Using Social Media Data to Reveal Patterns of Policy Engagement in State Legislatures

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Abstract

State governments are tasked with making important policy decisions in the United States. How do state legislators use their public communications—particularly social media—to engage with policy debates? Due to previous data limitations, we lack systematic information about whether and how state legislators publicly discuss policy and how this behavior varies across contexts. Using Twitter data and state of the art topic modeling techniques, we introduce a method to study state legislator policy priorities and apply the method to fifteen U.S. states in 2018. We show that we are able to accurately capture the policy issues discussed by state legislators with substantially more accuracy than existing methods. We then present initial findings that validate the method and speak to debates in the literature. For example, state legislators in competitive districts are more likely to discuss policy than those in less competitive districts, and legislators from more professional legislatures discuss policy at similar rates to those in less professional legislatures. We conclude by discussing promising avenues for future state politics research using this new approach.

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1 Introduction

The policy decisions of state governments profoundly impact people's day-to-day lives. States are tasked with providing for the education, health, welfare, and public safety of residents. With politics becoming more and more polarized and gridlocked at the national level, state legislatures are increasingly a key locus of policy action and innovation. While the 113th Congress passed only 352 bills, state governments passed over 45,000 during the same 2 year period.[1] These policies have far-reaching public consequences. In 2018, for example, 15 states adopted new restrictions on abortion and family planning; 18 passed legislation to increase the minimum wage; 43 states enacted new laws and resolutions related to either immigration enforcement or immigrant integration; and over 45 states considered laws to address the opioid crisis.[2]

Despite the dramatic effects that state policies have on people's health, welfare, and quality of life, we know little about the public communications patterns of state lawmakers. Existing research on state legislatures typically uses election data, roll-call votes, and surveys of lawmakers to document their behavior (Hamm, Hedlund, and Miller 2014). We have learned a great deal about the aggregate responsiveness of state policies to the public (e.g. Caughey and Warshaw 2016), the electoral consequences of legislator roll-call voting (e.g. Rogers 2017), and how the professionalism of state legislative institutions affects the lawmaking process (e.g. Squire 2007). However, we currently lack widely applicable and scalable measures of the public communications of state legislators, despite the potential for such measures to unlock key research questions in state politics in the areas of agenda setting, political responsiveness, and policy-making. This measurement problem stems primarily from data limitations: collecting and analyzing thousands of press releases from all state legislators, for example, is an incredibly time and resource consuming task. As a result, we lack

[1] https://info.cq.com/resources/states-six-times-more-productive-than-congress/
[2] http://www.ncsl.org/

systematic information about state legislator engagement via their public communications platforms and whether and how they use such platforms to discuss policy.

In an effort to overcome these limitations, we pursue an empirical strategy that has not yet been widely applied in the study of state politics. Building on extensive work that leverages social media data to document the communications of members of Congress and national legislators in many countries (e.g. Evans, Cordova, and Sipole 2014; Russell 2018; Barbera et al. 2019; Hemphill, Russell, and Schöpke-Gonzalez 2020; van Vliet, Törnberg, and Uitermark 2020), we study the public communications of state legislators from fifteen different states by analyzing all of the messages they posted on Twitter in 2018.[3] We begin by introducing a variety of basic facts about the presence of state legislators on Twitter, including the proportion of state legislators who are on platform, their levels of activity, and how this varies across state and party. Laying this descriptive groundwork is a critical first step for generating future research questions and developing new theory.[4] We find that over 75% of state legislators in our fifteen state sample have Twitter accounts, and they produce new messages on average once a day.

We then use state of the art topic modeling techniques to predict the policy issues that state legislators discuss in their public communications. Prior work shows that a large number of national legislators use Twitter often and that the issues they discuss on the platform approximate the issues they address in their other public communications (Casas and Morar 2015; Barbera et al. 2019). In order to discover the policy issues addressed in tweets by state legislators, we employ recent advances in the application of deep neural networks to text. We first use automated unsupervised feature extraction methods (so-called language models trained on large sets of unlabeled text) to transform each message into a

[3] We limit our sample to 15 states for computational reasons which we discuss along with our sampling criteria in the next section.

[4] For example, if state legislators spend little time discussing policy, it would not make sense to ask whether these policy stances appear to be responsive to public opinion.

list of word embeddings. We then feed these word embedding into a convolutional neural net (CNN) that is trained to classify each tweet into topics according to a well established policy issue categorization, the *Comparative Agendas Project* (CAP) codebook.[5] Our topic modeling approach is able to classify the policy content of state legislator tweets with 80% accuracy, and we demonstrate that state lawmakers discuss policy-relevant issues in 70% of their tweets.

Next, we demonstrate the value of the data and method by performing several initial empirical tests and validation checks that speak to debates in the state politics literature. For example, we find that while Twitter adoption is more common among state lawmakers in more professionalized legislatures, the rate of discussing policy areas is roughly equal across more and less professionalized states (conditional on being on the platform). We also discover that, contrary to existing theory, state legislators from competitive electoral districts are more likely to engage in policy debates than those from less competitive districts. Finally, we provide new evidence about which issues individual legislators discuss and whether state legislators focus on different topics than members of Congress. We show that legislators sitting on policy-relevant committees are generally more likely to tweet about the policy topic associated with that committee. Consistent with federalism literature on policy domains, we also find that state lawmakers are more likely than national legislators to discuss the areas traditionally associated with states politics—like education and crime—and less likely to weigh in on national issues such as foreign trade.

The rest of the paper is organized as follows. In Section 2, we introduce the data and present some initial descriptive statistics. In Section 3, we describe the machine learning method we designed to study the public communications of state legislators. In Section 4, we review the literature on state politics to develop several exploratory hypotheses that

[5] Our code is available in the replication files for this paper (Payson et al. 2022) and can be used by other scholars to study the twitter behavior of state legislators.

allow us to apply and validate our method. Section 5 presents our descriptive results, and Section 6 concludes by discussing some of the promising applications of this approach within the state politics literature.

2 Using Twitter Data and Machine Learning to Study the Public Communications of State Legislators

A growing literature examines how Congressional representatives use Twitter to engage in self-promotion, communicate with constituents, articulate their policy agendas, and discuss relevant public issues (e.g. Golbeck, Grimes, and Rogers 2010; Casas and Morar 2015; Barbera et al. 2019; Hemphill, Russell, and Schöpke-Gonzalez 2020). In general, research on social media has shown that political actors integrate social media platforms with their traditional campaign messaging strategies (Straus 2018; Shapiro and Hemphill 2017). Politicians often use Twitter and other social media platforms to link to content on their websites or in the traditional media (Kwak et al. 2010; Jungherr 2014), and journalists draw from social media messages in their political news coverage. Early work in this area uncovered few differences in the adoption and usage of social media platforms like Facebook, Twitter, and YouTube across politicians (e.g. Gulati and Williams 2011). However, over the past few years Twitter has become the dominant social media platform for most legislators as a result of its open network, which facilitates the ability to connect broadly with the public, as opposed to Facebook, which operates on a closed system (Evans, Ovalle, and Green 2016; Golbeck et al. 2018; Hemphill, Russell, and Schöpke-Gonzalez 2020).[6]

But while research on Twitter usage among members of Congress has burgeoned over the past decade, studies of whether and how state legislators use the platform have lagged

[6]For a review of differences and trends in social media usage by politicians across platforms, see Straus (2018).

behind. An exception is Cook (2017), which documents state legislator presence on Twitter in 2016 and establishes several individual and district correlates of Twitter usage. Cook (2017) finds that legislators with leadership positions from more professionalized legislatures and those representing younger districts are more likely to have a Twitter account, but he also emphasizes that studies of state legislators and social media are relatively rare and that we still know little about the topics that legislators are discussing. Our study begins to fill this gap.

2.1 Sample and Data Overview

There are a total of 7,383 state legislators in the United States. In order to render the data collection and analysis more manageable, we focused on all legislators with a Twitter account from a sample of fifteen states: Arizona, California, Florida, Illinois, Massachusetts, Montana, North Dakota, New Jersey, Nevada, New York, Ohio, Texas, Utah, Virginia, and Wyoming. Collecting and analyzing the tweets sent by these legislators proved to be an arduous task even for this subset of states. We obtained an initial set of state legislator Twitter handles via Google Civic API, and we then manually searched for accounts for every remaining lawmaker in our sample. We then had to operate within Twitter's data collection limits/restrictions, and the accounts needed to be queried frequently during the period of analysis to make sure we did not miss any of the messages they sent. Finally, substantial computing power and a high performing cluster were needed to train our machine learning model and to generate topic predictions for all the tweets in our dataset.

While the primary aim of this paper is to establish a method for analyzing the policy content of state legislator tweets, we also wanted to draw some initial, exploratory comparisons across states. While our fifteen state sample means that any cross-state differences we uncover are necessarily tentative, we nevertheless selected these states with the goal of maximizing variation across several key features, including size, geographic region, levels of legislative professionalization, the partisan composition of the chambers, and whether the legislature was in session versus out of session. 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.

Table 1: Key features of the states selected for the analysis.

State	Prof. Score	House Dem. Prop.	Senate Dem. Prop.	Region	In Session 2018	Population 2017
AZ	0.23	0.42	0.43	West	Yes	7,016,270
CA	0.63	0.68	0.68	West	Yes	39,536,653
FL	0.22	0.34	0.38	South	Yes	20,984,400
IL	0.26	0.57	0.63	Midwest	Yes	12,802,023
MA	0.38	0.77	0.85	Northeast	Yes	6,859,819
MT	0.08	0.41	0.36	West	No	1,050,493
ND	0.05	0.14	0.19	Midwest	Yes	755,393
NJ	0.24	0.68	0.62	Northeast	Yes	9,005,644
NV	0.14	0.64	0.48	West	No	2,998,039
NY	0.48	0.72	0.51	Northeast	Yes	19,849,399
OH	0.30	0.33	0.27	Midwest	Yes	11,658,609
TX	0.20	0.37	0.35	South	No	28,304,596
UT	0.06	0.17	0.17	West	Yes	3,101,833
VA	0.13	0.49	0.47	South	Yes	8,470,020
WY	0.05	0.15	0.10	West	Yes	579,315

Notes: Professionalism Score is from The Correlates of State Policy Project (http://ippsr.msu.edu/public-policy/correlates-state-policy), population is from the American Community Survey (https://www.census.gov/programs-surveys/acs/news/data-releases/2017/release.html) and the partisan composition variables are from the National Conference of State Legislatures (http://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx).

