax, because, business, businesses, companies, dow, law, news, stock, again, big, biggest, corporations
Defense	military, or, nuclear, war, iraq, parade, veterans, camps, detention, did, last, them, ve, attack, bin, children, end, families, family, korea
Technology	netneutrality, net, neutrality, vote, call, fcc, bill, democracy, public, senate, against, americans, cable, california, data, did, done, effort
Foreign Trade	trade, tariffs, canada, steel, war, trumps, could, get, tariff, would, •, act, aluminum, back, billion, china, country, easy, exports, fair
Intl. Affairs	russia, russian, north, people, russians, china, iran, korea, putin, state, sanctions, syria, breaking, israeli, trumps, gaza, house, killed, meeting, white
Gov. Operations	vote, gop, house, mueller, election, trumps, fbi, would, why, campaign, people, republican, or, did, breaking, never, state, me, against, cohen
Public Lands	native, americans, indigenous, american, hall, kylegriffin1, national, projects, survey, affairs, allow, americanindian8, asking, bought, bureau, challenges, cherokee, chronsnyder
Gun Control	nra, gun, school, guns, shooting, mass, people, children, students, violence, assault, parkland, take, weapons, breaking, high, ban, know, shootings, shannonrwatts

Appendix B Validating the method for identifying state partisans

In the paper we assess the extent to which shifts in issue-attention by Democratic and Republican party supporters from each state are also predictive of shifts of attention by state legislators, to account for the fact that previous work finds partisans to have the ability to influence the issue preferences of their representatives (more than, e.g., the mass public at large). Following Barbera et al. (2019)'s method (designed to identify partisans at the national level in the United States), we collected the list of followers of all the state legislators on Twitter from the 13 states we analyze in the paper, and then looked for those who followed at least 2 Democratic legislators from a given state, and none Republican legislators from that state (and vice versa), a total of 245,709, and 'classified' them as state partisan for that particular state and party.[15] By matching Twitter users with their voter registration records from states that make the data available for research, Barbera et al. (2019) show that this method is highly accurate at identifying partisans at the national level (based on whether they follow members of Congress of a given party and none of the other). However, to ensure the method also works for identifying partisans from particular states, we conducted the following validation exercise.

Table C1: Example of the *location* and *description* Twitter fields.

Location	**Description**
Brooklyn NY	Conservative Republican living in People's Republic of New York
California, USA	Experienced Multi-Media publisher with XX
Vermont	Moderate Democrat, husband and father. Opinions are my own.
Houston, TX	Realtor with XX Properties. Foodie. Houstonian. Texan.

First, we used the Twitter API to collect the profile of these users, in particular, the self-reported location field and their profile description (see Table C1 for some anonymized examples from our dataset). We obtained a self-reported location for about 63% of the users (N = 156,021). Then we looked for whether the full state name (Arizona, California, etc.) or the state abbreviation (AZ, CA, etc.) was mentioned in the location (case insensitive): 33% of all the users (N = 81,058). For these, we calculated the proportion that we had considered to be about a particular state, and that we could match them to that state based on their self-reported location string: 90.3%, corroborating that the method worked for identifying users from a particular state.

We obtained a self-reported profile description for 65% of the users (N = 159,735). Then we looked for whether the word Democrat or Republican was mentioned in these descriptions (case insensitive): 3,223 mentions of Democrat (1.3% of all partisans) and 1,896 mentions of Republicans (0.7%). Existing work already shows that only a very few people reveal

