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

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 more than 122 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 various 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 members of the public in their states and moderate responsiveness to regional media sources.

1 Introduction

Why do US state legislators publicly discuss certain policy issues over 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 increasingly relevant as growing gridlock and polarization in D.C. have led important policy battles to take place at the state rather than the national level, including 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 on 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 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 issue-attention 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. We perceive both as plausible and non-mutually exclusive. In turn, the goal of this study is not to settle an either/or debate, but to assess how much empirical support there is for each of these explanations.

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). We build here on literature that portrays public agendas as an important outcome to study on its own, as a key step in the policymaking process (Schattschneider 1960; Kingdon 1984; Baumgartner and Jones 2010), and do not focus on what legislators do in their chambers. Nevertheless, as we show in Appendix I, there is a very high correlation between the issues that state legislators discuss on Twitter and the topics of the bills they introduce in the legislatures, indicating that their public social media communications reflect their broader issue priorities.

We remain agnostic regarding the exact mechanism through which these actors learn about the issue priorities of the others given the many available channels (including direct offline interactions, other public statements, and opinion polls), and we treat their social media communication as a proxy for their public issue agenda. In Appendix J, however, we present evidence suggesting that social media platforms may be one of the channels through which political actors learn about each other's issue preferences. We hope that future research can disentangle more clearly the exact mechanisms at play.

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, (f) a "random" sample of users located in these states, and (g) a set 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. They shift their issue-attention in response to the policy discourse put forward by members of the public within their states, particularly partisan constituents that pay close attention to state-level politics. State media outlets also 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 state politics.

2 Avenues of 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 partisans and 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. 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 facilitating this bottom-up dynamic. 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, which politicians then address in order to not be perceived as 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 here, we study the impact of local issue priorities by focusing on the following three state level groups. First, we assess the role of the *general public* from each state under analysis. Then, we study what we refer to as *state partisans*, defined as partisan members of the public within each state that are particularly attentive to the politics of their state.[1] Finally, we examine *state media outlets* that may provide important channels through which local priorities emerge in public discourse and reach politicians. Building off the literature

[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.

described in the preceding paragraphs, we begin by testing the following two hypotheses:

H$_{1A}$: Increases in issue-attention by the public in each state (general public and partisans) will increase issue-attention by state legislators.

H$_{1B}$: Increases in issue-attention by state media outlets will increase 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. 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. 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:

> **H**$_{2A}$: Increases in issue-attention by members of Congress will increase issue-attention by state legislators.

> **H**$_{2B}$: Increases in issue-attention by the President will increase issue-attention by state legislators.

> **H**$_{2C}$: Increases in issue-attention by national media outlets will increase 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* theories, state legislators should shift their public communications in response to local level actors; the latter, which we call *top-down* influence, asserts that state legislators' issue priorities will follow those of national level actors. In here we assess, within the same research design, how much empirical support there is for each of these theoretical accounts (which we see as non-mutually exclusive).. We close with a Discussion of how these findings can serve as a launchpad for future research.

3 Data to Measure Issue-Attention

We use Twitter data to test our hypotheses. Twitter is widely and frequently used by both national (Barbera et al. 2019) and state-level (Payson et al. 2022) political elites. Besides, as we demonstrate in Appendix I, there is a very high correlation between the issues state legislators discuss on Twitter and the issues they address in their legislative activity. 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.

Alternative approaches to study issue-attention each suffer from significant limitations. Documents emerging from legislative settings (e.g., roll call votes, bill introduction, etc.) are perhaps one obvious alternative. Yet, they are heavily constrained by institutionalized processes 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 not allow for the kind of temporally fine-grained analyses we conduct. Given these issues, tweets provide an excellent proxy for attention being paid to various policy topics. They allow us to assess issue-attention 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

[2]Some U.S. state legislatures meet only in odd numbered years. In our sample, Montana, Nevada, and Texas

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 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

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.

[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.

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.

- **General Public**. We created a sample of 112,376 random[5] Twitter users messaging from one of the 13 states included in the analysis.[6] We then used the Twitter REST API to collect the messages these users sent in 2021, for a total of 17,073,132 messages from 48,809 unique accounts (out of 112,376) that sent at least 1 tweet in 2021. Data collection was not possible for this group for 2018.

- **State Partisans**. We identify partisan users who pay close attention to the politics in each state as follows. 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.[7] In Appendix B we also perform our own validation.

- **State Media**. We track the tweets of the most relevant news outlets from each of the 13 states.[8]

[5]We used two protocols to generate this random sample. First, (a) before Twitter switched to 64-bit IDs in 2016, we automatically generated 32-bit random numbers and checked for whether they were existing Twitter users. After the introduction of longer IDs, (b) we increased the sample size by: collecting tweets mentioning English stopwords (i.e., "the") for numerous short amounts of time selected at random and then pulled the authors of those tweets and information about how frequently they tweeted, and we subsampled a set of authors with a tweeting distribution similar to that of the users in the list created using the first approach (a). See Wojcieszak et al. (2022) for further details.

[6]Similar to Loynes (2021), we combine two approaches to identify the state location of users: (a) we use the self-reported location when there is one and it matches one of the 13 US states, or (b) place users in the modal location of the reciprocal friends that provide a self-reported location. Loynes (2021) estimate the precision of these methods to be around 83% and 63%, respectively.

[7]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)

[8]For 2018, we tracked the top 10 newspapers in each state, based on circulation data from

Table 1: Number of tweets and unique accounts by group

Group	2018 Unique accounts	2018 Tweets collected	2021 Unique accounts	2021 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
General Public	-	-	48,809	17,073,132
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**	161,587	**78,633,078**

3.1 Classifying policy issues

At the heart of our analytical strategy is an assessment of when different actors discuss different topics on Twitter. We rely on the comprehensive list of 21 policy issues defined by the Comparative Agendas Project (CAP):[9] economy, civil rights, healthcare, agriculture, labor, education, environment, energy, immigration, transportation, law and crime, social welfare, housing, domestic commerce, defense, technology, foreign trade, international affairs, government operations, public lands, and gun control.[10] 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

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.

[9] `https://www.comparativeagendas.net/codebook`. We excluded the CAP topic category *Culture*, as early analyses revealed that it was rarely discussed. And we added an additional category, Gun Control, which is usually considered part of the Law & Crime topic but that has become very salient as an issue in American politics.

[10] Although these are broad categories, we are still able to accurately trace issue responsiveness between groups, as discussions around two sub-issue domains of the same topic category are unlikely to correspond in time (see Appendix E).

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 topic.

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.[11] 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 rather than these shared areas.[12]

4 Methods

4.1 Modeling the Issues Discussed on Twitter

We rely on machine learning for the topic classification. Trained human annotators are likely do a better job at identifying topics in any given tweet, yet the large size of our dataset (more than 120 million messages) makes a manual approach unfeasible. A machine learning approach comes with its own limitations, such as nosier estimates that make it harder to

[11] https://openstates.org/

[12] Specifically, we classify education, healthcare, law and crime, transportation, social welfare, housing, and gun control as state issues and domestic commerce, defense, international affairs, technology, and foreign trade as federal issues.

detect small effects, but it unlocks here the possibility of studying issue responsiveness at scale.

We fine-tune a BERT model to classify the tweets sent by the groups we study into one of the 21 policy areas listed above, plus a non-policy category for those tweets 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 (trained) to solve downstream tasks by providing labeled data related to the task of interest (here, assigning policy areas to tweets).[13]

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 how our models perform in comparison with other approaches including ngram-based models or other transformer-based models like RoBERTa.

In Table 2, 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

[13]Research on LLMs is highly dynamic and new (usually larger) models are frequently released. However, for text classification in social science research, fine-tuning smaller models like BERT may currently still provide a good tradeoff when trained on sufficient amounts of labeled data (Chae and Davidson 2023). In our case, another important factor is the size of our dataset: models like BERT are less computationally intensive than recently-released LLMs, and thus scale up more easily to the hundreds of millions of observations in our dataset (see Terechshenko et al. (2020) and Laurer et al. (2024) for further details on fine-tuning language models for social science research).

estimation and to update the model weights at each training iteration, a validation set used for calculating the model loss and deciding when to stop the training, and a test set that remained unseen during training and that we used to perform a final accuracy test. In Table 2, we report the test 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 validation sets (the fully unseen test set remained the same across folds).

Table 2: Test Accuracy of three BERT models fine-tuned to predict the policy areas discussed by politicians, mass media, and the mass public.

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 (65% for the Politician Model, 77% for the Media Model, and 83% 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. In Table 3 we illustrate the high face validity of the classifier, by showing the top features for tweets from members of Congress classified into each topic (see Appendix A for further details).

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 accuracy that 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. Yet, given that our topic estimates have some noise, we advise caution when interpreting null results from statistical models that rely on these topic predictions.

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 general public and the partisans in each state.

Table 4 shows the average daily attention paid to each policy area by each of these groups in 2018 and 2021. *Government Operations* dominate the agenda. This broad category includes discussions related to political campaigns, government appointments, state and federal agencies, and political scandals. At the other end, topics such as *Agriculture* or *Public Lands* received relatively little attention.

Table 3: 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 4: Average daily issue-attention by group in 2018 and 2021. Values 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.

	State Legislators		State Media		General Public		State Partisans		Members Congress		National Media		President		**Mean**	
Issue	'18	'21	'18	'21	'18	'21	'18	'21	'18	'21	'18	'21	'18	'21	'18	'21
Gov. Operations	25.0	22.7	20.3	11.6	-	27.0	33.4	25.1	19.8	16.3	22.8	16.3	38.5	7.1	26.2	18.0
Civil Rights	8.1	9.2	9.8	10.0	-	17.0	13.3	15.2	6.8	8.5	10.9	12.7	1.6	7.0	9.8	11.4
Intl. Affairs	2.3	1.9	5.7	5.4	-	6.2	7.6	6.3	5.3	5.9	21.0	19.2	15.3	4.9	9.1	7.1
Immigration	3.7	2.4	4.9	2.5	-	3.9	7.1	4.5	6.5	6.1	6.6	4.2	14.7	1.6	7.0	3.6
Economy	7.9	7.1	6.4	6.4	-	4.0	4.2	4.4	9.4	9.2	4.9	4.3	9.0	18.1	6.5	7.6
Healthcare	8.6	16.3	6.6	19.9	-	10.0	4.2	11.4	9.5	13.6	4.2	14.7	1.5	22.3	5.8	15.5
Law and Crime	8.1	6.6	7.7	5.4	-	5.6	4.9	5.7	6.7	5.1	5.7	5.8	2.4	2.6	5.8	5.3
Gun Control	1.7	1.7	4.4	1.8	-	5.6	7.4	4.8	1.6	1.3	3.5	1.7	2.3	0.7	4.3	2.5
Defense	3.6	2.8	1.7	1.6	-	2.8	2.8	2.8	7.2	6.5	3.9	3.3	2.9	5.2	3.5	3.6
Education	7.3	6.2	5.6	6.0	-	2.4	2.5	3.4	3.1	2.9	1.6	2.1	0.2	2.2	3.4	3.6
Dom.Commerce	3.9	4.2	3.9	5.8	-	2.9	2.0	2.5	4.6	4.2	3.2	2.7	2.6	6.0	3.3	4.1
Environment	2.9	3.0	3.9	4.0	-	2.8	2.3	3.3	3.4	3.9	2.4	3.1	0.3	3.9	2.6	3.4
Foreign Trade	0.4	0.1	1.3	0.3	-	0.4	0.7	0.4	1.1	0.3	2.5	0.5	6.1	0.4	1.8	0.4
Transportation	3.1	2.5	3.5	3.4	-	1.0	0.9	1.3	2.1	3.2	0.9	1.6	0.7	6.9	1.7	2.9
Technology	1.5	1.2	1.2	1.3	-	1.8	1.5	1.6	2.0	1.8	1.7	2.1	0.2	1.2	1.6	1.6
Energy	1.9	2.0	2.9	2.6	-	1.3	1.1	1.7	1.5	2.3	1.0	1.5	0.5	0.8	1.5	1.8
Labor	2.9	2.5	1.7	2.2	-	1.3	1.1	1.6	2.6	3.1	0.9	1.5	0.1	6.2	1.5	2.6
Housing	1.7	2.5	4.6	5.8	-	1.1	0.8	1.3	1.0	1.2	0.7	0.9	0.0	0.7	1.4	1.9
Social Welfare	2.2	2.5	0.8	0.9	-	1.2	0.9	1.3	1.9	1.9	0.4	0.5	0.2	1.2	1.1	1.4
Agriculture	1.6	1.1	0.9	0.9	-	0.5	0.5	0.6	2.4	1.2	0.6	0.4	0.7	0.1	1.0	0.7
Public Lands	1.5	1.6	2.2	2.3	-	0.6	0.5	0.7	1.8	1.4	0.7	0.8	0.0	1.0	1.0	1.2

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 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.