Table 1 illustrates how the states in our study compare across these dimensions. The fifteen states vary widely in the level of professionalization, including seven of the country's most professionalized legislatures (Arizona, California, Illinois, Massachusetts, New Jersey, New York, and Ohio) and four of the least professionalized legislatures (Montana, North Dakota, Utah, and Wyoming), according to the Squire Index (Squire 2007). Moreover, these states vary dramatically in how politically competitive they are, with some legislatures serving as safe one-party bastions (e.g. Wyoming and Massachusetts) and others electing a close mix of Democrats and Republicans (e.g. Virginia). Additionally, four of these state legislatures did not actively convene in 2018 (North Dakota, Montana, Nevada, and Texas), allowing us to compare public communication patterns among legislators both in and out of session.

After selecting this set of states, we collected the Twitter handles for every legislator who was on the platform. First, we used the Google Civic API, which provides the user handles for most state legislators. Then, to make sure that we didn't miss any Twitter accounts for the remaining lawmakers, we manually searched for them online, finding a few additional twitter handles for active lawmakers.[7] Before examining the policy content of state legislator tweets, we begin by introducing several novel facts about Twitter presence among state legislators. In Table 2 we report the number of legislators by state and party—*Legislators (N)*—and the number and the proportion for which we found a Twitter account—*Legislators on Twitter (Prop)*. Overall, 75% of policy makers in these 15 states had a Twitter handle (1,515 out of 2,025). In some states, most legislators are on the platform (such as California and Texas), while in other states only a minority are Twitter users (e.g. Montana and North Dakota).

There is clearly more variation in Twitter adoption among state legislators than among members of Congress. In 2018, for example, all 100 U.S. Senators and every Member of the House of Representatives had an account (Straus 2018). Along with assessing whether legislators simply had a Twitter account, we also assessed average use. Twitter usage is particularly low among members of the least professionalized legislatures—i.e. Wyoming and North Dakota, where lawmakers on Twitter send fewer than 0.5 messages a day, on average—and much higher in states like California and Arizona, where state legislators tweet

[7]The collection of the Twitter handles took place at the end of 2017. We used the Twitter handles returned by the API, which varied from their personal to their campaign and official ones.

Table 2: State Legislator Twitter Activity by State and Party.

State	Party	Legislators (N)	Legislators on Twitter (N)	Legislators on Twitter (Prop.)	Total Tweets '18	Daily Avg. Tweets '18	Daily Avg. while in Session '18
AZ	D	35	32	0.91	27,254	2.33	2.68
AZ	R	50	41	0.82	23,199	1.55	1.64
CA	D	77	75	0.97	39,314	1.44	1.51
CA	R	38	38	1.00	10,706	0.77	0.82
FL	D	54	46	0.85	15,233	0.91	1.32
FL	R	98	96	0.98	24,841	0.71	0.91
IL	D	102	78	0.76	17,483	0.61	0.62
IL	R	72	53	0.74	7,667	0.40	0.41
MA	D	150	125	0.83	45,704	1.00	1.01
MA	R	36	30	0.83	13,049	1.19	1.14
MT	D	57	29	0.51	2,837	0.27	–
MT	R	91	35	0.38	8,441	0.66	–
ND	D	21	7	0.33	218	0.09	–
ND	R	118	17	0.14	2,920	0.47	–
NJ	D	80	67	0.84	11,738	0.48	0.47
NJ	R	42	34	0.81	4,803	0.39	0.39
NV	D	36	34	0.94	24,424	1.97	–
NV	R	24	18	0.75	3,763	0.57	–
NY	D	136	123	0.90	75,108	1.67	1.66
NY	R	71	57	0.80	21,400	1.03	1.21
OH	D	40	33	0.82	17,272	1.43	1.41
OH	R	88	76	0.86	15,090	0.54	0.55
TX	D	65	59	0.91	58,913	2.74	–
TX	R	115	102	0.89	44,082	1.18	–
UT	D	18	15	0.83	10,876	1.99	2.62
UT	R	86	61	0.71	10,329	0.46	0.85
VA	D	53	46	0.87	27,285	1.63	1.99
VA	R	84	63	0.75	11,077	0.48	0.68
WY	D	12	4	0.33	497	0.34	1.37
WY	R	76	21	0.28	938	0.12	0.14
Total		2,025	1,515	0.75	576,461	1.04	1.08

more than once a day.[8]

We note here that the self-selection of state legislators onto Twitter across states necessarily limits our analysis to descriptive inference. If only a small proportion of lawmakers in states like Wyoming and North Dakota choose to adopt the platform, these legislators are likely different from other representatives in their states. They might be younger, more tech savvy, more concerned about representation, or any combination of factors. We stress that

[8]Figure B3 in the Appendix visualizes rates of Twitter adoption broken down by state, chamber, and party.

one of the main contributions of this paper is introducing a method that allows us to collect, classify, and analyze the policy content of state legislators' tweets. While the preliminary analyses that we conduct with these data and this method are exploratory in nature, they nonetheless suggest several important avenues for future research in state politics and public communications.

3 Classifying Policy Relevant Tweets

We collected every tweet sent by these legislators from January 1st to December 31st 2018, using the Twitter REST API to collect the legislators' timelines every month. The API allows developers to collect the last 3,200 messages sent by a given user, so this data collection strategy meant that we were able to collect all the tweets that the legislators sent during this time period: a total of 576,461 messages. The next step was to identify policy topics discussed in tweets (as well as classify non-policy relevant messages). Given the large number of tweets, manual coding was not practical for the full corpus. Instead, we trained a machine learning model (a Convolutional Neural Net or CNN) predicting whether each tweet discussed one of the 20 topics of the Comparative Agendas Project (CAP) (Baumgartner and Jones 2010), a comprehensive and widely used classification scheme for studying political agendas.[9] We also added a non-policy-issue category reserved for tweets that did not address any policy area, such as tweets commemorating holidays.[10]

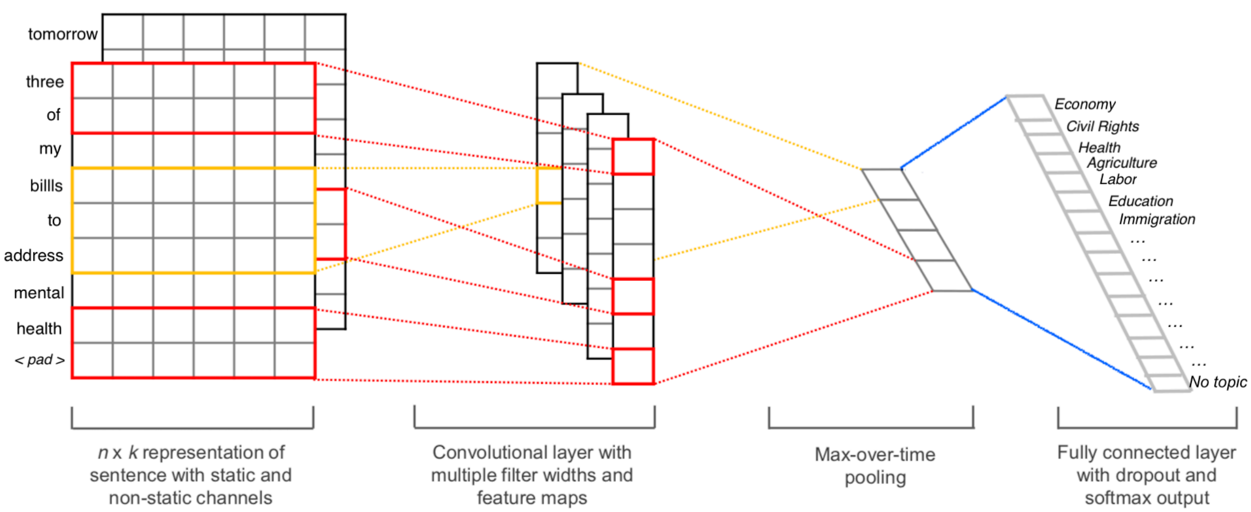
We chose to train a neural network, rather than a more simple bag-of-words or ngram-based model (such as a decision tree or a support vector machine) or an unsupervised model (such as LDA) (Blei, Ng, and Jordan 2003) for three main reasons. First, in recent years neural networks have been shown to outperform more simple models in many textual tasks,

[9]Note that we excluded *Culture* topics from the 21 topics of the CAP codebook because in initial tests we saw very low numbers of tweets about this topic.
[10]See Table 5 for a list of topics.

including text classification (Joulin et al. 2016; Hassan and Mahmood 2017). Moreover, as we show in Table A2 in Appendix A, after running some initial tests we found that the CNN model outperformed a support vector machine, the ngram-based model that previous research had found to be most accurate in predicting the CAP-topics discussed in congressional bills as well as tweets (Collingwood and Wilkerson 2012; Hemphill and Schöpke-Gonzalez 2020).

Finally, although unsupervised topic models have also been shown to be useful for studying tweets and the public communications of politicians (Barbera et al. 2019), recent studies (e.g. Denny and Spirling 2018) suggest that supervised approaches may yield more stable and robust results, making them a preferable option. Similar to Kim (2014), we trained a three-layer CNN. Figure 1 illustrates the architecture used to identify CAP-topics. We next describe our two main model architectures and then outline our training data-sets and validation scheme in detail.