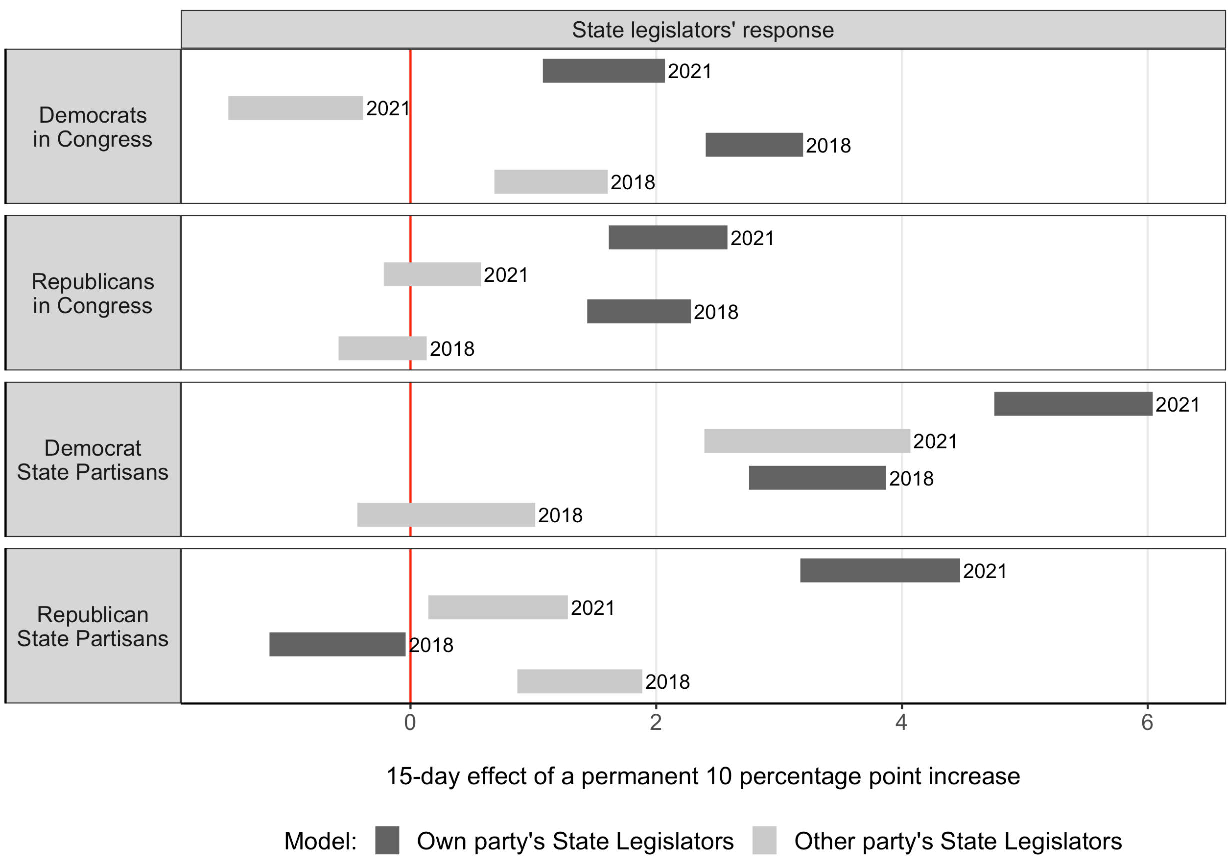
[15]Not all these users were included in the analysis because some did not tweet during the period of analysis. See Table 1 for the exact number of users included in the analysis.

their party preferences on their Twitter profile (Eady, Hjorth, and Dinesen 2022), however, despite not being representative of the whole sample, this data allows us to run an additional validation to make sure that Barbera et al. (2019)'s method is likely to work well to identify partisans at the state level. We are confident that this is indeed the case, since 94% of those who mentioned the word Democrat in their descriptions we had classified as being democrats, and the same for 89% of those who mentioned the word Republican.

Appendix C Exploring Partisan Differences

Although we didn't have theoretical expectations 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 3 as well as to provide some descriptive results that can inform future research on the topic.

Figure C2: Issue Responsiveness by Party



Note: The estimates 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 another group 15 days ago. The bands represent 95% confidence intervals. Dark gray bands represent the effect for legislators and partisans of the same party while the light gray bands represent effects between legislators and partisans of different parties.

In Figure C2, the dark gray bands represent the effect for legislators and partisans of the same party while the light gray bands represent effects between legislators and partisans of different parties.

For example, the estimates in the first row indicate that a permanent 10-percent increase in issue-attention by Democrat members of is associated with cumulative 1.6 (2021) and 2.9 (2018) percentage point increases in issue-attention by Democratic state legislators. The estiamtes immediately below them in light gray indicate that the same increase in issue-attention by Democrat members of Congress is associated with noticeably weaker (2018) or no (2021) increases in issue-attention by Republican state legislators.