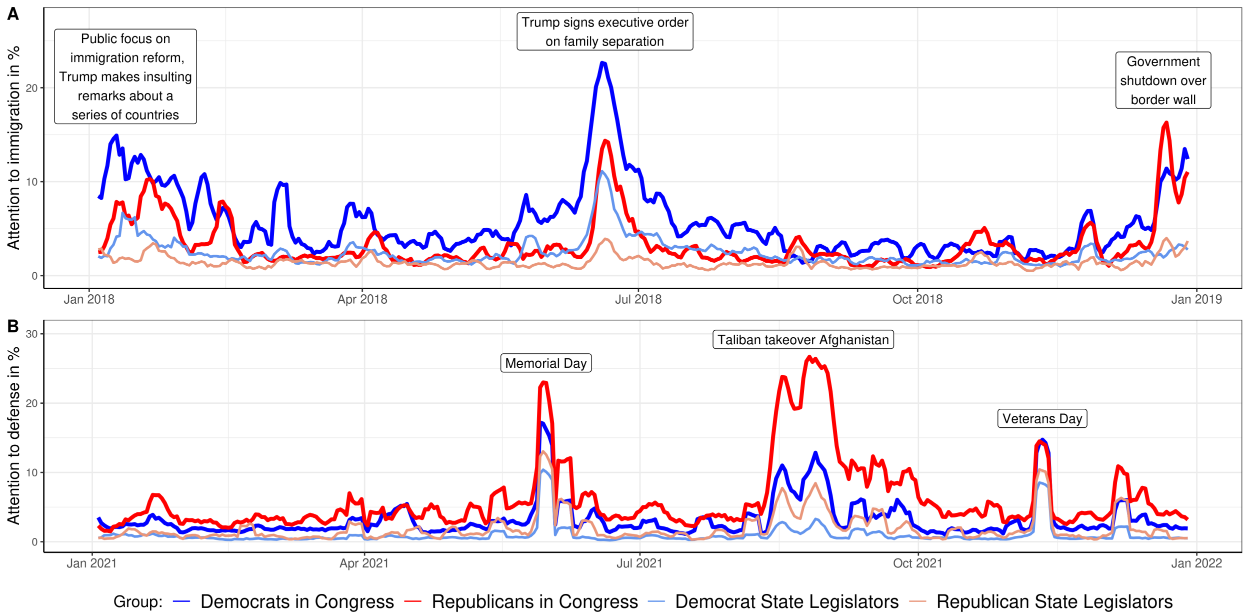
4.2 Vector Auto Regressive Models

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; Carsey et al. 2011; Edwards and Wood 1999; Wood and Peake 1998). To illustrate the logic of this approach, consider Figure 1, 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 sometimes 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 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 sometimes happens around particular points in time,

Figure 1: 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.

these distributions can be 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).[14] External events and unexpected shocks play an important role in agenda setting (Kingdon 1984; Birkland 1998). Not all actors necessarily react to (or are affected by) all shocks, nor is it a given that all actors would react in the absence of others doing so. Yet, to address potential concerns about results being mainly driven by actors systematically reacting to the same shocks at a different pace, this transformation softens the ability of big shocks to influence the model. Additionally, we show in Appendix H that big sudden spikes in attention are actually rare in the data, suggesting that systematic delays in reacting to the same shocks are unlikely to drive results. Our VAR model comprises a system of equations,

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

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 .[15] 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, and work with time series that are at the day-topic-state level. We thereby make two simplifying assumptions: (a) that dependencies between our groups are constant across state and issue; and (b) that state legislators are attuned to the general public and state partisans from the whole state and not only from their own specific district. While these assumptions are inaccurate to some extent (i.e., responsiveness dynamics among actors are likely to vary across issues), they are reasonable: legislators from a given state should on average still be more responsive to members of the public from their own state (even if these are not from their district) than those from other states. They also help to drastically reduce the complexity of our data, making the analysis more tractable and feasible (i.e., data at the day-topic-district level would unfortunately be too sparse). Within this framework, we can express the degree to which changes in issue-attention by one group are predictive of changes in issue-attention by another group. In a subsequent analysis we relax these assumptions

[15]Partial auto-correlation analyses conducted on these time series indicated the inclusion of up to 5 lags in our models. In Appendix K we present the results of a series of augmented Dickey-Fuller tests, which indicate that our time series are mostly stationary.

and explore, different responsiveness patterns across issues.

5 Results

5.1 Bottom-Up: State Level Actors

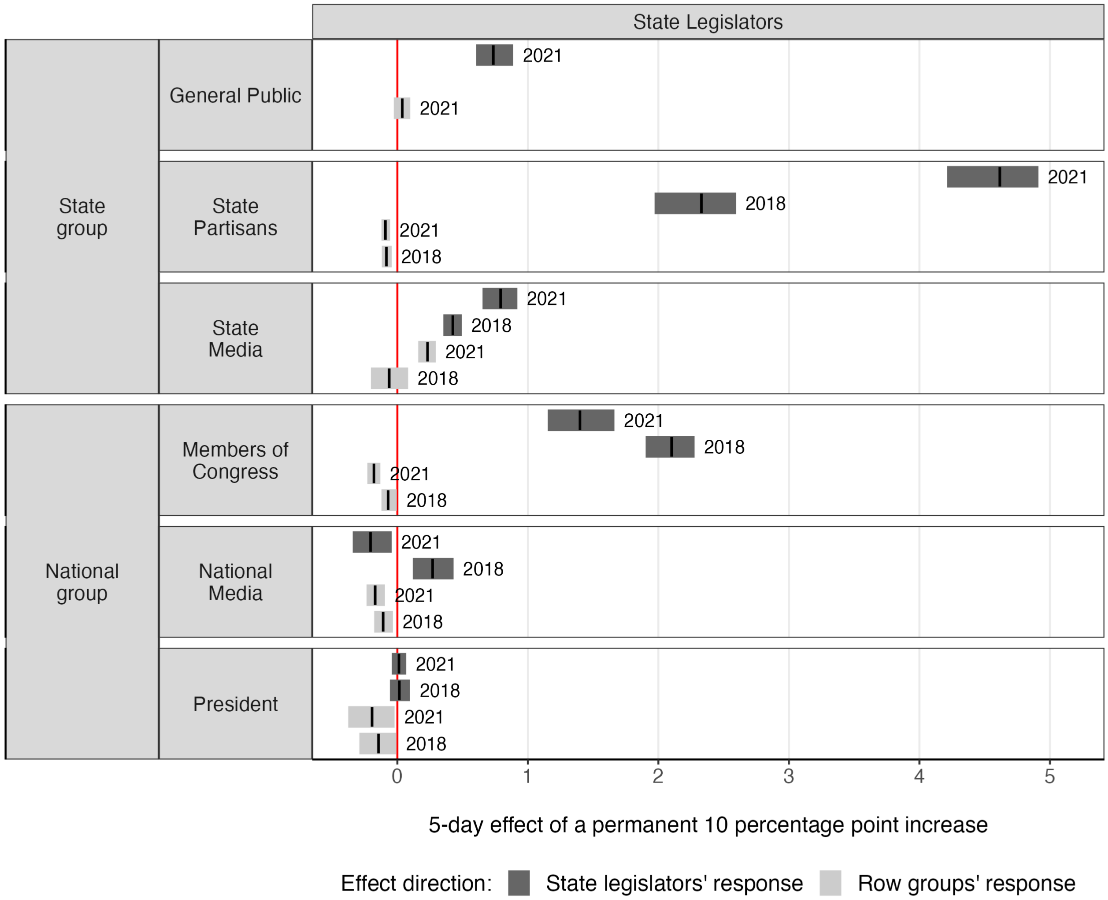
VAR coefficients are difficult to interpret, so we use cumulative impulse response functions (IRFs) to display the results of our models. IRFs trace the effect of simulated shocks to the VAR system of equations.[16] In our case, we simulate a sudden increase in attention to an issue by one group to observe the resulting changes in cumulative attention devoted to that issue by another group over time. We estimate cumulative IRFs for a 5-day period. We follow Barbera et al. (2019) and present our results as responses to a permanent attention change to a given issue from 0% to 10%.[17] We then use the VAR parameters to calculate the cumulative change by the other groups over the next 5 days. If a group reacted by increasing attention to the topic by 1 percentage point in day 1, 0.5 in day 2, and 0 the remaining three days, we would observe a cumulative 5-day effect of 1.5 percentage points.

In all models we control for the influence of each group 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 2 shows the 5-day effects from the main model for both national and state actors with 95% confidence intervals. The full coefficient table for the model is available in Appendix L. The effects are expressed in percentage points. The dark gray bands are the main focus of our analysis, as they represent responses by state legislators to increases in issue-attention by each of the six 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'

[16] When estimating the IRFs we assume no contemporaneous effects between the different groups under analysis. For VAR models to be identified (Linn and Webb 2020), one needs to either impose a small set of restrictions regarding who can influence whom at day 0, or not allow for any influence at all at day 0. We decided for the latter to avoid making strong one-directional assumptions for these day-0 effects.

[17] 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%, see Barbera et al. (2019).

Figure 2: Cumulative 5-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 5 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.

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 5 and are substantively meaningful, given that shifting the agenda of other groups is extremely difficult (Jones and Baumgartner 2005; Schattschneider 1975). The few negative effects in Figure 2 are small and possibly due to an actor often moving to another topic by the time another actor responds to shifts in attention by the former; and/or two actors focusing on a (at least slightly) different set of issues.