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



First, we represented each word in a given sentence as a 300-dimension word- embedding (a vector that ideally represents an integration of each word's meaning and context/position in the text as dense features for further analysis) (Terechshenko et al. 2020). We obtained the model used to produce word-embeddings by finetuning a pretrained Word2Vec model for an additional 10 epochs (Mikolov et al. 2013), to which we had first added all unique new vocabulary present in our training datasets as well as in the tweets to which we wanted to apply the resulting model.[11] This results in a three-dimensional matrix ($n \times k \times d$) that is used as our primary model input, where n is the maximum word length for all training documents, k is the size of the embedding (300), and d is the number of documents to pass through to the CNN.

The CNN that comprises our second model (the model used to classify CAP topic and political relevance) has three convolutional layers of different sizes, each processing 3-, 4-, and 5-word embeddings at a time, which produces hidden layers of different sizes. These hidden layers are joined into a single vector for each document by max-pooling the weights in each word-vector. The last stage of the CNN is comprised of a fully connected layer mapping the previous max-pooled vector to the 21 CAP issue classes (20 policy areas plus the "non-policy/not-relevant" class). We employ a cross-entropy loss function, and gradient optimization is performed via adaptive moment estimation (Kingma and Ba 2015). We use a batch size of 64 for training the model.

3.1 Model Training and Accuracy

We trained the model with four datasets and a total of 855,854 text records, described in Table 3: (A) all available CAP-labeled datasets for the United States available on the CAP website (789,004 records), (B) 45,394 tweets from Senators who served during the 113th Congress and that were labeled by Russell (2018), (C) 18,088 tweets sent by media accounts and followers of our state legislators that we coded according to the CAP classification,

[11] We used the python `Gensim` word2vec model and methods, and GloVe pretrained embeddings: Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download).

Table 3: Public datasets coded using the CAP 21-issue classification, used for training and testing a classifier predicting *Policy Issues* in tweets from state legislators.

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	Tweets sent by media accounts	2018	8,802
	Tweets sent by followers of state legislators	2018	9,286
D	Tweets sent by state legislators	2018	3,368
	Total	1944-2018	855,854

and (D) 3,368 tweets sent by the state legislators that we also coded.[12] Building on recent advances in transfer learning, we combined these datasets and tried many data combinations when training the model. We assessed the out-of-sample accuracy of each model/data-combination pair and selected the best performing model-data pairing to generate topic predictions for all tweets sent in 2018 by the state legislators in our sample. In Appendix A we provide a detailed explanation of the training process, as well as evidence showing how the CNN model outperformed an SVM algorithm—the ngram/bag-of-words model that to

[12] A total of six coders (research assistants) participated in the annotation of sets C and D. Two coders annotated the tweets sent by media accounts (C.a): 89% agreement and 0.7 Cohen's Kappa. Two other coders annotated the tweets sent by followers of state legislators (C.b): 91% agreement and 0.77 Cohen's Kappa. And finally, a different pair of coders annotated the tweets sent by state legislators (D): 87.1% agreement and 0.74 Cohen's Kappa.

date has been shown to perform best at classifying text into the CAP topic categories.

In Table 4, we report accuracy measures for our best performing CNN. During training, we split the labeled data into a train, test, and validation set. We used the *Train* set to calculate the model loss and update the model weights at each iteration. We used the *Test* set to calculate at each iteration how well the model was performing on a held out set, as well as to calculate the final out-of-sample accuracy of the trained model. Although we did not use this test set for training the model *per se*, we did rely on it during training to evaluate the model loss and update the model parameters at each iteration, and to decide for how many iterations the model needed to be trained. For this reason we also report the accuracy of the model when generating predictions for a completely untouched *Validation* set. Moreover, we assess the accuracy when predicting all tweets in the test/validation split (*All*), and also when only predicting the tweets coded as being about one of the policy areas after excluding the non-policy tweets (*Policy*). Because the tweets not related to any policy area represented a large part of the tweets we coded from state legislators, we wanted to ensure that our model did well at both distinguishing overall policy relevance and at distinguishing between policy areas.

Table 4: Out of sample accuracy of best performing CNN model we trained predicting the political topics of the Comparative Agendas Project.

Test Set		Validation Set	
All	Policy	All	Policy
0.78	0.79	0.59	0.55

Table 4 indicates that the best performing CNN does a good job at distinguishing between tweets that are about policy issues and those that are not, and between policy-relevant tweets on different topics. Predicting a large number of (unbalanced) topic classes (n = 21) is a very complicated task, yet the test accuracy in both cases is close to 80%. More importantly, the validation accuracy based on the untouched labeled tweets sent by state legislators is close to 60%. Despite many precautions to avoid over-fitting on the training and test sets (e.g. including a drop-out rate during estimation and waiting for the test accuracy to slightly decline before stopping the training), the drop in accuracy between the test and validation sets is expected given that the test set has been used to calculate the model loss and update the model parameters at each iteration, whereas the validation set has been completely untouched.

The largest issue category in the annotated set (*Govt. Operations*) accounts for 26% of all messages coded as being about a policy issue. Hence, a naive model classifying all tweets into the modal category would only get it right 26% of the time. This best performing CNN is 79% and 55% accurate when distinguishing between issue categories, substantially more accurate than this naive model. In addition, as pointed out, this CNN outperforms more simple ngram/bag-of-words models such as a SVM algorithm (see Table A2).

We run many additional validation exercises to assess the performance of the model. In Table 5, we show that the accuracy and f-score (based on the held-out test sets) are very high for all the topic classes, despite most of them being rarely discussed. To assess the face validity of the model, in Table 6 we show the top distinctive text features of the tweets predicted to be about each topic. Reassuringly, the top features seem to be relevant to each policy area. As a final test, we examine the proportion of daily tweets on immigration in 2018 to see whether attention to that topic peaked at moments where we would expect them to, such as when the President presented his immigration plan in the beginning of the year, during the child separation crisis at the end of June, and when the "caravan" of central-American refugees heading north became salient at the end of October. We find that the tweets classified as being about immigration indeed increased when immigration was actually salient in the news during 2018 (see Figure B1 in the Appendix B for details).

In sum, these many validations indicate that this CNN model does a satisfactory job at distinguishing between tweets about a policy (*versus* non-policy relevant messages) and

Table 5: Class accuracy and f-score for the best performing model

Policy Area	Class Proportion	Test Accuracy	Test F-score
No Policy	0.48	0.74	0.82
Govt. Operations	0.13	0.81	0.75
Health	0.06	0.80	0.73
Economy	0.05	0.74	0.76
Education	0.03	0.83	0.67
Civil Rights	0.03	0.69	0.58
Housing	0.02	0.36	0.46
Environment	0.02	0.58	0.61
Transportation	0.02	0.73	0.68
Agriculture	0.02	0.93	0.72
Energy	0.02	0.83	0.70
Social Welfare	0.02	0.53	0.61
Law & Crime	0.02	0.67	0.48
Intl. Affairs	0.01	0.71	0.63
Immigration	0.01	0.92	0.92
Public Lands	0.01	0.67	0.63
Labor	0.01	0.70	0.56
Domestic Commerce	0.01	0.75	0.45
Technology	0.01	0.38	0.50
Defense	0.00	0.75	0.35

between different policy issue categories. However, we note that less than perfect accuracy suggests that we are measuring our variables of interest with measurement error. But, as will be seen in the analysis, we are aggregating over many tweets, and thus any stochastic measurement error becomes smaller.

4 Applying the Method to Study State Politics

Having introduced the data and our topic modeling method for classifying the policy content of state legislator tweets, we now zoom back out to consider how this approach can contribute to the study of state politics. We begin by drawing from the state politics literature to develop theoretical intuition about the state-level and individual-level variables that might

Table 6: Top distinctive features of tweets predicted by the CNN to be about each topic or policy area.

Topic	Top Features
No policy issue	me, happy, good, time, thanks, join, proud, community, see, like, family, many, love, people, state
Gov. Operations	vote, election, state, voting, primary, early, house, time, campaign, democratic, people, county, democrats, last, elections
Healthcare	health, care, maternal, mental, new, flu, healthcare, work, state, medicaid, mortality, committee, people, access, cancer
Intl. Affairs	russia, russian, putin, trumps, world, american, dead, peace, people, says, again, americans, like, much, mueller
Public Lands	park, state, fire, during, public, wildlife, beautiful, city, confederate, contained, discussion, grand, heritage, history, land
Labor	job, workers, fair, jobs, community, employees, need, todays, work, workforce, working, youth, according, better, business
Law and Crime	children, gun, violence, families, law, parents, sexual, separated, guns, people, child, school, community, family, kids
Defense	military, veterans, war, women, state, families, honor, veteran, friend, happy, hearing, awards, troops, very, community
Immigration	daca, children, border, immigration, immigrants, immigrant, families, dreamers, policy, parents, detention, migrant, family, stand, trumps
Domestic Commerce	harvey, flooding, community, business, small, city, need, local, businesses, hurricane, many, disaster, state, flood, federal
Civil Rights	women, rights, scotus, redistricting, voter, case, every, join, people, court, families, justice, against, vote, womens
Economy	tax, taxes, property, budget, economy, state, tariffs, need, spending, economic, new, families, local, sales, trumps
Environment	water, climate, change, earthday, air, cleanup, lake, nasa, san, brownsville, could, mars, parks, planet, plants
Transportation	transportation, nasa, southwestair, without, airlines, future, hearing, like, bus, glad, inst, aviation, beneficial, chips, congratulations
Energy	energy, gas, oil, solar, texasoilnews, oilandgas, texasoil, txenergy, back, coal, committee, cpsenergy, look, nasa, natural
Agriculture	food, farm, farmers, agriculture, taking, agricultural, bureau, campus, elgin, farming, good, grande, hd50, learning, new
Social Welfare	food, snap, hunger, meals, help, million, free, program, put, children, kids, nutritious, people, summer, child

Education	school, students, education, public, schools, teachers, state, finance, college, high, teacher, funding, kids, student, week
Technology	nasa, space, station, mission, astronaut, international, students, media, new, crew, launch, satellite, speak, astronauts, awards
Foreign Trade	trade, trumps, war, abandons, bad, barrel, beijing, billion, breath, c, ca, canada, chinese, cover, currently
Housing	housing, affordable, hearing, association, citys, gentrification, meeting, neighborhood, policy, 7th, aacogceo, access, aff, affairs, affordability

matter for state legislator behavior on Twitter. After developing some tentative hypotheses, we perform a variety of exploratory analyses that both validate the method and allow us to investigate how state legislators use Twitter to discuss policy.