The main results provided strong evidence that state legislators adjust their public communication in response to the agenda of national lawmakers in Congress. Overall, we see that this dynamic is primarily driven by agenda setting dynamics within party, and less so across party. Only in 2018 do we find that Democrats in congress exerted influence on Republican state legislators.

State law makers also appear to be more responsive to partisan members of the public from their own party. At least, this is what we find for Democrat state legislators in both years and for Republican state legislators in 2021. The year 2018 provides a curious exception here with Republican state legislators being unresponsive to constituents of their own party.

Appendix D Differentiating between state legislators from low vs. highly professionalized legislatures

One of the key findings in the main analysis is that shifts in issue-attention by members of Congress are highly predictive of congruent shifts in issue-attention by state legislators, while we find no evidence for the vice versa effect. We do find however that state representatives follow shifts in issue-attention by partisans from their states, as well as from state media accounts.

One caveat of the analysis in the main paper is that we do not distinguish between state representatives from more vs. less professionalized legislatures. State legislatures vary significantly on many professional dimensions, such as how often they meet, and the number of resources and staff available. These varying levels of professionalization could be predictive of different patterns in terms of how often they react or lead national conversations on relevant policy issues, or how they respond to key political actors in their states (e.g., media and partisans). For example, representatives from legislatures with more resources may be able to build a more solid portfolio of issues they want to push onto the agenda, and so be less likely to react to shifts in issue-attention at the national level. More resource can also mean that they are better equipped to track the issues their constituents deem relevant and to more quickly react to shifts in issue-attention by the public.

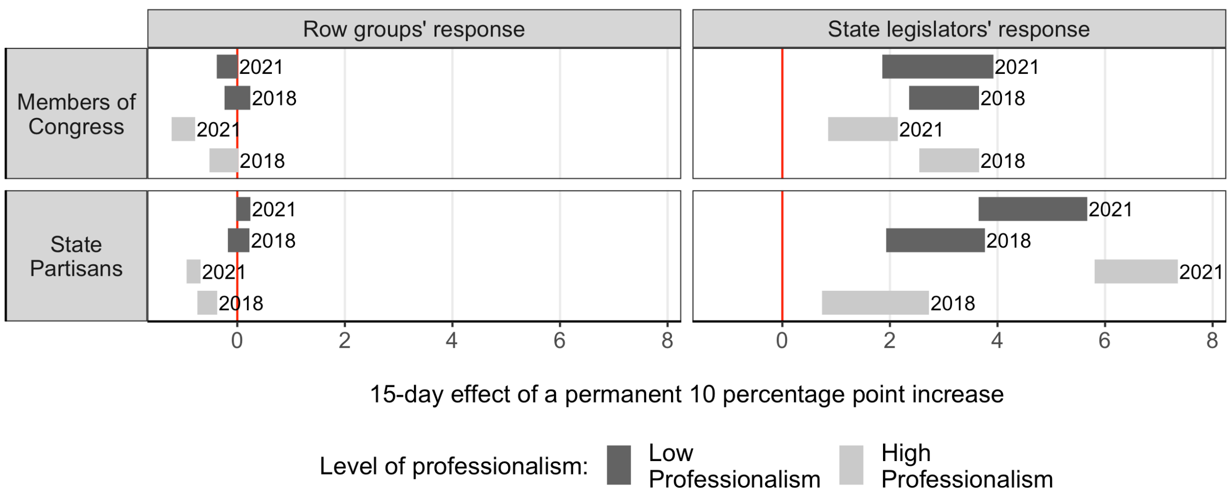
Table D1: Legislative professionalization scores.