Arguably the most striking takeaway from Figure 2 is that state legislators are strongly influenced by changes in issue-attention of the mass public from their own state, particularly by state partisans who follow the politics of each state closely. The corresponding effects are shown in the top two rows. We observe that in 2021, an increase in attention of 10 percentage points by the general public on average translates into an increase in attention by state legislators of about 0.7 percentage points in the next 5 days. In line with previous research (Barbera et al. 2019), the effects are more striking for partisans. In both 2018 and 2021, state legislators increased their attention by 2.3 and 4.6 percentage points, respectively, in response to a similar shift in attention by state partisans. 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. Explaining the difference in effect size for partisans between 2021 and 2018 is beyond the scope of this paper, yet it suggests that are conditions under which state lawmakers are more attuned to public discourse, which should be an important area for further research.

We also find support for $\mathbf{H}_{1B}$. State legislators are moderately influenced by the state media (row 3). These effects are weaker than those for state partisans (.8 percentage points in 2021 and .4 percentage points in 2018), and more in line with the effects observed for the general public, and suggest 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 fourth row. The estimated effects indicate that a 10-point increase in attention to an issue by members of Congress is predicted to increase the cumulative attention of state legislators by 2.1 (2018) and 1.4 (2021) percentage points. The 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 Appendix C we break down our analysis by party and observe that in most cases this is due to state legislators following shifts in issue-attention by members of Congress of the same party. In Appendix F we fit issue-level VAR models, and differentiate national and state legislators by party, to explore the correlation between issue salience by party (as a proxy for issues they own) and how much members of Congress are predicted to influence state legislators. We do not find higher levels of responsiveness on issues owned by each party. In Appendix G we correlate the issue-level VAR models with issue salience, and show that these dynamics are not simply driven by high levels of responsiveness on a few salient issues.

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 small effect (0.4) 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 are not able to reject the null hypothesis for $\mathbf{H}_{2B}$. We see both presidents having a very small effect, around 0.1 percentage point, that is not distinguishable from 0. Given that our topic estimates have some noise, we should be cautious when interpreting these null findings.

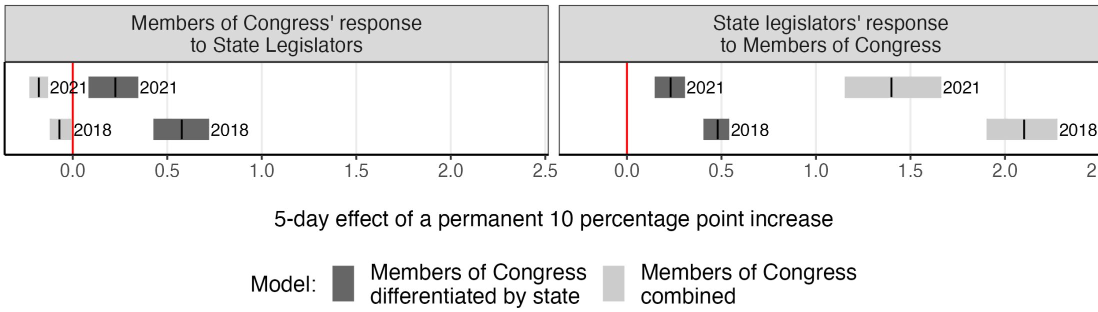
The lack of state legislator responsiveness to the tweets of President Trump is perhaps a bit surprising given the extensive social media use of the former president. However, existing research tends to emphasize that Trump embraced an emotional, anti-elitist approach to his twitter behavior that emphasized populist narratives and attacking his political enemies over public policy (e.g. Shear et al. 2019; Lacatus 2021). While we find no evidence that Trump drove policy issue-attention among state legislators (including Republican state legislators), it is possible that other political actors adopted his tone and rhetoric. We note that exploring the diffusion of such qualities among political actors with a similar identification strategy as ours could provide an interesting avenue for future research.

Together, these results show that U.S. state legislators react strongly to the discourse of the public in their state (particularly of partisans who pay close attention to state politics), as well as to 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. As discussed with regard to bottom-up effects, the negative coefficients we observe here may be due to others groups shifting to other topics by the time state legislators reacted to their initial change in attention, as well as to the fact that groups tend to focus on somewhat different sets of issues (see Table 4). These coefficients are small and partially insignificant however, so that we abstain from drawing any major conclusions from them beyond the fact that there does not seem to be much influence between the groups. For some actors (the President and the national media) the null (or mildly negative) effects are 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 2 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 across states. In Figure 3, 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. The model controls for each group included in the main model in Figure 2, but in Figure 3 we report only the effects for members of Congress. 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 2 (lighter gray estimates).

Figure 3: 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 5 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.

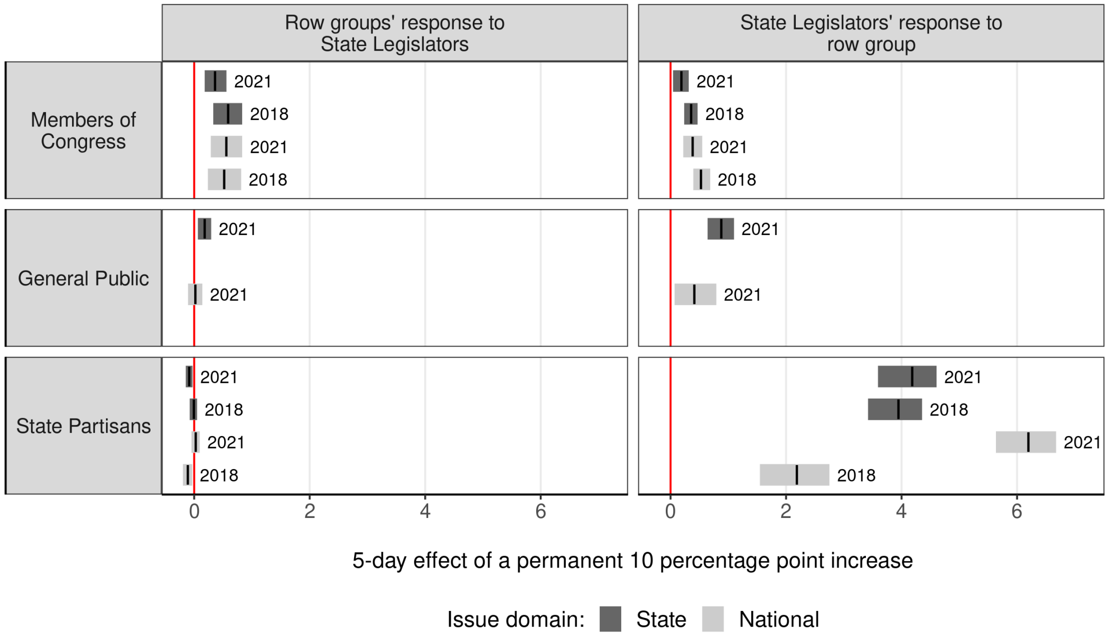
In the right panel we observe state legislators to be considerably more likely to respond to spikes in issue-attention by Congress as a whole than they are to spikes in attention by the representatives of only their state. Interestingly, the left panel in Figure 3 shows that members of Congress do at times respond to the issue agenda of state legislators *from the state they represent*. The effect is more pronounced in 2018 compared to 2021.

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.

To assess whether agenda setting dynamics differ according to issue domain, we estimate

Figure 4: 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 Footnote 12. 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 5 days ago.

two distinct models: one for state issues and one for federally issues (both listed in Footnote 12). Figure 4 shows the results, where 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 left panel shows how members of Congress and the public from their own state respond to state legislators' attention on the two sets of issues, while the right panel shows how state legislators respond to shifts in attention by these groups. Because we only observed members of Congress to respond to shifts in issue-attention by state legislators of the same state (in Figure 3), we continue to distinguish members of Congress by their state for this analysis. To avoid overcrowding the figure we only report the results for these 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 the public when the topic being discussed is a policy area traditionally delegated to the states such as education and housing. In the same vein, we do not see the other 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 the general public and 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 computational methods to address these open questions. Using comprehensive Twitter data from two full calendar years under two different presidential administrations to strengthen 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 issue-attention for these different groups and draw conclusions about who leads and who follows in the world of state politics.

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, the general public and 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 intriguing patterns 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 also find that some relevant national actors (e.g. national media, the President) exert little-to-no influence on the issues discussed by state legislators and the presence of bottom-up dynamics to be stronger in 2021 compared to 2018.

Hence, in this paper we not only offer crucial tests showing that issue-attention in state politics follows both a bottom-up and top-down dynamic, but we also reveal a rich set of descriptive results 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 influence the issue-attention of policymakers in their states more strongly. We see relevant differences between the two years we studied in the paper, 2018 and 2021. We hope that future research can address whether this variation stems from some state legislatures not meeting in odd years, the emergence of the COVID-19 pandemic in 2020, or other underlying circumstances. Additionally, in Appendix I we uncover a very high correlation between the issues state legislators discuss on social media and their legislative work. Future research may explore further for example whether this is because legislators use their public communications for credit claiming and advertise what they do in the floor, or to push their peer policymakers to take action on particular issues. Overall, this paper provides the most fine-grained picture to date of issue-attention dynamics at the state level, and we hope that the evidence uncovered here will motivate 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).[18]

[18]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 (Laurer et al. 2024) 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, chosen at random from the full set A), (5) set C.n and set B, (6) set C.n and a small sample of set B (1,300 tweets, chosen at random from the full set B)), and (7) set C.n and the other C sets. Hence, apart from trying out adding the full set A (789k observations) and set B (45k) to the training data, we also tried only adding smaller random samples of 1,300 observations each. We did so to augment the size of the training set with other kinds of CAP-coded data, while still making sure that our own annotated tweets represented a majority of the training data. Excessive data augmentation, specially when using data of a different nature (congressional bill titles *v.* tweets), can sometimes lead to worse performance (Laurer et al. 2023).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, validation, and test set. The test set is composed of 30% of our own labeled tweets in the C.n set. The train and validation sets are composed of 80 and 20% (respectively) of *all* labeled cases used for training (after excluding those tweets in the test 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 test sets, not on the training nor validation 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

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.

(SVM) that previous research has found to perform well at classifying text into the CAP topic categories (Collingwood and Wilkerson 2012). Given that all annotated datasets in Table A1 are unbalanced, with some topic classes having many more documents/observations (e.g. government operations) than others, we also tried to train the models with smaller yet more balanced versions of these datasets (which in some occasions may help boost performance). In particular, in each fold we only used half of the training data, discarding observations from the most populated classes in each case (and keeping all observations from the least populated), leveling the number of observations across classes. However, the results in Table A6 show no improvement (for the Politician model), and we decided to stick with the original models we trained. In Table A5 we also show that more recent transformer-based models such as RoBERTa do not necessarily perform better across our tasks than a BERT base model. 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 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	0.61	0.44	0.45
(1) set A	0.30	0.57	0.23	0.47
(2) set C.3	0.64	0.54	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: Comparing the performance (based on 3-fold cross-validation, and on an untouched test set) of base BERT and **RoBERTa**.