4.1 State-Level Correlates of Twitter Activity

As a first cut to examine how Twitter behavior varies across state contexts, we focus on three institutional variables: term limits, degree of legislative professionalism, and whether a legislature is in session or not. Proponents of term limits have hypothesized that limiting the time that lawmakers can serve will lead them to spend more time on legislative activities and less time pursuing reelection goals (Glazer and Wattenberg 1996; Carey, Niemi, and Powell 2009). Legislators in term limited states might be forced to engage with new ideas and be less wed to the status quo by experiencing frequent turnover. At the same time, a constant influx of new members might make it difficult for lawmakers to get up to speed with current policy debates. Empirical work tends to support this latter view (Moncrief and Thompson 2001; Peery and Little 2002), but Kousser (2005) finds that legislators at the end of their term often experience a burst of productivity as they seek to enact policies before being termed out. Given the additional informational hurdles associated with term limits, we tentatively expect state legislators in term-limited states to be less active on Twitter than those in non-term-limited states.

One of the most important institutional variables in the state politics literature is legislative professionalization. State legislative professionalism refers to the ability of legislative bodies to generate and digest information throughout the policy-making process (Squire 2007). Legislators from states with professionalized legislatures spend more time in session and have more staff resources at their disposal. For example, the two most professionalized legislatures are California and New York, where state legislators earn over $100,000 a year and have access to over 2,000 permanent staffers. In contrast, legislators in Wyoming meet only every two years, earn $150 a day, and collectively employ only 100 staffers. Given these differences in resources, legislators in professionalized states tend to be more attentive to constituent concerns (Maestas 2003; Lax and Phillips 2009) and pass a higher proportion of bills than their colleagues in less-professionalized chambers (Tan and Weaver 2009). We therefore expect legislators in the most professional states to be more likely to have Twitter accounts and to discuss policy-relevant issues than legislators in states with less professionalized legislatures.

Finally, we examine whether being in session predicts Twitter use among state legislators. In the U.S., forty-six states meet in annual legislative sessions, but four meet only every other year. When legislators are off-session, do they substitute social media activity for their regular legislative duties? The theoretical expectations here are unclear. Legislators who are currently in session are more likely to be actively dealing with policy issues related to current bills. But lawmakers in states with significant time spent out of session are often quite active in their district, particularly in terms of communicating with constituents (Jewell 1982). They also might have more time to spend on Twitter compared to legislators that are in session. Because session length is one of the components used to generate measures of legislative professionalism (Squire 2007), we caution against any sort of causal interpretation. Nevertheless, four of the states in our sample weren't in session in 2018—Montana, Nevada, North Dakota, and Texas—and in our predictive models we include an indicator for being in session to account for any differences in Twitter activity (after adjusting for overall professionalism).

4.2 Individual Correlates of Twitter Activity

We also consider several individual-level correlates of Twitter behavior among state legislators. These include standard demographic traits such as race and gender, as well as political traits such as leadership position, number of committees served on, seniority (in years), whether the legislator is serving their last term, and the electoral margin of victory in the district. Existing empirical work shows that lawmakers in leadership positions are more active on Twitter (Scherpereel, Wohlgemuth, and Lievens 2018), likely because of their public facing role and the additional resources at their disposal. Serving on more committees may or may not influence Twitter behavior, although we tentatively expect that more committee service will be associated with more active Tweeting across different policy areas. Similarly, seniority might cut either way: more senior members could lag behind in terms of technological adoption (Cook 2017), but they might also possess unique policy expertise. Building on the literature on term limits discussed above, we expect those legislators serving in their last term to focus less on their public communications and so to be less active on social media.

The literature offers a more clear-cut prediction when it comes to district competitiveness. Legislators in competitive districts face different communication incentives than representatives from safer districts. For example, competitive elections can cause candidates to avoid engaging directly on policy issues in debates (Simon 2002), and representatives in competitive districts tend to avoid articulating specific positions (Grimmer 2013; Casas and Wilkerson 2017). We therefore expect legislators from competitive districts to discuss policy issues on Twitter at lower rates than other lawmakers.

4.3 Which Policy Areas Do State Lawmakers Focus On?

Finally, we turn to the question of which specific policy issues state legislators dedicate their attention to. As an initial validity check, we examine whether legislators on committees with a clear policy focus are more likely to tweet about that policy area. We find strong evidence that this is the case for most committees. We then draw from two competing theoretical accounts to examine whether state legislators are more likely to discuss policy issues that are generally considered to be the domain of state government, or if they focus equally (or more) on national issues.

Research on federalism typically argues that candidates for different levels of office tend to focus on the policy areas that are most directly tied to that office (e.g. Jacob and Vines 1965; Laumann and Knoke 1987). An extension of this logic would suggest that state legislators should pay more attention to issue areas that are primarily the domain of state government as opposed to the federal government. The policy areas that are traditionally the focus of the federal government are finance and domestic commerce, defense, science and technology, foreign trade, and international affairs and aid (Kollman 2017). Most state legislatures do not have standing committees on these issues (Fouirnaies and Hall 2018*b*), and the federal government has sole power to conduct foreign affairs and regulate interstate commerce. On the other hand, states are constitutionally tasked with providing for health, education, welfare, and public safety. The following policy areas are generally the realm of state government and also comprise the largest share of legislation passed by state legislatures (Jewell 1982): health, education, labor and employment, transportation, law and crime, social welfare, and housing.[13]

At the same time, the increasingly nationalized nature of American politics might blur these traditional boundaries. If voters tend to be more engaged with and knowledgeable

[13] There are also several policy areas where the state and federal government share concurrent powers and are both active in terms of regulating and legislating. These include the economy, civil rights, the environment, energy, immigration, government operations, public lands and water, and agriculture.

about issues that are the purview of the federal government, it would make sense for state legislators to focus on those national issues as well (Hopkins 2018). In summary, if we find that state legislators are more likely to discuss issues that have traditionally been the focus of state government, that would be consistent with the predictions of the policy domain literature. In contrast, null findings here would be consistent with recent arguments about the nationalization of politics.

5 Predicting Twitter Usage Across State Legislators

We now demonstrate how our data and policy classification approach can be used to study the political communication behavior of state legislators. We begin by examining how the state-level and individual covariates introduced in the previous section predict three key outcomes: (1) whether a legislator is on Twitter (a binary outcome estimated via logistic regression), (2) whether the legislator is an active user (based on logged number of tweets estimated via linear regression), and (3) whether the legislator discusses policy issues (i.e. the proportion of tweets about a policy issue estimated via linear regression). The unit of observation in the following analyses is an individual legislator. We run two sets of models. In the first set, in order to explore the correlations for our state-level covariates (*Legislative Professionalization*, *Legislature in Session '18*, and *Term Limits*), we do not estimate any state-level parameters, although we do cluster the standard errors at the state level.

However, given that the data points are not fully independent because groups of legislators belong to the same state, we also run a set of multilevel models with state random intercepts. This second set of analyses allows us to explore individual-level correlations while accounting for state-level differences. Equations (1) and (2) show the specifications for the first set of logistic and linear regressions, respectively, where we model outcomes for legislator i in state j with a single intercept (α) and standard errors clustered at the state (j)

level.

$$y_{ij} = \frac{1}{1 + e^{-(\alpha + \beta X_{ij} + \epsilon_{ij})}} \tag{1}$$

$$y_{ij} = \alpha + \beta X_{ij} + \epsilon_{ij}. \tag{2}$$

We then estimate equations (3) and (4), which include state random intercepts (α_j):

$$y_{ij} = \frac{1}{1 + e^{-(\alpha + \beta X_{ij} + \alpha_j + \epsilon_{ij})}} \tag{3}$$