Utah	0.06
Montana	0.08
Virginia	0.13
Nevada	0.14
Texas	0.20
Florida	0.22
Arizona	0.23
New Jersey	0.24
Illinois	0.26
Ohio	0.30
Massachusetts	0.38
New York	0.48
California	0.63

To assess the validity of these arguments, in this Appendix we run two versions of the model reported in Figure 3, for both of which we use the same data for the national actors (members of Congress, national media, and the president), but vary the data we use from state actors (state legislators, state representatives, and state media). In one of the model we include data from state actors from states with less professionalized legislatures, and in the other one we include data from state actors from states with more professionalized legislatures.

We rely on data from Squire (2007) and *The Correlates of State Policy Project*[16] to obtain professionalization scores for the legislatures in the 13 states included in our analysis (see Table D1). For a more stark comparison, we drop the more 'middle-ground' states in terms of professionalization (Texas, Florida, Arizona, and New Jersey), and compare the ones with the lowest professionalization scores (Utah, Montana, Virginia, and Nevada) to the ones with the highest scores (Illinois, Ohio, Massachusetts, New York, and California).

Figure D2: Issue Responsiveness with state legislators differentiated by the level of professionalization of their legislatures.



In Figure D2 we report the results for these two models. For simplification, we only report the 15-day cummulative IRFs comparing members of Congress to state legislators (and vice versa) and state partisans and state legislators (and vice versa), although both models include all the actors included in the main model in Figure 3. The darker estimates show the results for the states with the least professionalized legislatures, while the lighter estimates report the results for the most professionalized. On the left panel (*Row groups' response*) we report how much *Members of Congress* (top row) and State Partisans (bottom row) increased their attention to a given issue 15 days after a shift in attention by state legislators. On the right panel we report the vice versa effect, by how much state legislators shifted the attention to a given issue in response to a previous shift in attention by members of Congress and by state partisans.

The findings are very similar for state legislators from the least and the most professionalized legislatures, indicating barely any difference between state representatives from these different states. The findings are also relatively consistent across time. In both years, and for legislators from both types of legislatures, members of Congress did not react to changes

[16] http://ippsr.msu.edu/public-policy/correlates-state-policy

in attention by the state representatives yet they had a strong (and about equally large) influence on their issue-attention. We see a very similar story when we look at the relationship between the issue-attention distribution of state partisans and state legislators, although in there we see a mild difference. In 2018 and 2021, neither state representatives from the least professionalized or the most professionalized influenced state partisans. We do not see a consistent difference for the vice versa effect. Although in 2021 state representatives from the most professional legislatures reacted more strongly than the least professionals to shifts in attention by state partisans, we observe the opposite for the 2018 data.

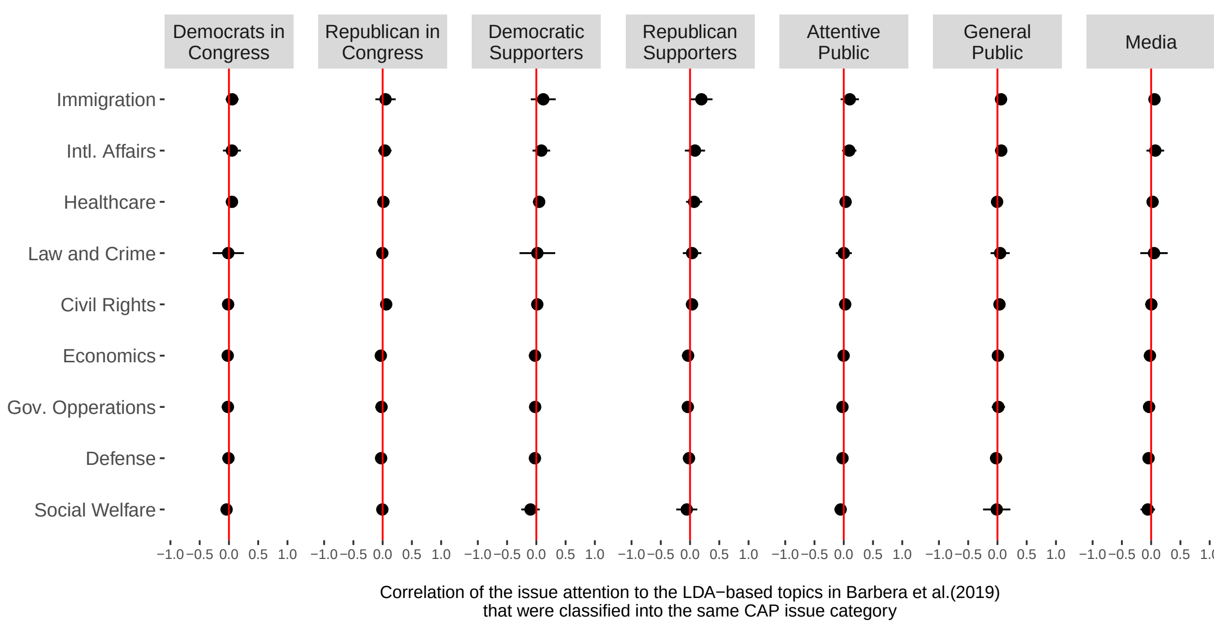
Overall, although as mentioned in the beginning, there are some reasons to expect state legislators from less vs. more professionalized legislatures to behave differently when it comes to influencing or adapting to shifts in attention by national legislators or from partisans within their states, the results in Figure D2 show that in practice state legislators from these different legislatures behave very similarly when it comes to influencing, and being influenced by, the issue agenda of other relevant political actors.