Statistic	Group	BERT	RoBERTa
Accuracy	Politician	0.65	0.70
PolicyF1	Politician	0.62	0.66
Accuracy	Media	0.77	0.77
PolicyF1	Media	0.67	0.70
Accuracy	Partisans	0.83	0.81
PolicyF1	Partisans	0.65	0.69

Table A6: Comparing the performance of the BERT **POLITICIAN** model when trained with the full yet unbalanced corpora, v. smaller but more **BALANCED** coropra

	Original		Balanced	
Model version	Acc.	Policy F1	Acc	Policy F1
(5) set C.3 and B	0.65	0.62	0.32	0.57
(4) set C.3 and small A	0.66	0.62	0.57	0.53
(6) set C.3 and small B	0.66	0.61	0.47	0.46
(7) set C.3 and C.1&C.2	0.65	0.60	0.52	0.53
(3) set C.3 and A	0.64	0.61	0.38	0.58
(1) set A	0.30	0.57	0.30	0.56
(2) set C.3	0.64	0.54	0.57	0.37

Table A7: 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 A8: 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 A9: 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 A10: 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.[19] 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

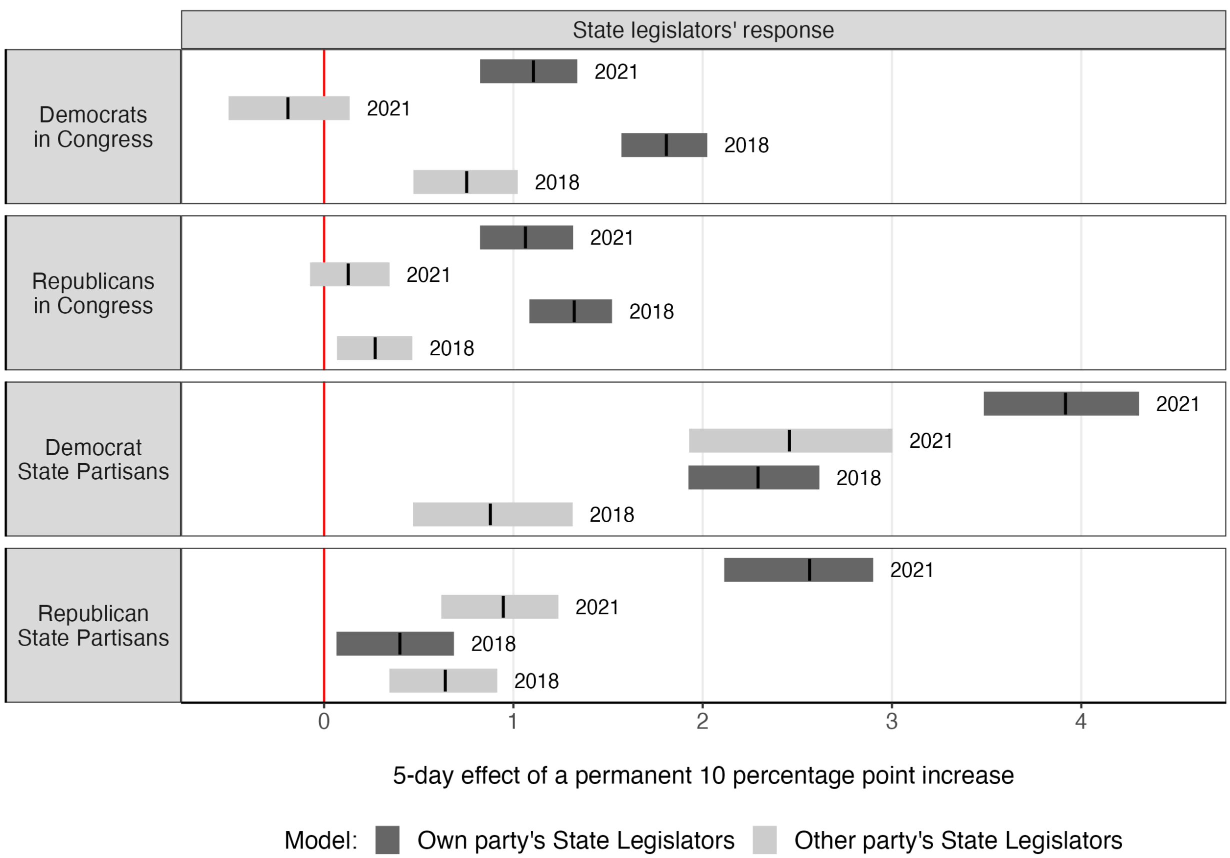
[19] Not all these users were included in the analysis because some did not tweet during the period of analysis. See Table 1 for the exact number of users included in the analysis.

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 2 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 5 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 estimates 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. We hesitate to over-interpret this result given that it is not the main focus of our study and lack clear theoretical expectations. It could also be a Type 1 error given the many statistical tests than we run in the study. Having said that, 2018 was a challenging year for Republicans, who lost seats both in Congress and in state legislatures across the country. Democrats successfully flipped over 350 state legislative districts that year, and Republicans lost control of 7 chambers. It is possible that electoral competitiveness leads state legislators to focus more on national issues and less on local issues. We believe that these are the kind of findings that make this paper very interesting and needed, as it puts forward rich empirical evidence that can help with further theorizing and hopefully inspire future studies that provide more clear tests for particular hypotheses. Future research for example might explore if state legislators are less responsive to public issue-attention within their own states during competitive years.

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.

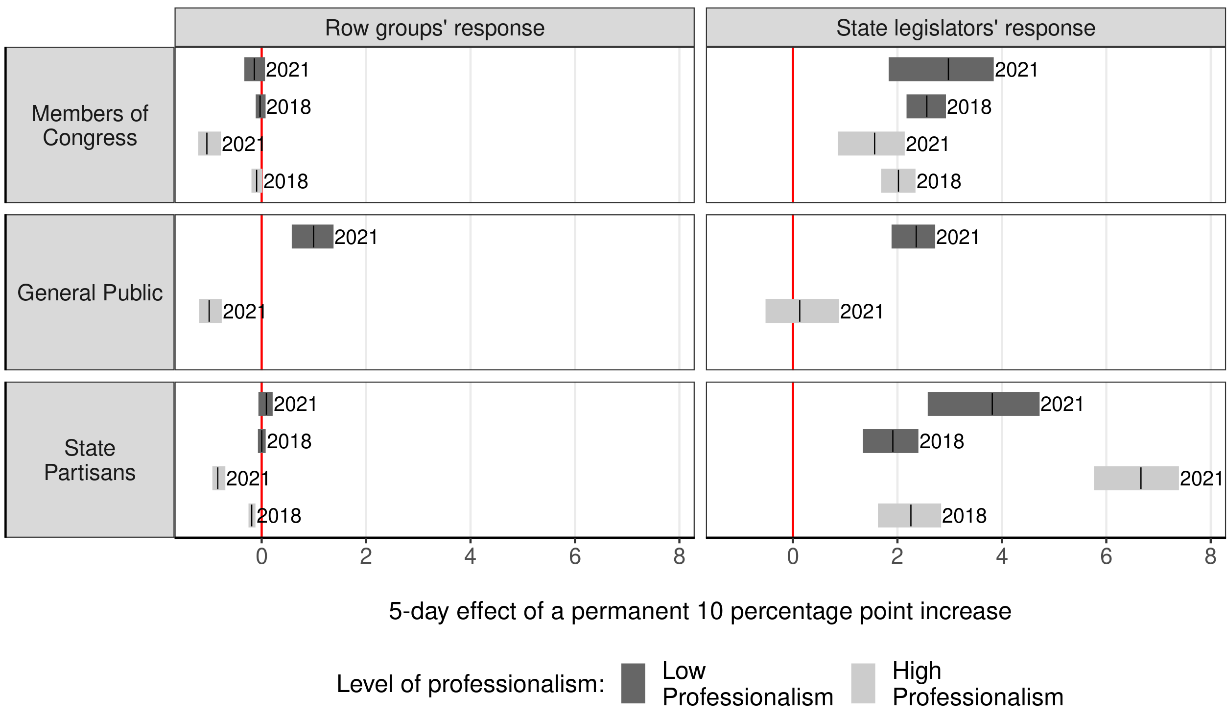
Table D1: Legislative professionalization scores.

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 2, 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*[20] 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 D1: Issue Responsiveness with state legislators differentiated by the level of professionalization of their legislatures.



In Figure D1 we report the results for these two models. For simplification, we only report the 5-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 2. 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 5 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

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

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 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.

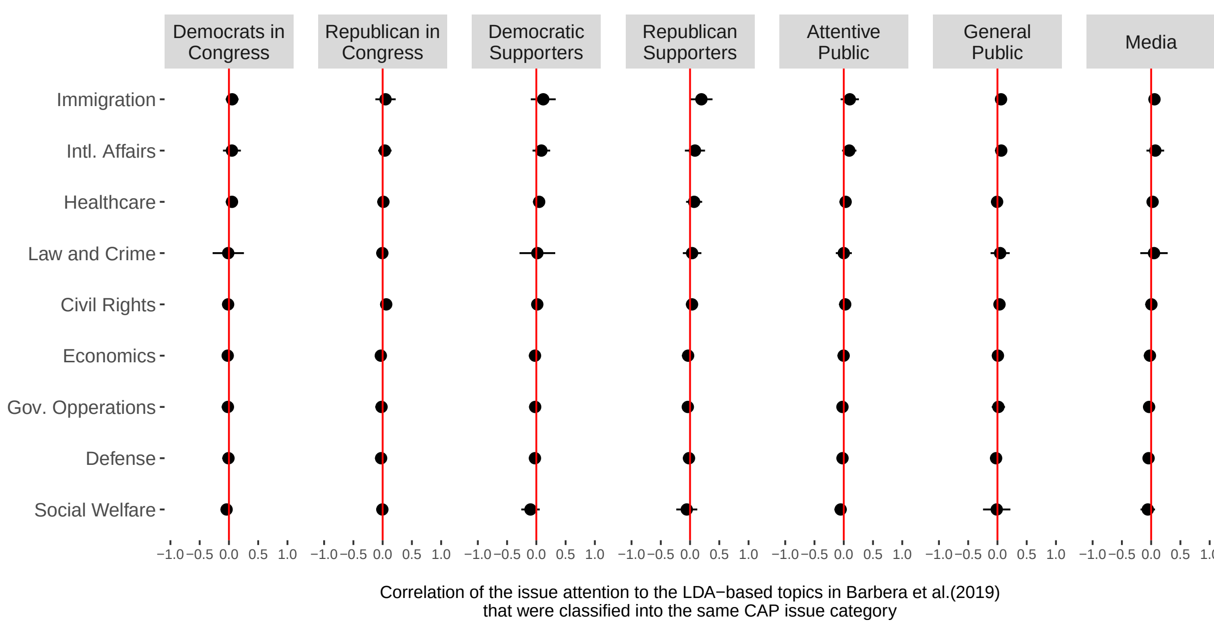
Overall, although as mentioned in the beginning, there are some reasons to expect state legislators from less vs. more professionalized legislatures to behave differently when it comes to influencing or adapting to shifts in attention by national legislators or from partisans within their states, the results in Figure D1 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 E1: 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



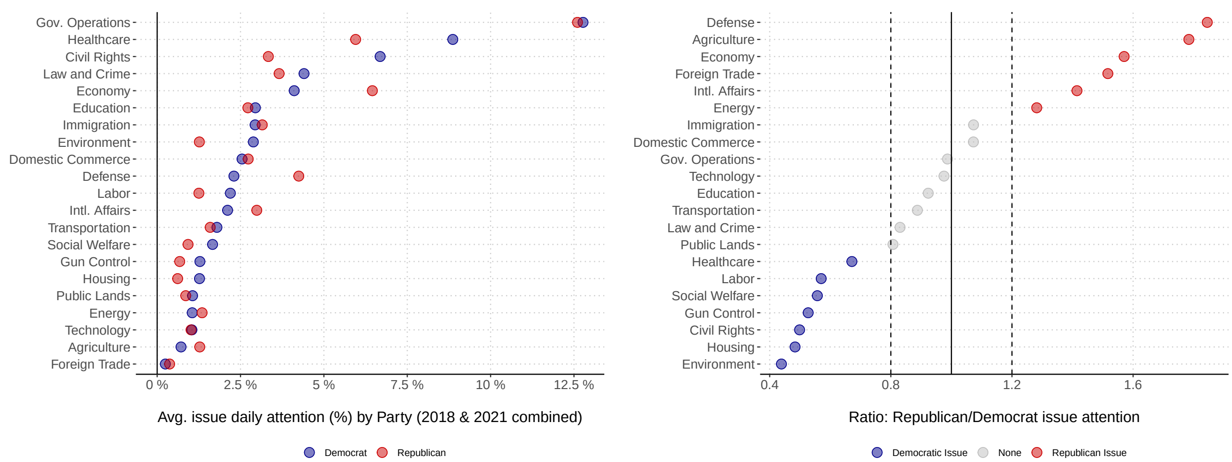
We conducted the following analysis to assess whether this is indeed the case. We take advantage of the data used by Barbera et al. (2019) in their analysis. In their paper, rather than using a supervised approach and to classify their analyzed tweets into broad issue categories, they chose an inductive 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 E1 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.