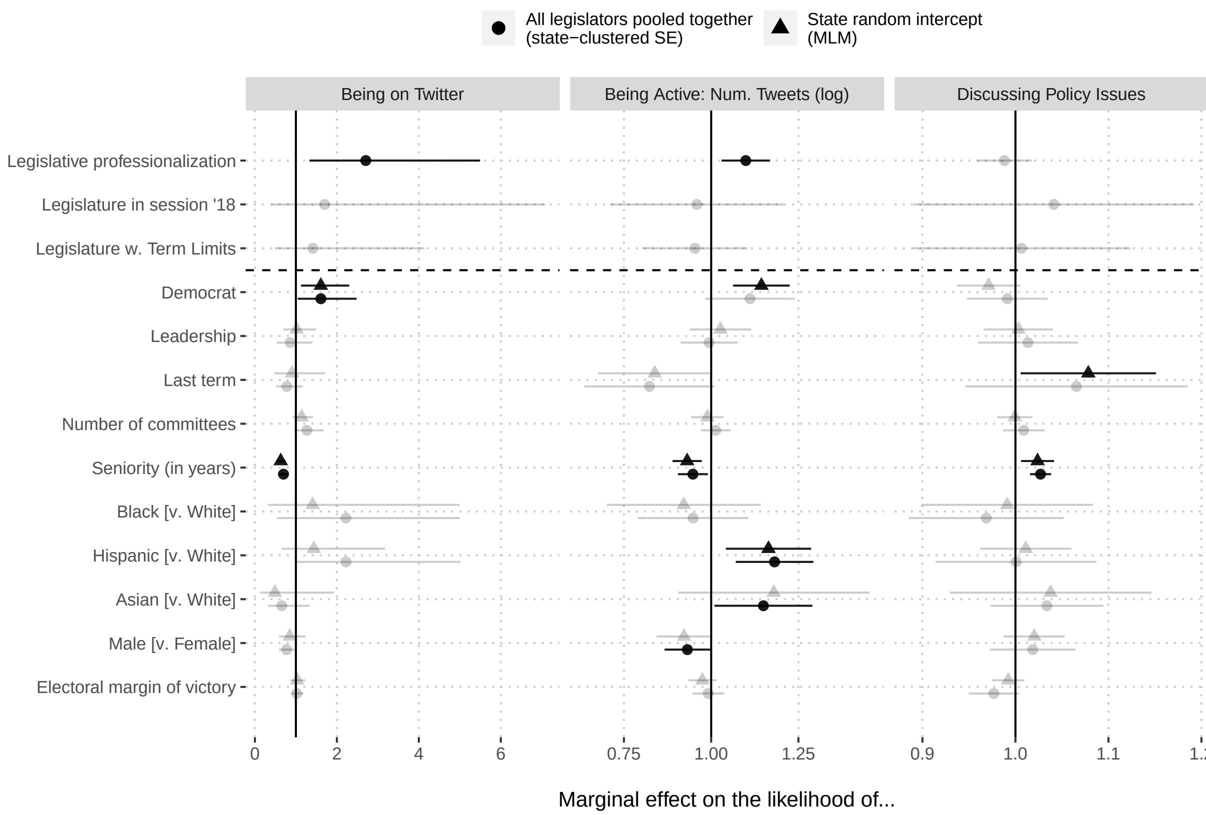
$$y_{ij} = \alpha + \beta X_{ij} + \alpha_j + \epsilon_{ij} \tag{4}$$

In Figure 2, we use the results from these models to report the marginal effects of each covariate on the likelihood of each of these outcomes. The coefficients from the pooled models are shown in blue, and the results from the multilevel models are shown in brown. For continuous variables we express the marginal effect of a one standard deviation change, and for dummy/categorical variables we expressed the marginal effect of belonging to the specified group (compared to the reference category).[14]

As suggested by the raw data presented in Table 2, legislators in more professionalized states are more likely to have a Twitter account (about 3 times more likely) as well as to be active on Twitter. A one standard deviation increase in the legislative professionalization score correlates on average with a 15% increase in the number of tweets sent by individual

[14]We estimated the multilevel models using the `lmer` package in `R`. We used the following protocol to transform the coefficients from the logistic and linear regressions into marginal effects on the likelihood of each outcome. First, before estimating the model, we transformed each continuous variable and expressed individual values as standard deviation from the mean. Then, for calculating the marginal effects for the logistic regression, we first transformed the log-odd coefficient (e.g. 0.47) into a probability ($0.61 = \frac{exp(0.47)}{1+exp(0.47)}$) and calculated the ratio with the remaining probability ($\frac{0.61}{0.61-(1-0.61)} = 1.56$). For the linear regressions, we calculated the ratio between the coefficient for each covariate and the sum of the covariate coefficient and the coefficient for the (fixed) intercept.

Figure 2: Logistic regressions (left panel) and linear models (two right panels) predicting which legislators are on Twitter (binary outcome), how active they are on the platform (count variable), and how often they use it to discuss policy issues (proportion of tweets about one of the CAP policy areas).



Note: The top three rows (above the dotted line) are state-level covariates, while the other covariates measure individual-level attributes. Results of the "Being on Twitter" model are based on 1,267 legislators for which all covariates are available. Results for the "Being Active: Num. Tweets" are based on 998 legislators (those from the previous model that are on Twitter). The results of the final model are based on 829 legislators (those from the previous model that sent more than 1 tweet in 2018). For continuous variables, we calculate the marginal effect of a 1 standard deviation change (Legislative professionalization, Number of committees, Seniority, and Electoral margin of victory). For binary and categorical variables, we calculate the marginal effect of belonging to that category (i.e. being a Democrat rather than a Republican). Coefficient tables for these regressions are available in Table B1 in Appendix.

legislators in 2018. Although social media drastically lowers the costs for state legislators to directly communicate with their constituents, the level of professionalization (salary, number of permanent staffers, etc.) still appears to correlate with the adoption and usage of such communication channel. However, legislators in more professionalized legislatures are not more likely, *ceteris paribus*, to discuss policy issues in their tweets than legislators from less professionalized legislatures.[15]

This last finding may indicate positive selection among the set of legislators who are on Twitter in less-professionalized states. Perhaps only the most ambitious or policy-oriented lawmakers make an additional effort to "go public" and join Twitter in these states, so conditional on having an account, these lawmakers are equally likely to tweet about policy. But even if this result is merely an artifact of self-selection, the fact that the public communications of certain legislators in less professionalized states resemble those of their peers in more professionalized legislatures is a finding that warrants additional attention in future research. We typically observe stark differences in the behavior and output of legislators from more or less professionalized states (e.g. Malhotra 2008; Maestas 2003; Berry, Berkman, and Schneiderman 2000; Kousser and Phillips 2009). However, it remains unclear whether these differences reflect hard institutional constraints or differences in the types of lawmakers that serve in different states. Future work in this area might explore whether social media platforms like Twitter can allow policy-oriented lawmakers with fewer resources at their disposal to substitute for more costly public communication.

Interestingly, legislators in session are not more likely to discuss policy topics compared to legislators out of session. While we might expect legislators in session to be more likely to engage with policy debates related to current bills being considered, journalistic accounts of state legislators indicate that members spend a great deal of time working on local issues and communicating with constituents when they are away from the capitol. As John McDonald of the New York State Assembly explains, "During the off season...I spend a significant amount of time talking to local government officials and assisting when appropriate on local issues."[16]

[15] In the Appendix, we also re-estimate the models using the number of staff in each legislature instead of the professionalization score (Table B2). The results are substantively very similar.

[16] https://blog.timesunion.com/johnmcdonald/what-do-legislators-do-when-theyre-not-in-session-2/3388/

While we caution that being in session is closely correlated with legislative professionalism, this finding indicates that the data and method used in this paper might be useful in shedding light on how legislators shape the policy agenda during their time out of session.

Finally, legislators from states with term limits are not systematically more likely to be on Twitter, to be more active, or to discuss policy issues at a higher rate. However, this dichotomous state-level variable does not fully capture whether legislators at the end of their term behave differently. When turning to the individual-level correlates, we observe that those legislators from states that have term limits and who are serving in their last term are less active in terms of number of tweets sent compared to other policymakers. This makes sense if state lawmakers in their final term are no longer driven by re-election pressures and put less effort into communicating their messages to their constituents (Carey 1994; Alt, Bueno de Mesquita, and Rose 2011; Fouirnaies and Hall 2018*a*). At the same time, these legislators in their final term are marginally *more* likely to discuss policy-related issues, consistent with the idea that lawmakers might feel more free to take positions on hot-button policy issues relative to their peers who are facing potential re-election.

We examine several additional individual-level characteristics that predict the activity of state legislators on Twitter. In general, note that the estimated coefficients are quite similar substantively between the pooled and the multilevel models, suggesting that any observed individual differences are not merely picking up public communication tendencies that vary across states. The most surprising result is that we find no effect of district margin of victory on either the likelihood of being on Twitter or discussing policy-relevant issues. If anything, it appears that as margin of victory increases (i.e. as districts become safer), legislators become *less* likely to discuss policy (although the difference is not statistically significant). Existing theoretical and empirical work typically predicts that candidates in more competitive elections will avoid articulating specific policy positions (e.g. Simon 2002; Grimmer 2013). A topic ripe for future research would be to determine whether strategic engagement with policy issues operates differently at the subnational level, or if this result reflects something distinct about social media as a policy platform.

We uncover additional interesting findings when looking at the other individual-level predictors. We observe Democrats to be around 50% (1.5 times) more likely to be on Twitter. Given that most legislators in large states and professionalized legislatures are on the social media platform, this difference is mainly driven by Democrats in smaller states and less professionalized legislatures who are more likely than their Republican counterparts to have an account on Twitter (i.e. legislators from North Dakota, Utah, and Montana). Out of those state legislators on the platform, Democrats also sent around 10% (1.1 times) more messages than Republican state legislators. In terms of seniority, we find younger members to be more likely to be on the platform and to be active users. However, conditional on these two previous factors, we observe senior members to be more likely to discuss substantive policy issues in their tweets. Given their extended policymaking experience, we speculate that those senior members who decide to be on the platform are better equipped to engage in policy-oriented conversations.

We also examine several individual correlates of Twitter activity for which we lack ex-ante hypotheses but which nonetheless reveal intriguing initial patterns. First, legislators who are Black or Hispanic are on average more likely to be on Twitter (although the difference is not statistically significant), but this correlation appears to be largely driven by the fact that non-white legislators are more likely to serve in states where Twitter adoption is high. After including random state effects in the models, the coefficients on both of these variables shrink. However, we do observe a positive and precise difference for Hispanic legislators when it comes to being active on Twitter: on average they send around 20% (1.2 times) more tweets than white legislators. This correlation holds in both the pooled and the multilevel models.

Finally, we find no difference in Twitter presence or activity between men and women. Previous work has shown that women in Congress are more likely to discuss policy on

Twitter relative to men (Evans and Clark 2016; Evans, Ovalle, and Green 2016).[17] This research typically argues that women face additional obstacles in demonstrating their merit for office and that they can use social media platforms such as Twitter to counter coverage in the mainstream news that often focuses on their personal traits. However, after adjusting for each of the other state-level and individual-level predictors, we uncover no correlation between gender and Twitter activity. Whether this result indicates that women and men behave more similarly in their social media usage in state legislatures relative to Congress is beyond the scope of this paper but deserves additional attention in future research.