Appendix E Exploring whether spikes in attention to sub-issues of the main CAP topic categories are likely to happen simultaneously

In the analysis in the paper we rely on the 21 topic categories of the Comparative Agendas Project (CAP) to assess whether shifts in issue-attention to one of these categories by one of the groups under analysis, is predictive of shifts in attention by the other groups. The CAP categories are rather broad (e.g., immigration, economy, civil rights, etc.), which means that a given one (e.g., civil liberties) encompasses many sub-issue dimensions (e.g., gender inequalities, race inequalities, etc.). A potential limitation of our approach is that if we find a correlation between a spike in attention to given topic by a given group, to be predictive of a spike in attention to the same topic by another group, these two groups may actually be increasing their attention to different sub-issues within the same category, and so the agenda of the former to not really be influencing the agenda of the latter.

Given the nature of our analysis, we believe this is unlikely to happen. Our models are based on day-level time series, which means that we calculate shifts in attention for a given topic and group in a given day. We believe that is unlikely that in the same (or closely subsequent days) two groups will be increasing their attention to two different sub-issue domains of the same CAP issue category.

Figure E2: Correlation between the issue-attention to the LDA-based topics in Barbera et al. (2019) that have been classified into the same CAP topic category



We conducted the following analysis to assess whether this is indeed the case. We take advantage of the data used by Barbera et al. (2019) in their analysis. In their paper, rather than using a supervised approach and to classify their analyzed tweets into broad issue categories, they chose an inductive approach and used an unsupervised LDA model to identify more narrow topics discussed by members of Congress in 2013: 53 political topics in total. In their SI.A, they classified these 53 topics into the 21 CAP categories, and replicated their analysis based on these broader categories and found no meaningful differences. In here we used this mapping between their 53 topics and the 21 CAP categories, and the replication dataset of their paper, to assess the time correlation between the groups of topics they classified into the same CAP category. If indeed a given group of users (or different groups) is likely to increase their attention 'simultaneously' to more than one sub-issue domain of the same CAP category, we should see some substantial correlations between the attention devoted to these finer grained topics that have been matched to the same CAP category. If that's not the case, the correlation should be rather low.

In Figure E2 we show the results of this analysis. For the different subsets of the 53 political topics that Barbera et al. (2019) classified into the same CAP topic category, and for each group of users they studied in their paper, we calculated the average correlation for the daily issue-attention to any potential pairs of topics in the set (and a 95% confidence interval around the average correlation). We excluded from this analysis the CAP topic categories for which they only had classified one of their 53 political issues. Across the board we observe null correlations: they are all either very small, or negative, and the 95%confidence interval cross zero. Only two are positive and the confidence intervals do not cross zero, but they are very small. Overall, we believe that this corroborates our intuition that it is highly unlikely to observe substantial spikes in attention to sub-issue domains of the same CAP topic category around the same days; and so we believe that the findings in the paper are not a function of this unlikely scenario.