Appendix F Exploring Issue Ownership Differences

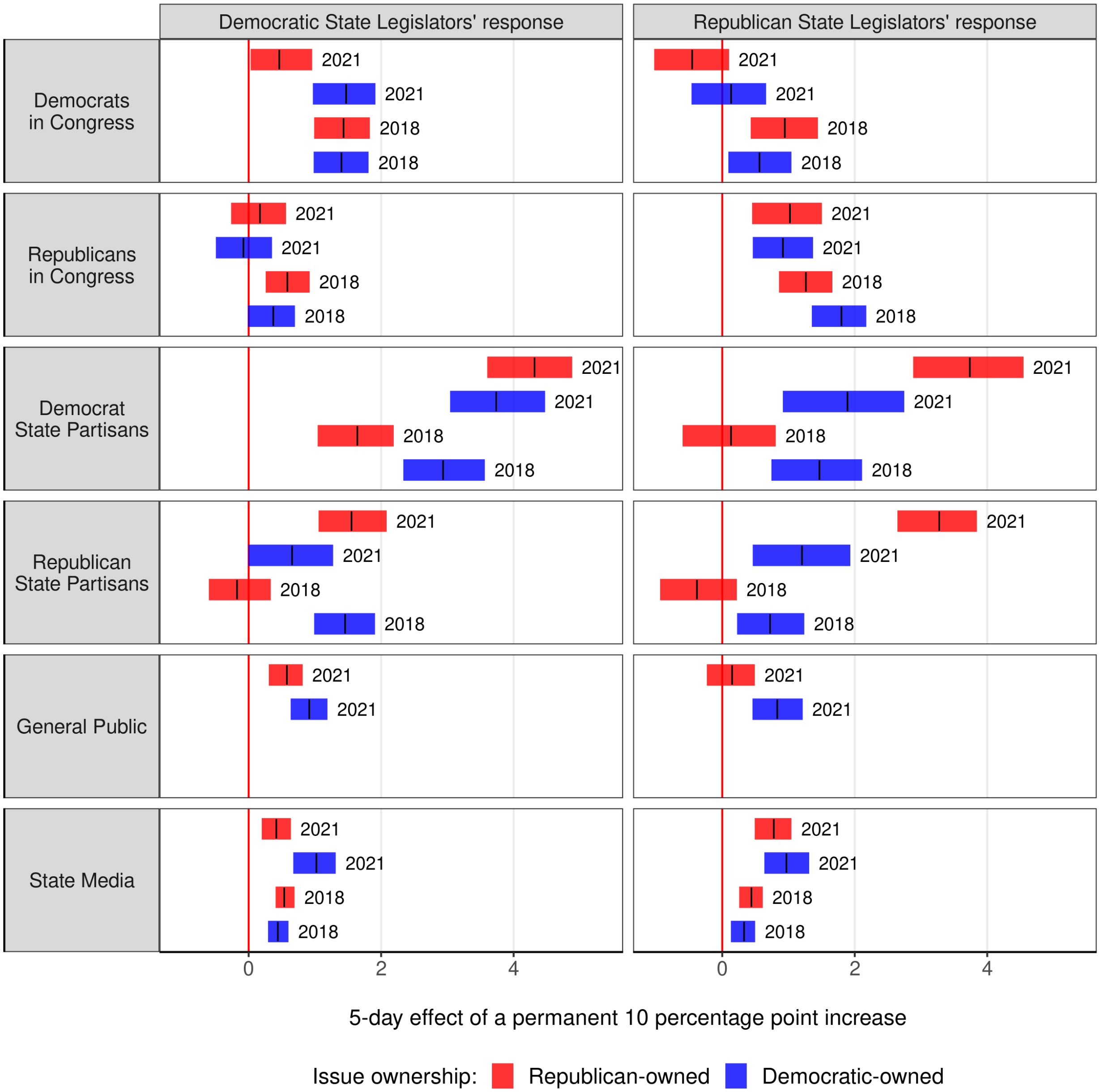
Issue ownership theory argues that parties are more likely to focus on those issues on which they are perceived as being more competent (Petrocik 1996). Regarding the topic of interest in this paper (understanding the issue agenda of state legislators), and the finding if Figure 2 showing that state legislators often follow shifts in attention by members of Congress, one could build on this logic to argue that states legislators are more likely to follow shifts in attention by members of Congress when these discuss issues

Figure F1: Issue-attention by party: identifying issues 'owned' by Republicans v. Democrats.



To account for these potential heterogeneous effects, we averaged, across 2018 and 2021, the average daily attention paid to each topic by state legislators and members of Congress of the same party. We show these issue-party level measures on the left panel in Figure F2. To facilitate the comparison between Democrats and Republicans, in the panel on the right we calculated the ratio between the average daily attention paid by Republicans to a given issue, and the attention paid by Democrats. We used this ratio to identify issues "owned" (if not, mostly frequently discussed) by Republicans v. Democrats v. None. The resulting classification has high face validty, with e.g. Republicans discussing more often issues on which they are likely to be perceived as more competent (e.g. Defense, Agriculture, Economy, and Foreign Trade), and in the other end of the spectrum, the same for Democrats (e.g. Environment, Housing, Civil Rights, and Gun Control). We use this classification next to fit two different VAR models, one for the issues classified here as Republican-owned issues, and another one for the Democratic-owned ones.

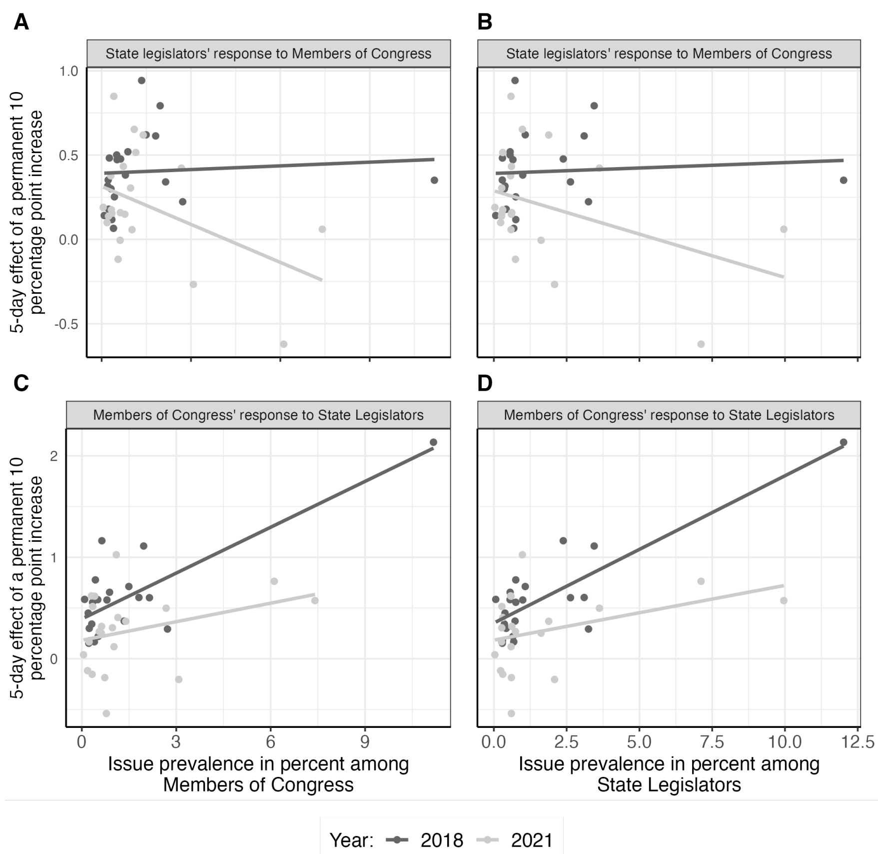
Figure F2: Issue-attention by party: identifying issues 'owned' by Republicans v. Democrats.



Appendix G Responsiveness by Issue Prevalence

In this Appendix we examine whether there is a correlation between issue salience and responsiveness. Rather than fitting a single VAR model, for this analysis we used the same specification as in model shown in Figure 3, but in this case we fit a separate model per issue. In Figure G1 we report two 5-day cumulative IRFs from these models: how much state legislators changed their attention to each issues as a response to a shift in attention by members of Congress (top panels A and B), and the *vice versa* relationship (bottom panels C and D). In addition, we correlate these IRFs (y-axis), to the salience of each issue (x-axis), measured as the average daily attention in 2018 and 2021 (separately) by members of Congress (left panels A and C), and by state legislators (right panels B ane D).

Figure G1: Responsiveness by issue prevalence



Note: The figure shows issue prevalence plotted against issue responsiveness coefficients (between state legislators and Members of Congress). The coefficients stem from independent models for each issue. These follow the logic of the models presented in Figure 3 where members of Congress were differentiated by state. Note that issue prevalences shown here are slightly smaller than in Table 4 because percentages were computed without removing the tweets classified as referring to no policy issue.