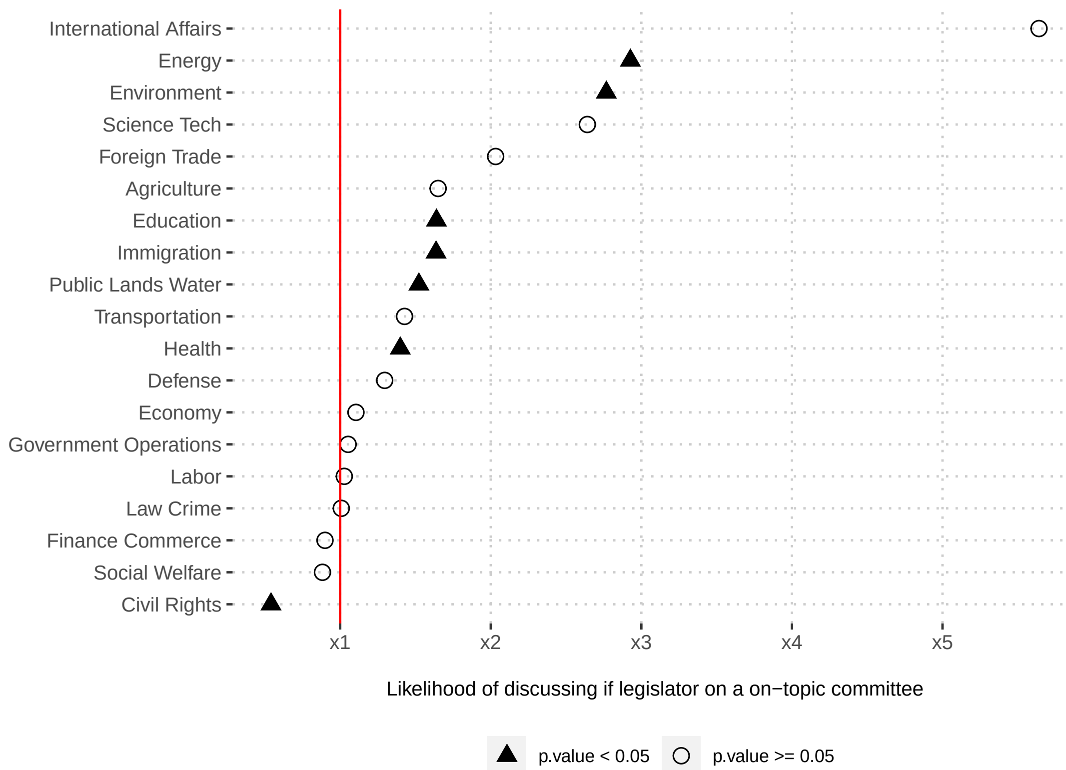
5.1 State Legislators and Tweets about Policy

Next, we turn to the question of which specific policy areas state legislators are discussing. As an initial validity check, we examine if members are more likely to discuss policy areas when they serve on the associated policy-relevant committee. For example, are legislators on the education committee more likely to discuss education in their tweets? We find strong evidence that this is indeed the case across a variety of committees and display the likelihoods in Figure 3. In general, serving on a specific committee (such as energy, environment, education, immigration or public lands) is correlated with discussing that topic on Twitter. For example, those serving on an Energy-related committee are around 3 times more likely to discuss energy-related topics in their tweets. Note that for the policy areas where committee-service is not predictive (e.g. civil rights and the economy), it is likely that simply all legislators are actively engaged in discussing these topics.

We can also examine attention to issues by state as opposed to by committee. In Figure 4, we show the relative attention given to each topic by state. For each state (column), the cell entry gives the percentage of tweets from legislators in that state's legislature that are

[17] Although note that more recently Hemphill, Russell, and Schöpke-Gonzalez (2020) find that this is only true for Democratic rather than Republican women.

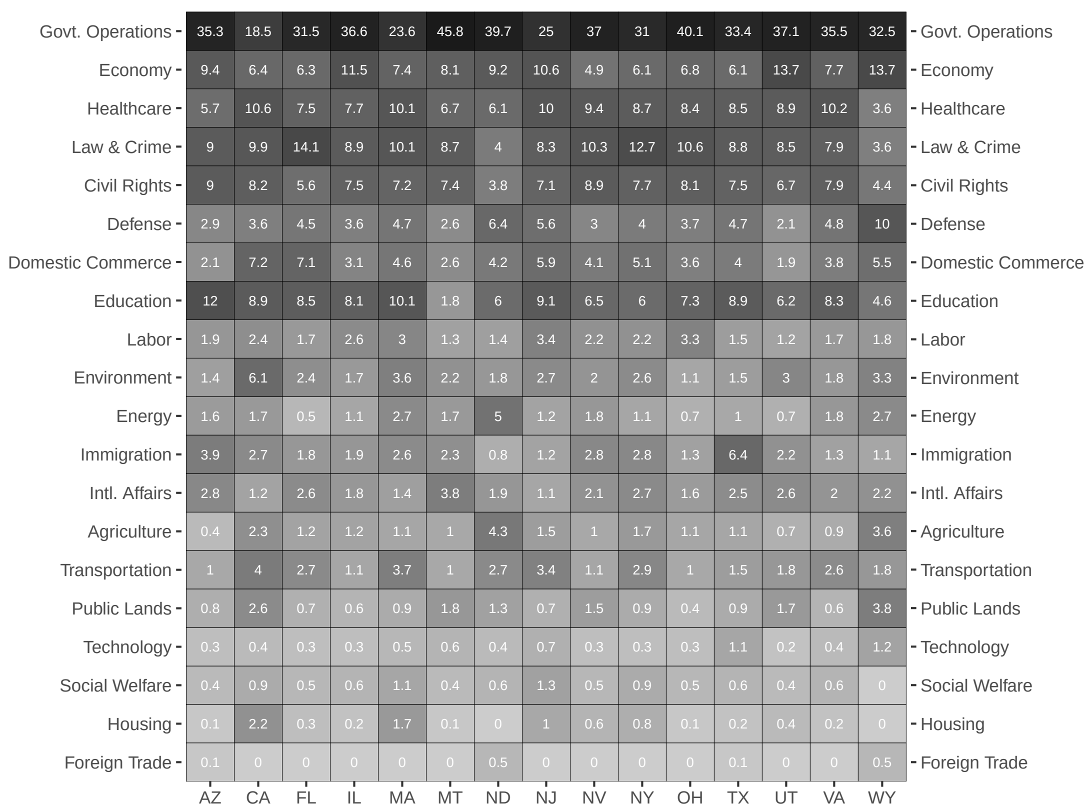
Figure 3: OLS models predicting the proportion of tweets legislators dedicate to discussing each topic as a function of being on a committee on the topic, plus the covariates included in the models in Figure 2. Standard errors clustered by state.



Note: We estimated a separate OLS model for each topic and we report in the figure the coefficient for the variable indicating whether the legislator served in a committee about that topic. The coefficient for the *Housing* policy area (estimate of 22.7 with a confidence interval from 12.6-32.7) has been excluded because its large value made it difficult to interpret the rest of the coefficients.

about the row topic, *conditional on the tweets being about a policy topic.* While we mainly present this as an example of the type of analysis that can be done in this regard, it is worth noting that there are some interesting observable patterns that are consistent with the idea that state legislators are more likely to discuss issues that are more important for their particular state. For example, legislators from California, North Dakota, and Wyoming are more likely to discuss agriculture, and lawmakers from Arizona, California, New York, and Texas are more likely to discuss immigration. These unsurprising patterns add validity to the measure and suggest several useful applications for our classification approach in terms of documenting agenda setting at the state-level.

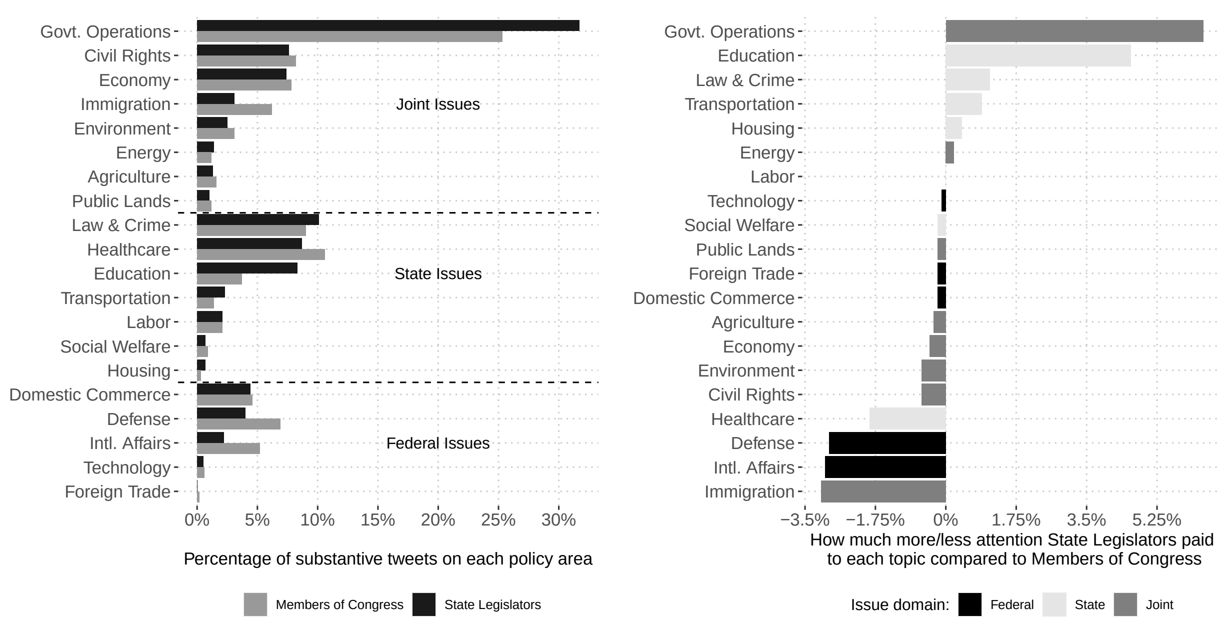
Figure 4: Proportion of attention that legislators from each state devoted to each issue area in 2018.