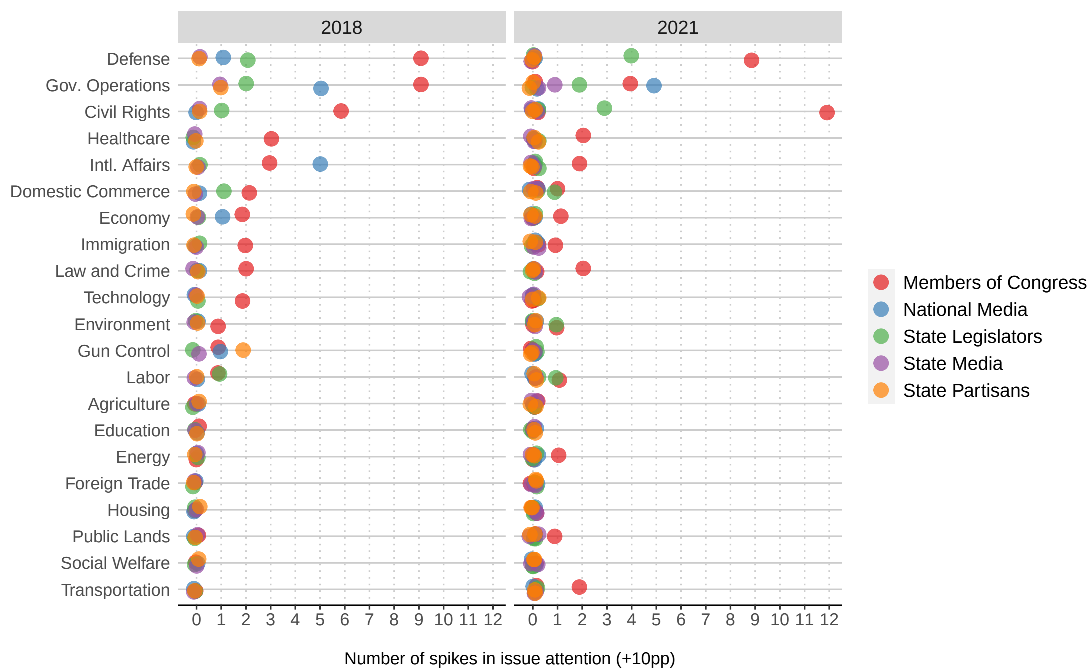
Overall, we find no conclusive evidence regardings the association between issue prevalence and responsiveness. For effects on Members of Congress from the same state, we do see a positive correlation, however the correlation is far from perfect (and considerably more pronounced in 2018 than in 2021). In the other direction, we find almost no association in 2018 and a somewhat negative association in 2021. Together, these patterns indicate that although results for salient topics may have a slightly stronger influence on the overall results, they are not the sole drivers of the dynamics we observe in the main analyses.

Appendix H External shocks and events

In this Appendix we look into the extent to which the findings in our models (e.g. main model in Figure 2) may simply be a function of some actors systematically taking longer to respond to external shocks and events; especially the findings regarding the ability of shifts in attention by members of Congress to predict subsequent changes in attention by state legislators.

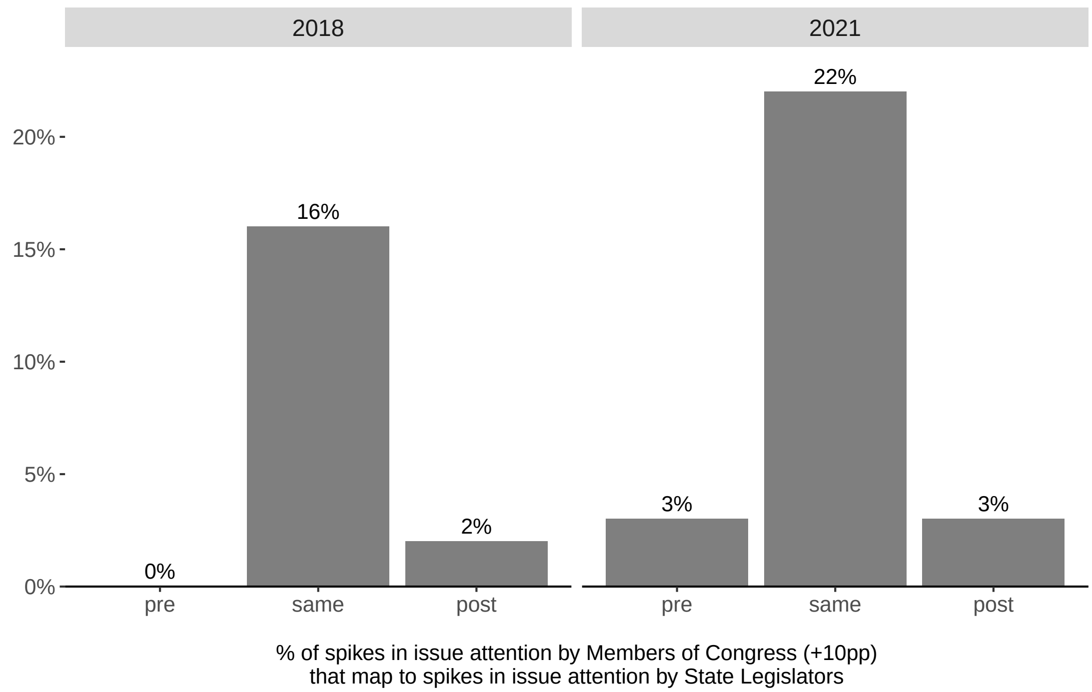
We address this concern in two ways. First, we look at how often big shifts/spikes in attention occur (+10 percentage points increase, v. previous day) – across issues, actors, and time (Figure H1), as such spikes should be characteristic of actors responding to external events or shocks. Then, for the spikes in attention seen in Figure H1 for members of Congress, we look at whether there was a similar increase in attention to that topic by state legislators: right before (within 3 preceding days), the same day, or right after (within 3 subsequent days). If it takes systematically longer for state legislators to respond to external shocks (v. members of Congress), we should see their attention to spike right after, rather than on the same day, or the immediate preceding days.

Figure H1: Spikes in issue-attention (+ 10 percentage point increase v. previous day), across years, topics and actors under analysis.



Two main takeaways emerge from Figure H1. First, although spikes in attention happen (particularly for some issues, such as defense, government operations, and civil rights), they are not very prevalent. We see practically no spikes for 12 of the 21 issues under analysis (from Technology to the bottom of Figure H1). Second, for the issues that we do see some spikes, these are most common among members of Congress. The other actors seem to react less frequently (and/or less strongly) to external events.

Figure H2: Percentage of spikes in issue-attention by members of Congress that map to similar spike in attention to the same issue by state legislators: during the three-days prior (pre), the same day (same), or three subsequent days (post)



In Figure H2 we show the percentage of spikes, by year of analysis, in attention by members of Congress that we were able to map to a similar spike by state legislators on the same issue. We observe that in 2018, 18% of the time, when members of Congress increased the attention to an issue by at least 10 percentage points compared to the previous day, there was a similar spike in attention by state legislators, to that issue, around the same time. Around 16% correspond to instances where the sudden increase in attention happened in the same exact day for both actors, and only 2% correspond to instances were there was a delay in the reaction of state legislators. We observe a very similar pattern for 2021. Additionally, we also see attention spikes by state legislators to sometimes (3%) precede the spikes by members of Congress. The analyses in Figures H1 and H2 are very similar when using alternative values for identifying spikes in attention (+5 and +15 percentage points increases), and for mapping spikes in attention by members of Congress to attention spikes by state legislators (1 and 5-day windows).

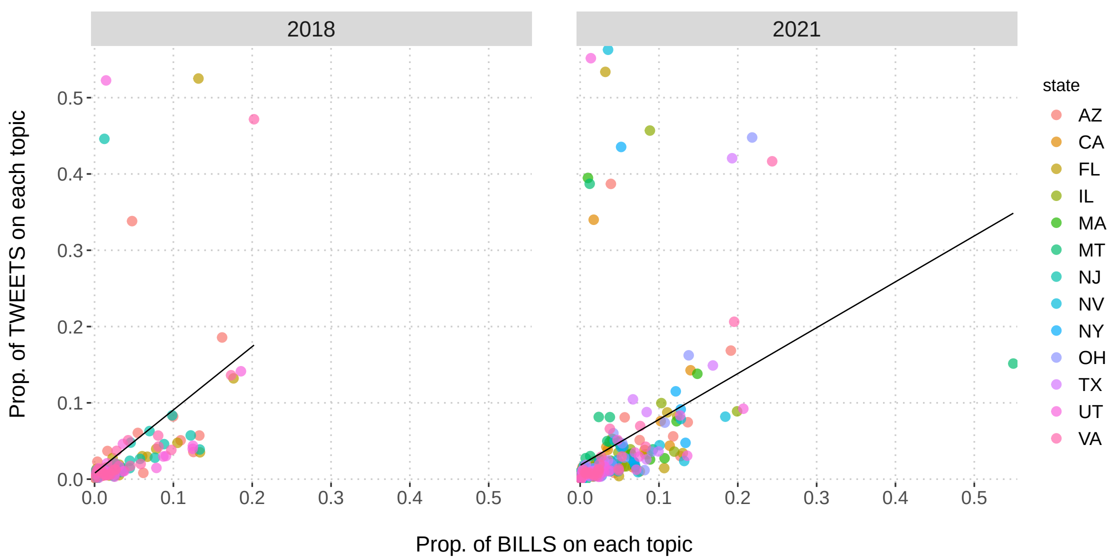
In sum, we believe that the evidence reported here indicates that the VAR/IRF results reported in the different models in the paper, particularly those regarding the ability of members of Congress to precede changes in attention by state legislators, is unlikely to be simply a function of state legislators systematically taking longer to react to external events or shocks.

Appendix I Correlation between Twitter and Legislative activity

In this Appendix we explore the correlation between the issues state legislators discuss on Twitter, and the issues they work on in the chamber.

First, we used the LegiScan API to collect information (title and introduction date) about all the bills introduced, in 2018 and in 2021, to the legislatures of the 13 states included in the analysis (note that some were not in session in 2018), a total of 70,502 bills. We then used the BERT Politicians model fine-tuned in the paper, to predict the topic of these bills based on their title. Finally, we calculated the proportion of bills, by state and year, on each of the 21 topics. We calculated the same topic proportions, by state and year, for the topics of the tweets sent by state legislators.

Figure I1: Correlation between the proportion of bills, and the proportion of tweets, on each topic, by state and year.



In Figure I1 we show the correlation between the proportion of introduced bills, and the proportion of tweets, on each topic, by state and year. For a few state-topics, we see higher twitter attention compared to bill introduction. However, overall we observe a very high correlation between the two. Of course, this analysis does not provide any information regarding any underlying causal relation: whether legislators increase attention to an issue on social media before legislating on it at higher rate (or the other way around), nor the motivation behind doing so (e.g. to push an issue into the agenda, or to advertise an upcoming bill introduction, etc.). However, we believe that this high correlation is an indication that the issues state legislators emphasize in their public communications are a reflection of their issue priorities more broadly, including the issues in which they actually propose legislation.

Appendix J Network dynamics

In the paper we argue that the social media communications of the actors under analysis are a proxy measure for their broader issue priorities, and that there are many ways for them to learn about the issue priorities of the others (such as direct offline interactions, other public communications, and opinion polls). Nevertheless, in this Appendix we explore the Twitter networks of state legislators, in order to provide additional details regarding potential underlying mechanisms for the main findings presented in the paper. In particular, we look at: (a) whether state legislator are connected to some of these other actors on Twitter, as a potential way they may be learning about shifts in the public issue priorities of these actors; and (b) whether state partisans @mention state legislators in their tweets, also as a way to learn about the issue priorities of the party supporters in their state.

Table J1: Number of Twitter accounts state legislators follow, from: members of Congress, national media (out of HuffPost, CNN, AP, and FoxNews), state media, and state partisans included in the analysis.

Group	Sample	Average	Median	Std.Dev.
Members of Congress	All	11.89	8	14.69
Members of Congress	Same party	10.44	7	11.55
Members of Congress	Same state	6.92	5	6.23
Members of Congress	Same state and party	6.02	5	5.28
National Media	All	1.2	1	1.27
National Media	Same party	-	-	-
National Media	Same state	-	-	-
National Media	Same state and party	-	-	-
State Media	All	7.54	6	8.26
State Media	Same party	-	-	-
State Media	Same state	6.74	5	7.73
State Media	Same state and party	-	-	-
State Partisans	All	-	-	-
State Partisans	Same party	-	-	-
State Partisans	Same state	-	-	-
State Partisans	Same state and party	6.02	5	5.28

In Table J1 we show the average (plus standard deviation), and median, number of accounts that state legislators follow from the other actors included in the analysis. At the beginning of the project we collected the list of accounts that each state legislator followed, and to create this table we merged that information with the list of accounts included in each group that we tracked for the study (as described in Section 3). We observe state legislators to be quite tuned to these other actors on the platform. In line with the findings in the paper, they seem strongly tuned to members of Congress (the average state legislator follows 11.89 members of Congress on Twitter), as well as key actors in their own state: on average they follow 7.54 state media accounts, and 6.02 partisan constituents. The table hence provides some suggestive evidence that Twitter on itself may be a way for state legislators to learn about the issue priorities of these other actors.

Table J1: Average number of daily tweets (and 95% confidence interval) by state partisans that mention: any state legislator from the 13 state included in the analysis (*All*), from the same state of the partisan user (*Same State*), and from the same state and party (*Same State & Same Party*)

State	Party	All	Same State	Same State & Same Party
NY	democrat	17.16 [15.79-18.54]	13.73 [12.5-14.95]	12.63 [11.5-13.77]
MA	democrat	15.61 [14.38-16.85]	13.37 [12.2-14.55]	13.31 [12.14-14.48]
CA	democrat	14.69 [13.55-15.82]	12.41 [11.33-13.48]	12.33 [11.26-13.4]
VA	democrat	11.46 [10.5-12.42]	5.29 [4.7-5.88]	4.89 [4.35-5.44]
NJ	democrat	8.75 [7.41-10.09]	6.18 [5-7.36]	2.75 [2.18-3.32]
AZ	democrat	7.76 [6.75-8.76]	4.79 [3.9-5.69]	4.52 [3.64-5.4]
IL	democrat	7.31 [5.64-8.98]	6.01 [4.36-7.66]	5.66 [4.02-7.3]
OH	democrat	5.19 [4.49-5.89]	4.05 [3.4-4.71]	3.07 [2.49-3.64]
TX	democrat	5.16 [4.65-5.67]	2.18 [1.86-2.51]	1.74 [1.47-2.02]
NV	democrat	4.19 [3.77-4.61]	2.08 [1.82-2.35]	2.01 [1.75-2.26]
FL	democrat	2.12 [1.75-2.48]	1.6 [1.24-1.96]	0.9 [0.72-1.09]
UT	democrat	1.14 [0.97-1.3]	0.35 [0.26-0.44]	0.12 [0.07-0.16]
MT	democrat	0.3 [0.22-0.38]	0.08 [0.04-0.12]	0.06 [0.03-0.1]
FL	republican	9.58 [8.73-10.43]	7.98 [7.19-8.78]	7.65 [6.9-8.4]
TX	republican	5.9 [5.22-6.59]	3.26 [2.83-3.68]	3.13 [2.71-3.54]
CA	republican	2.83 [2.41-3.25]	2.35 [1.94-2.75]	0.19 [0.13-0.25]
NY	republican	2.44 [1.99-2.9]	1.73 [1.32-2.13]	1.51 [1.12-1.9]
VA	republican	1.97 [1.73-2.21]	0.81 [0.66-0.96]	0.7 [0.56-0.84]
IL	republican	1.8 [1.54-2.06]	1.67 [1.42-1.92]	1.57 [1.33-1.81]
OH	republican	1.79 [1.58-2]	1.16 [1.01-1.32]	1.06 [0.92-1.2]
AZ	republican	1.76 [1.52-2.01]	1.21 [0.99-1.42]	0.69 [0.56-0.81]
NJ	republican	1.55 [1.33-1.77]	1.11 [0.94-1.28]	1.06 [0.89-1.23]
UT	republican	0.62 [0.49-0.76]	0.39 [0.29-0.5]	0.37 [0.27-0.47]
MA	republican	0.49 [0.15-0.84]	0.35 [0.02-0.69]	0.09 [0.05-0.12]
NV	republican	0.43 [0.33-0.53]	0.24 [0.16-0.32]	0.17 [0.1-0.24]

Additionally, in Table J1 we show the average number of daily tweets from state partisans that @mention: any state legislator, a state legislator from the same state, and from the same state and party. We observe these ordinary partisan users to mention state legislators in non-trivial amounts of tweets. Particularly in states where there are larger amounts of legislators on the platform, such as NY, MA or CA, we see these users tagging state legislators in 15+ tweets every day. Similar to our takeaway from Table J1, we take this as suggestive evidence that Twitter on itself may be a relevant channel through which state legislators learn about the issue priorities of their constituents. Moreover, we also believe the evidence in this table adds additional robustness to the validation presented in Appendix B, and so to our method for identifying state partisans, given that we see these users mostly to engage with state legislators from the party and state to which we have classified them. For example, state partisans from NY, on average, mention state legislators in 17.16 of their tweets every day, and 12.65 of these are mentions to state legislators from NY and from the party to which we have classified them.

Appendix K Testing stationarity of time series

Our analyses are premised on the stationarity of the time series. In order to test this systematically, we perform a series of augmented Dickey-Fuller tests with the null hypothesis that a time series has a unit root.

Table K1: Stationarity by group, issue, and year. Numbers indicate the share of time series within each combination that can be considered stationary at $p < .05$, that is, the null hypothesis of the augmented Dicker-Fuller test can be rejected at this level.

Group or issue	Both years	2018	2021
Membergs of Congress	0.98	0.95	1
National media	1	1	1
President	1	1	1
State Legislators	0.99	0.99	1
State Media	0.97	0.96	0.97
State Partisans	0.96	0.96	0.96
Random Public	0.97		0.97
Agriculture	1	1	1
Civil Rights	0.96	0.95	0.96
Defense	0.94	0.95	0.93
Domestic Commerce	1	1	1
Economy	0.99	0.98	1
Education	1	1	1
Energy	1	1	1
Environment	1	1	1
Foreign Trade	0.98	0.98	0.98
Gov. Operations	0.91	0.88	0.93
Gun Control	1	1	1
Healthcare	0.91	1	0.84
Housing	1	1	1
Immigration	0.89	0.79	0.96
Intl. Affairs	0.92	0.9	0.93
Labor	1	1	1
Law and Crime	1	1	1
Public Lands	1	1	1
Social Welfare	1	1	1
Technology	1	1	1
Transportation	1	1	1

For this, we use the log-odds transformed time series that are used in our main VAR model. Like for our VAR models, we use a lag of 5 days. For the national groups, we have a total of 126 time series (three groups, 21 issues, and two years). Of these, we find that 121

(96.0%) can be considered stationary in the sense that the null can be rejected at the $p <$ .01 level and 125 (99.2%) can be considered stationary at $p < .05$. For the state-level groups, there are considerably more time series because these are unique for every state. Of the 1911 unique time series (819 in 2018 and 1092 in 2021, due to the inclusion of the Random Public), 90.7% can be considered stationary at $p < .01$ and 97.4% can be considered stationary at $p < .05$. Overall, these results make us confident that the vast majority of the time series in our model can be considered stationary and are suitable for use in VAR analysis.

In Table K1, we break down these results by groups, issues, and year and compute the share of time series within each combination that can be considered stationary at $p < .05$. For instance the value .95 in row one indicates that of the 21 time series (one for each issue) for Members of Congress in 2018, 20 could be considered stationary. The general takeaway here is that stationarity seems fairly randomly distributed in the sense that there are no groups or issues that are particularly prone to non-stationary time series.

Appendix L Coefficient tables for main VAR models

Table L1: Coefficient table for main VAR model reported in Figure 2 (2018 data, N = 99,640). State-topic fixed-effects included but not reported.

Predictor	State Legislator	State Partisans	State Media	Members of Congress	National Media	President
Intercept	-3.087 (0.103)*	-1.802 (0.028)*	-2.267 (0.13)*	-1.187 (0.046)*	-1.687 (0.065)*	-2.272 (0.133)*
State Legislators (l1)	0.11 (0.003)*	0.003 (0.001)*	0.011 (0.004)*	0.006 (0.001)*	0.001 (0.002)	-0.003 (0.004)
State Legislators (l2)	0.042 (0.003)*	-0.006 (0.001)*	-0.009 (0.004)*	-0.008 (0.001)*	-0.009 (0.002)*	-0.006 (0.004)
State Legislators (l3)	0.024 (0.003)*	-0.004 (0.001)*	-0.013 (0.004)*	-0.007 (0.001)*	-0.002 (0.002)	0 (0.004)
State Legislators (l4)	0.027 (0.003)*	-0.003 (0.001)*	0.002 (0.004)	-0.002 (0.001)	-0.003 (0.002)	-0.002 (0.004)
State Legislators (l5)	0.031 (0.003)*	0.002 (0.001)*	0.002 (0.004)	0.004 (0.001)*	0.006 (0.002)*	-0.009 (0.004)*
State Partisans (l1)	0.213 (0.013)*	0.435 (0.004)*	0.293 (0.016)*	0.14 (0.006)*	0.245 (0.008)*	0.248 (0.017)*
State Partisans (l2)	-0.041 (0.014)*	0.076 (0.004)*	-0.05 (0.017)*	-0.053 (0.006)*	-0.02 (0.009)*	-0.012 (0.018)
State Partisans (l3)	-0.024 (0.014)	0.058 (0.004)*	-0.059 (0.018)*	-0.009 (0.006)	-0.023 (0.009)*	0.004 (0.018)
State Partisans (l4)	-0.055 (0.014)*	0.04 (0.004)*	-0.013 (0.017)	-0.017 (0.006)*	-0.026 (0.009)*	-0.028 (0.018)
State Partisans (l5)	0.013 (0.013)	0.074 (0.003)*	0.029 (0.016)	-0.004 (0.006)	0.039 (0.008)*	0.06 (0.016)*
State Media (l1)	0.029 (0.003)*	0.007 (0.001)*	0.19 (0.003)*	0.012 (0.001)*	0.014 (0.002)*	0.01 (0.003)*
State Media (l2)	0.008 (0.003)*	0.001 (0.001)	0.103 (0.003)*	0.001 (0.001)	0.004 (0.002)*	0 (0.003)
State Media (l3)	0.001 (0.003)	-0.003 (0.001)*	0.087 (0.003)*	-0.003 (0.001)*	-0.004 (0.002)*	-0.005 (0.003)
State Media (l4)	-0.005 (0.003)	-0.001 (0.001)	0.076 (0.003)*	-0.004 (0.001)*	-0.004 (0.002)*	0.003 (0.003)
State Media (l5)	-0.004 (0.003)	0.002 (0.001)*	0.086 (0.003)*	-0.001 (0.001)	0 (0.002)	-0.006 (0.003)
Members of Congress (l1)	0.195 (0.008)*	0.064 (0.002)*	0.079 (0.01)*	0.374 (0.003)*	0.116 (0.005)*	0.107 (0.01)*
Members of Congress (l2)	-0.034 (0.008)*	-0.044 (0.002)*	-0.068 (0.01)*	0.064 (0.004)*	-0.016 (0.005)*	-0.038 (0.011)*
Members of Congress (l3)	-0.002 (0.008)	-0.018 (0.002)*	-0.05 (0.01)*	0.045 (0.004)*	0.013 (0.005)*	-0.031 (0.011)*
Members of Congress (l4)	-0.013 (0.008)	-0.014 (0.002)*	-0.016 (0.01)	0.018 (0.004)*	0.01 (0.005)	0.022 (0.011)*
Members of Congress (l5)	0.009 (0.008)	-0.001 (0.002)	0.028 (0.01)*	0.08 (0.004)*	0.003 (0.005)	0.006 (0.01)
National Media (l1)	0.028 (0.005)*	0.03 (0.001)*	0.057 (0.007)*	0.027 (0.002)*	0.241 (0.003)*	0.033 (0.007)*
National Media (l2)	-0.013 (0.005)*	-0.003 (0.001)	-0.016 (0.007)*	0.007 (0.002)*	0.044 (0.003)*	0.004 (0.007)
National Media (l3)	-0.014 (0.005)*	0 (0.001)	-0.009 (0.007)	-0.009 (0.002)*	0.032 (0.003)*	0.013 (0.007)
National Media (l4)	0.002 (0.005)	0 (0.001)	0 (0.007)	0.004 (0.002)	0.074 (0.003)*	-0.011 (0.007)
National Media (l5)	0.003 (0.005)	0 (0.001)	0 (0.007)	0.006 (0.002)*	0.036 (0.003)*	-0.004 (0.007)
President (l1)	-0.006 (0.003)*	0.01 (0.001)*	-0.002 (0.003)	0.003 (0.001)*	0.012 (0.002)*	0.174 (0.003)*
President (l2)	0.001 (0.003)	0.003 (0.001)*	0.002 (0.003)	0.004 (0.001)*	0.006 (0.002)*	0.055 (0.003)*
President (l3)	0.002 (0.003)	-0.001 (0.001)	-0.001 (0.003)	0.001 (0.001)	0.003 (0.002)	0.041 (0.003)*
President (l4)	0.001 (0.003)	0.001 (0.001)	-0.003 (0.003)	0.006 (0.001)*	0 (0.002)	0.04 (0.003)*
President (l5)	0 (0.003)	-0.002 (0.001)*	0 (0.003)	-0.008 (0.001)*	-0.004 (0.002)*	0.046 (0.003)*
R Squared	0.508	0.924	0.442	0.734	0.746	0.38
Adjusted R Squared	0.506	0.924	0.44	0.734	0.745	0.378
Log Likelihood	-162507.531	-32850.058	-185223.873	-82161.795	-117013.599	-187719.374
AIC	325623.062	66308.117	371055.747	164931.59	234635.197	376046.748
BIC	328513.061	69198.116	373945.746	167821.589	237525.196	378936.747