Finally, we turn to the question of whether state legislators tend to focus on "state issues."

According to literature on federalism, we would expect lawmakers to pay special attention to the domains over which they have the most impact. At the same time, as suggested by recent work by Hopkins (2018), it could be that the increasing nationalization of U.S. politics leads state actors to focus equally or more on national issues. Using traditional classification schemes from work on functional federalism, we divided each policy issue into one of three categories: state, federal, or joint. In the left panel of Figure 5 we show the percentage of policy relevant tweets on each topic broken down by issue type sent by state legislators and members of Congress in 2018. Then in the right panel, for each of the policy areas, we take the difference between the proportion of tweets sent by state legislators and the proportion sent by members of Congress, which allows us to more clearly display how much more (or less) state legislators discuss particular policy areas relative to members of Congress.

Figure 5: Percentage of policy related tweets on each topic: Members of Congress and State Legislators.



Note: On the left panel, **darker bars** indicate how much of the policy related tweets from State Legislators are about each topic. *Lighter bars* indicate the attention paid by Members of Congress.

We find that state legislators and members of Congress pay similar amounts of attention to most policy areas. However, at the margins, we find evidence consistent with the policy domain literature. State legislators do seem to be more likely to discuss areas that are traditionally the domain of state government, such as education, law and crime, transportation, and housing. Members of Congress are more likely to discuss national issues such as defense, international affairs, and foreign trade. These differences are fairly small—often only a few percentage points—but they suggest that state legislators are nominally focused on a different set of issues, many of which are at the forefront of major policy battles today.

6 Discussion

In this paper, we used state of the art deep learning techniques to uncover the topics discussed by policymakers from fifteen U.S. states on the social media platform Twitter, providing a valuable new method and measurement technique for studying state politics. In doing so, we also make several contributions to the study of agenda setting and public communications in state legislatures. First, we add to a nascent body of work demonstrating that state legislators use Twitter as one of their main public communications platforms (e.g. Cook 2017). We also provide new evidence that both Twitter adoption and social media use by lawmakers varies substantially across states, and we validate an original approach to classifying the policy content of state legislator tweets.

Using these new data and measurement approaches, we uncovered several interesting patterns that are relevant to work on state-level policy and public communications. For example, in contrast to research showing that lawmakers working in less professionalized state legislatures are less politically ambitious and less productive (Maestas 2000; Malhotra 2008; Hogan 2008), we find that the state legislators that use Twitter in these states are actually *equally* likely to discuss policy issues as their counterparts in more professionalized settings. We also find that state legislators in competitive districts are no less likely to discuss policy issues on Twitter compared to legislators in safe districts. According to most theoretical research, marginal legislators should spend more effort emphasizing their appropriations or constituency casework compared to discussing policy (Weingast, Shepsle, and Johnsen 1981; Ashworth and Mesquita 2006; Grimmer 2013). The fact that this doesn't appear to be true for state legislators on Twitter poses an intriguing puzzle for future research in this area.

Finally, we also find that state legislators are marginally more likely to discuss policy areas that are traditionally the domain of state government—such as law and crime, education, and transportation—than are members of Congress. At the same time, they are slightly less likely to discuss national issues such as defense and international affairs. These findings suggest that even given the nationalization of American politics over the past decade, state and federal lawmakers are still focusing their attention on distinct sets of issues that are directly relevant to the functions of each level of government.

One of the benefits of studying state politics is that researchers can examine how institutional or other environmental factors affect political phenomena of interest. We uncover evidence that substantial variation exists in terms of Twitter adoption and engagement across states. While we demonstrate that legislative professionalism and term limits appear to explain some of this variation, further unpacking when and how state legislative activity on Twitter varies across states will be a clear next step for this research agenda.

More broadly, we hope that the results and methodological approach introduced in this article serve as a launchpad for scholars interested in studying agenda setting, policy-making, and communication at the state-level. This paper demonstrates that classifying the policy content of state legislator tweets is indeed possible, which opens up a wide variety of future avenues for work in this area. For example, how does the Twitter usage of state politicians in communicating with their constituents and discussing their policy positions compare with national politicians? How do policy priorities of state legislators vary across states and in relationship to important state-specific events over time? How does the agenda setting process differ between the state and federal level? And finally, how responsive are state legislators to the mass public when it comes to issue attention? These are just a few of the areas ripe for future research that might use the data collection and classification approaches established in this paper.

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On-Line Appendix for "Using Social Media Data to Reveal Patterns of Policy Engagement in State Legislatures"

Appendix A Training of the CNN topic classifier

We trained the model architecture described in the paper (Figure 1) with the four datasets that we describe again in Table A1. The first one is composed of publicly available data. The second one comes from the replication material of a published study, and we created two final dataset for the purpose of this study. 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 18,088 tweets sent by media accounts and followers of our state legislators that we coded according to the CAP classification. The fourth dataset (D) consists of 3,368 tweets sent by the state legislators that we also coded.[18]

We trained the same CNN model nine times using the following data combinations, with the goal of taking advantage of transfer learning (Terechshenko et al. 2020) and training more accurate models than simply training the model with the tweets from state legislators that we had coded (so only set D): (1) only set A, (2) only set D, (3) set A and set D, (4) set D and a small sample of set A (1,300 observations), (5) set D and a smaller sample of set A (650 observations), (6) set D and set B, (7) set D and a small sample of set B (1,300 tweets), (8) set D and a smaller sample of set B (650 tweets), (9) set D and set C.

To assess the performance of these nine versions of the model we split the data used in each case into a train and test set. Moreover, we split set D (the tweets sent by state legislators that we coded) into a train, test, and validation set. This validation set is particularly useful for two reasons. First, although the test sets were not used for training the models, they were somewhat involved in the training process, as we decided the number of training iterations based on how well the CNNs predicted the coded documents both in the train and test tests.[19] Assessing accuracy based on a totally untouched validation set hence gives us a better indication of how the model will perform in predicting the topics of the unlabeled tweets. Furthermore, at the end of the day we wanted to specifically know how each CNN performed at predicting the topics in tweets sent by state legislators, rather than the documents in the test sets (which could be a combination of different types of documents: tweets, titles of congressional bills, newspaper headlines, etc.).

In Table A2 we report the accuracy of the nine versions of the model we trained (based on 3-fold cross-validation), based on held-out test sets, and on the validation set composed only of tweets sent by state legislators. We assess the test accuracy when predicting all tweets in the test split (*All*), and also when only predicting the tweets coded as being about one of

[18] See Footnote 12 for information on inter rater reliability for the tweets we coded in this study.

[19] We settled for fifty iterations, as at that point the accuracy based on the train set kept improving while test accuracy started declining.

Table A1: Public datasets coded using the CAP 21-issue classification, used for training and testing a classifier predicting *Policy Issues* in tweets from state legislators.

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	Tweets sent by media accounts	2018	8,802
	Tweets sent by followers of state legislators	2018	9,286
D	Tweets sent by state legislators	2018	3,368
	Total	1944-2018	855,854

Table A2: Out of sample accuracy of the nine versions of the CNN model we trained predicting the political topics of the Comparative Agendas Project.

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

the policy areas, so after excluding the non-policy tweets (*Policy*). The tweets not related to any policy area represented a large part of the tweets we coded from state legislators (set D) and we wanted to make sure that our model did well at both distinguishing overall policy relevance and at distinguishing between policy areas.

The model trained with the coded tweets by state legislators plus the coded tweets sent by Senators of the 113th Congress returned the best results. The test accuracy in both cases (all tweets, and just tweets we determine to be about policy areas) is close to 80%, and more importantly, the validation accuracy based on the untouched labeled tweets sent by state legislators is around 60% (very high given that the model is predicting 21 topic classes). In Table A2 we also compare the performance of our CNN models to a baseline n-gram based model, a Support Vector Machine (SVM).[20] We note that the CNN model clearly outperforms the SVM model in our validation set. To use an SVM with accuracy over all tweets (including non-policy tweets) as high as we achieve with our CNN classifier, we would have to choose an SVM trained on one of the sets listed in rows 4 through 9 of Table A2. However, none of those classifiers achieve an accuracy on policy tweets of over 0.31 (compared to an accuracy of 0.55 on policy tweets for our CNN). Thus the CNN model is much preferred to SVM here, and allows us to much more accurately assess which policy different tweets are about. Hence, we used the model reported in the first row of Table A2 to generate topic predictions for the rest of the tweets sent by state legislators and for the analysis and results presented in the paper.

[20] We chose an SVM as the baseline model because it outperformed other n-gram based models when we run some initial explorations and because previous research has shown SVM to perform the best out of the commonly used ngram/bag-of-words models, see Collingwood and Wilkerson (2012) and Hemphill and Schöpke-Gonzalez (2020).

Appendix B Additional figures

Figure B1: Construct Validity: Percentage of daily tweets predicted to be about Immigration.