Table L2: Coefficient table for main VAR model reported in Figure 2 (2021 data, N = 99,640). State-topic fixed-effects included but not reported.

Predictor	State Legislator	General Public	State Partisans	State Media	Members of Congress	National Media	President
Intercept	-1.88 (0.119)*	-2.094 (0.071)*	-1.911 (0.028)*	-3.315 (0.087)*	-0.877 (0.046)*	-2.126 (0.08)*	-2.107 (0.21)*
State Legislators (l1)	0.122 (0.003)*	0.008 (0.002)*	0.003 (0.001)*	0.018 (0.002)*	-0.001 (0.001)	0.003 (0.002)	0.02 (0.006)*
State Legislators (l2)	0.046 (0.003)*	-0.002 (0.002)	-0.006 (0.001)*	0.006 (0.002)*	-0.01 (0.001)*	-0.006 (0.002)*	-0.016 (0.006)*
State Legislators (l3)	0.029 (0.003)*	-0.001 (0.002)	-0.002 (0.001)*	0.001 (0.002)	-0.003 (0.001)*	-0.006 (0.002)*	-0.016 (0.006)*
State Legislators (l4)	0.025 (0.003)*	-0.006 (0.002)*	-0.005 (0.001)*	-0.002 (0.002)	-0.004 (0.001)*	-0.012 (0.002)*	-0.015 (0.006)*
State Legislators (l5)	0.03 (0.003)*	0 (0.002)	0.002 (0.001)*	0.006 (0.002)*	0.001 (0.001)	-0.003 (0.002)	0 (0.006)
General Public (l1)	0.041 (0.005)*	0.191 (0.003)*	0.018 (0.001)*	0.019 (0.004)*	0.002 (0.002)	0.009 (0.004)*	0.019 (0.01)*
General Public (l2)	0.007 (0.005)	0.13 (0.003)*	-0.007 (0.001)*	0.003 (0.004)	-0.011 (0.002)*	-0.001 (0.004)	-0.007 (0.01)
General Public (l3)	-0.005 (0.005)	0.097 (0.003)*	0.003 (0.001)*	0.017 (0.004)*	-0.001 (0.002)	0.005 (0.004)	0.014 (0.01)
General Public (l4)	0.017 (0.005)*	0.104 (0.003)*	-0.004 (0.001)*	0.003 (0.004)	-0.009 (0.002)*	-0.001 (0.004)	-0.002 (0.01)
General Public (l5)	0.018 (0.005)*	0.118 (0.003)*	0.006 (0.001)*	0.026 (0.004)*	0.002 (0.002)	-0.007 (0.004)	0.026 (0.01)*
State Partisans (l1)	0.469 (0.015)*	0.295 (0.009)*	0.473 (0.004)*	0.254 (0.011)*	0.241 (0.006)*	0.314 (0.01)*	0.486 (0.027)*
State Partisans (l2)	-0.092 (0.016)*	-0.083 (0.01)*	0.026 (0.004)*	-0.031 (0.012)*	-0.043 (0.006)*	-0.031 (0.011)*	-0.141 (0.029)*
State Partisans (l3)	-0.076 (0.016)*	-0.025 (0.01)*	0.041 (0.004)*	-0.044 (0.012)*	-0.02 (0.006)*	-0.02 (0.011)	-0.102 (0.029)*
State Partisans (l4)	-0.069 (0.016)*	-0.062 (0.01)*	0.027 (0.004)*	-0.057 (0.012)*	-0.041 (0.006)*	-0.059 (0.011)*	-0.061 (0.029)*
State Partisans (l5)	-0.003 (0.015)	-0.035 (0.009)*	0.068 (0.004)*	0.032 (0.011)*	-0.009 (0.006)	0.016 (0.01)	-0.2 (0.027)*
State Media (l1)	0.058 (0.004)*	0.018 (0.003)*	0.011 (0.001)*	0.101 (0.003)*	0.014 (0.002)*	0.025 (0.003)*	0.044 (0.008)*
State Media (l2)	0.005 (0.004)	-0.002 (0.003)	-0.006 (0.001)*	0.037 (0.003)*	-0.005 (0.002)*	0.003 (0.003)	-0.017 (0.008)*
State Media (l3)	0.008 (0.004)	0.007 (0.003)*	-0.005 (0.001)*	0.042 (0.003)*	-0.003 (0.002)	0.001 (0.003)	-0.008 (0.008)
State Media (l4)	0.008 (0.004)	0.005 (0.003)*	-0.001 (0.001)	0.025 (0.003)*	0.003 (0.002)	0.004 (0.003)	-0.029 (0.008)*
State Media (l5)	0.001 (0.004)	0.004 (0.003)	0.002 (0.001)*	0.04 (0.003)*	0.002 (0.002)	0.006 (0.003)*	-0.02 (0.008)*
Members of Congress (l1)	0.106 (0.009)*	0.049 (0.006)*	0.066 (0.002)*	0.06 (0.007)*	0.317 (0.004)*	0.11 (0.006)*	0.247 (0.016)*
Members of Congress (l2)	-0.036 (0.01)*	-0.028 (0.006)*	-0.023 (0.002)*	-0.015 (0.007)*	0.075 (0.004)*	0.002 (0.006)	0.073 (0.017)*
Members of Congress (l3)	0.024 (0.01)*	-0.028 (0.006)*	0.012 (0.002)*	0.018 (0.007)*	0.069 (0.004)*	0.069 (0.006)*	-0.043 (0.017)*
Members of Congress (l4)	-0.031 (0.01)*	-0.03 (0.006)*	-0.014 (0.002)*	0 (0.007)	0.039 (0.004)*	-0.014 (0.006)*	0.004 (0.017)
Members of Congress (l5)	0.025 (0.009)*	-0.025 (0.006)*	0.009 (0.002)*	0.004 (0.007)	0.086 (0.004)*	-0.007 (0.006)	0.116 (0.016)*
National Media (l1)	0.003 (0.005)	0.007 (0.003)*	0.012 (0.001)*	0.026 (0.004)*	0.028 (0.002)*	0.17 (0.003)*	0.049 (0.009)*
National Media (l2)	-0.026 (0.005)*	-0.012 (0.003)*	-0.006 (0.001)*	-0.008 (0.004)*	-0.007 (0.002)*	0.053 (0.003)*	0.028 (0.009)*
National Media (l3)	-0.015 (0.005)*	-0.002 (0.003)	-0.003 (0.001)*	0.006 (0.004)	0.005 (0.002)*	0.048 (0.003)*	0.028 (0.009)*
National Media (l4)	0.001 (0.005)	-0.008 (0.003)*	0 (0.001)	0.003 (0.004)	0.02 (0.002)*	0.041 (0.003)*	0.003 (0.009)
National Media (l5)	0.004 (0.005)	0.01 (0.003)*	0.007 (0.001)*	0.007 (0.004)	0.004 (0.002)*	0.044 (0.003)*	0.027 (0.009)*
President (l1)	0.007 (0.002)*	0.004 (0.001)*	0 (0)	0 (0.001)	0.008 (0.001)*	-0.002 (0.001)	0.147 (0.003)*
President (l2)	-0.002 (0.002)	-0.002 (0.001)	-0.002 (0)*	-0.003 (0.001)*	-0.002 (0.001)*	-0.003 (0.001)*	0.073 (0.003)*
President (l3)	-0.003 (0.002)	-0.002 (0.001)	-0.002 (0)*	-0.004 (0.001)*	0.003 (0.001)*	-0.005 (0.001)*	0.015 (0.003)*
President (l4)	-0.003 (0.002)	0.002 (0.001)*	0 (0)	-0.004 (0.001)*	0.002 (0.001)*	0.006 (0.001)*	0.057 (0.003)*
President (l5)	0.002 (0.002)	0.003 (0.001)*	0.004 (0)*	0.004 (0.001)*	0.006 (0.001)*	0.006 (0.001)*	0.077 (0.003)*
R Squared	0.539	0.716	0.926	0.636	0.806	0.715	0.285
Adjusted R Squared	0.538	0.715	0.926	0.635	0.806	0.714	0.283
Log Likelihood	-167431.752	-116355.752	-23812.218	-135563.139	-72831.645	-127374.953	-223741.731
AIC	335481.504	233329.505	48242.435	271744.278	146281.289	255367.907	448101.462
BIC	338419.883	236267.884	51180.815	274682.658	149219.669	258306.286	451039.842