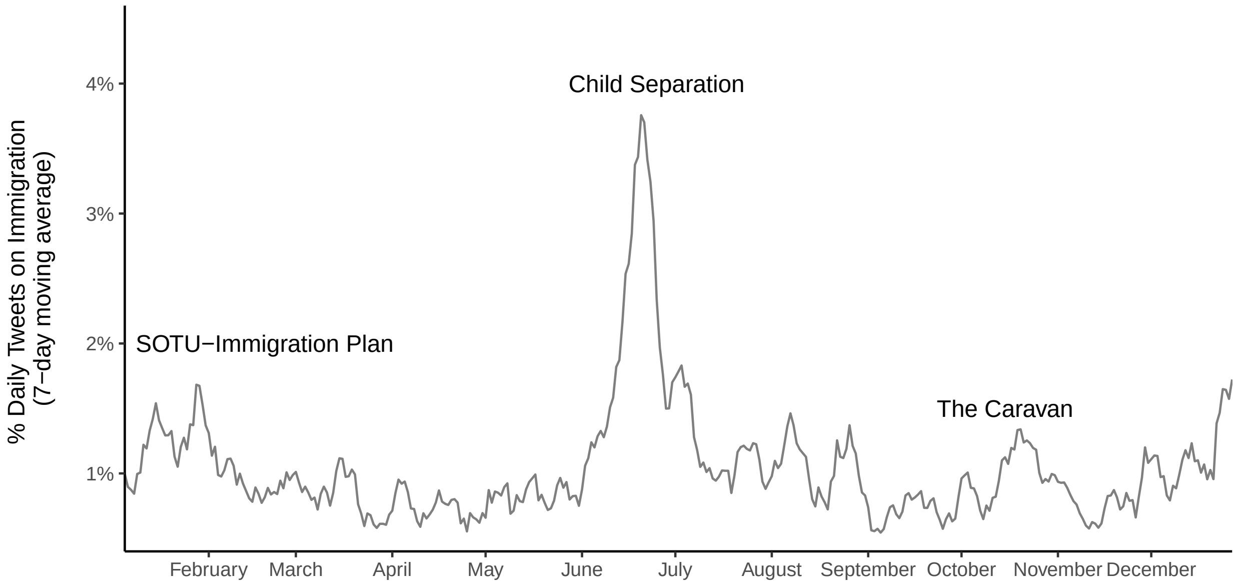

Figure B2: Logistic regression (left panel) and linear models (two right panels) predicting which legislators are on Twitter (binary outcome), how active they are on the platform (count variable) and how often they use it to discuss policy issues (proportion of tweets about one of the CAP policy areas). Replication of the pooled models in Figure 2 in which we replaced the *Legislative professionalization* score with the number of *Staff* members available for the entire legislature in each state (state-level covariate). Source of the new *Staff* variable: https://www.ncsl.org/research/about-state-legislatures/staff-change-chart-1979-1988-1996-2003-2009.aspx. Standard errors are clustered by state. Coefficient tables for these models are available in Table B1 (see Version 2 of the models).

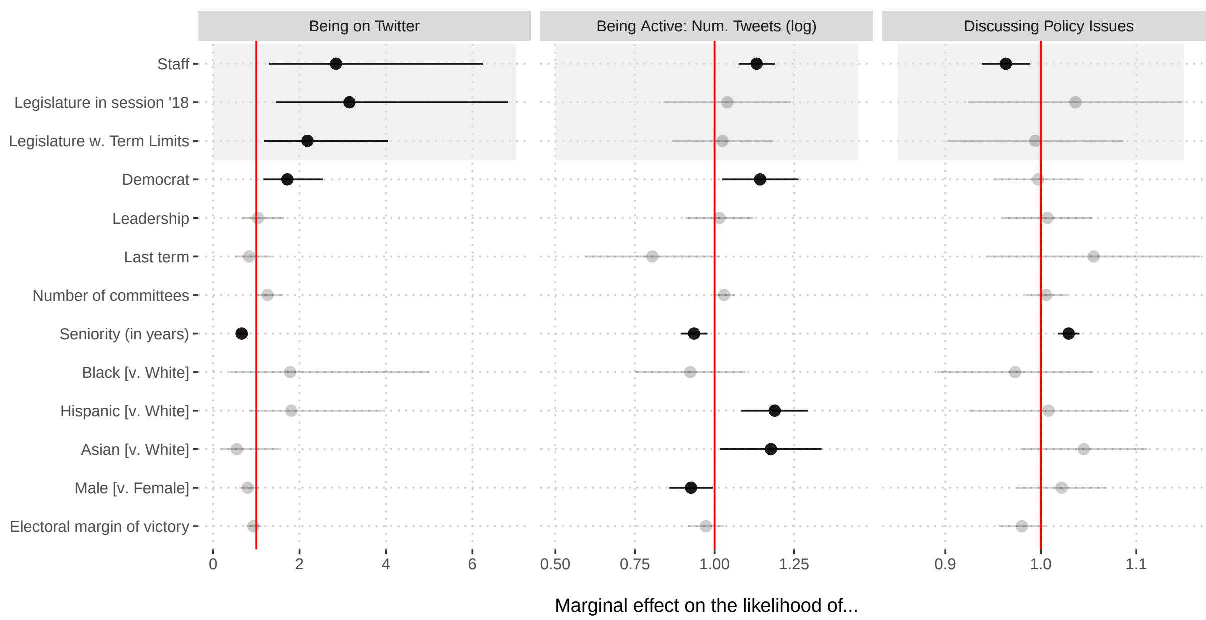

Table B1: Coefficient tables for the models in Figure 2 and Figure B2. In version 1 and 2 of the models we cluster standard errors by state. In version 3 we run multilevel models with state random intercepts.

	Being on Twitter (Binary) (Logistic regression)			Being Active: Num Tweets (Logged count) (Linear model)			Discussing Policy Issues (Proportion) (Linear model)		
Variable	Version 1	Version 2	Version 3	Version 1	Version 2	Version 3	Version 1	Version 2	Version 3
(Intercept)	0.89 (0.883)	0.165 (0.491)	1.561 (0.422)*	4.353 (0.561)*	3.858 (0.35)*	4.558 (0.279)*	0.621 (0.044)*	0.628 (0.033)*	0.717 (0.018)*
Leg. Prof.	0.995 (0.361)*			0.432 (0.154)*			-0.007 (0.009)		
Staff		1.045 (0.401)*			0.51 (0.112)*			-0.023 (0.008)*	
Leg. in session '18	0.532 (0.728)	1.149 (0.394)*		-0.179 (0.552)	0.155 (0.394)		0.026 (0.048)	0.023 (0.036)	
Leg. w. Term Limits	0.347 (0.547)	0.781 (0.315)*		-0.203 (0.335)	0.096 (0.314)		0.004 (0.037)	-0.004 (0.03)	
Democrat	0.476 (0.221)*	0.542 (0.199)*	0.476 (0.183)*	0.484 (0.285)	0.551 (0.237)*	0.575 (0.165)*	-0.005 (0.014)	-0.002 (0.015)	-0.019 (0.011)
Leadership	-0.147 (0.248)	0.038 (0.233)	0.019 (0.195)	-0.026 (0.182)	0.059 (0.211)	0.105 (0.179)	0.008 (0.017)	0.004 (0.015)	0.002 (0.012)
Last term	-0.25 (0.205)	-0.184 (0.248)	-0.1 (0.325)	-0.77 (0.414)	-0.754 (0.414)	-0.646 (0.33)	0.041 (0.038)	0.035 (0.036)	0.051 (0.024)*
Num. committees	0.238 (0.143)	0.231 (0.129)	0.131 (0.111)	0.057 (0.095)	0.115 (0.069)	-0.043 (0.095)	0.006 (0.007)	0.004 (0.007)	0 (0.006)
Seniority (in years)	-0.36 (0.084)*	-0.414 (0.085)*	-0.461 (0.086)*	-0.228 (0.095)*	-0.249 (0.083)*	-0.275 (0.085)*	0.017 (0.004)*	0.018 (0.004)*	0.015 (0.006)*
Black [v. White]	0.798 (0.724)	0.578 (0.776)	0.342 (0.756)	-0.225 (0.353)	-0.294 (0.342)	-0.315 (0.45)	-0.019 (0.026)	-0.017 (0.026)	-0.006 (0.031)
Hispanic [v. White]	0.799 (0.415)	0.593 (0.392)	0.363 (0.404)	0.79 (0.247)*	0.728 (0.206)*	0.656 (0.249)*	0 (0.027)	0.005 (0.027)	0.007 (0.016)
Asian [v. White]	-0.421 (0.364)	-0.602 (0.522)	-0.717 (0.701)	0.652 (0.312)*	0.682 (0.313)*	0.717 (0.56)	0.021 (0.019)	0.028 (0.021)	0.025 (0.036)
Other [v. White]	-1.215 (1.005)	-1.474 (1.273)	-1.368 (1.164)	-0.007 (1.444)	-0.01 (1.428)	-0.214 (1.591)	-0.029 (0.162)	-0.042 (0.162)	-0.091 (0.1)
Male [v. Female]	-0.257 (0.142)	-0.222 (0.143)	-0.161 (0.19)	-0.297 (0.145)*	-0.285 (0.134)*	-0.311 (0.161)	0.012 (0.015)	0.014 (0.015)	0.013 (0.011)
El. margin of victory	0.022 (0.076)	-0.07 (0.094)	0.032 (0.09)	-0.036 (0.101)	-0.105 (0.112)	-0.102 (0.083)	-0.014 (0.009)	-0.012 (0.008)	-0.005 (0.006)
State intercepts									
AZ			1.561			4.558			0.717
CA			2.979			4.879			0.659
FL			2.583			3.844			0.577
IL			1.036			3.349			0.669
MA			1.699			4.335			0.661
MT			-0.462			2.859			0.721
ND			-1.364			3.036			0.668
NJ			1.663			3.53			0.685
NV			1.275			4.117			0.601
NY			2.049			4.905			0.634
OH			1.484			3.839			0.655
TX			3.207			4.847			0.58
UT			0.767			3.847			0.646
VA			1.498			4.857			0.669
WY			-0.794			3.119			0.63
N	1267	1267	1267	998	998	998	829	829	829
Log Likelihood	-577.25	-552.96	-542.03			-2224.24			418.06
AIC	1184.51	1135.92	1110.05			4462.99			-886.48
R-squared				0.1	0.11		0.03	0.05	
Adjusted R-Squared				0.08	0.1		0.02	0.04	

Figure B3: Percentage of State Legislators with a Twitter Account, by State and Party.