Political Science Research and Methods (2024), page 1 of 13
doi:10.1017/psrm.2024.52

RESEARCH NOTE

The national network of US state legislators on Twitter

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(Received 3 January 2023; revised 9 August 2023; accepted 14 August 2023)

Abstract
Networks among legislators shape politics and policymaking within legislative institutions. In past work on legislative networks, the ties between legislators have been defined on those who serve in the same legislature or chamber. Online information networks, which have been found to play important roles in legislative communication at the national level, are not bounded by individual legislative bodies. We collect original data for over four thousand US state legislators and study patterns of connection among them on Twitter. We look at three types of Twitter networks—follower, retweets, and mentions. We describe these networks and estimate the relationships between ties and salient attributes of legislators. We find that networks are organized largely along geographic and partisan lines and that identity attributes—namely gender and race—exhibit strong associations with the formation of ties.

Keywords: American politics; legislative politics; political networks; political communication; social media and politics

Legislative networks shape fundamental legislative processes, such as overall productivity (Tam *et al.*, 2010), the dissemination of support for legislation (Kirkland, 2011; Phadke and Desmarais, 2019), the distribution of campaign funds (Kettler, 2020), and electoral outcomes (Wojcik and Mullenax, 2017). Conventional approaches to drawing ties between legislators–e.g., through cosponsorship relationships (e.g., Bratton and Rouse, 2011), co-voting (e.g., Moody and Mucha, 2013), and co-membership in legislative caucuses (e.g., Victor and Ringe, 2009)—limit the networks to include only those who serve in the same legislature, and often the same chamber. In research on US state legislatures, a cross-state/cross-legislature perspective on legislative networks provides an important complement to the study of intra-state legislative networks (e.g., Masket and Shor, 2015). Given the long-established importance of interstate ties in the process of policy diffusion (Gray, 1973), a cross-state view of legislative networks contributes to our understanding of state policymaking. Further, state politics is becoming more nationalized, with local issues losing ground to national matters (Hopkins, 2018; Butler and Sutherland, 2022). Cross-state legislator data can enable us to explore the role of individual-level networks in promoting this phenomenon.

Our objectives in this note are to introduce new data on, and provide initial analyses of; a relatively new form of tie formation among state legislators: interaction on Twitter. State legislators are highly active on Twitter, and use this platform to engage broad audiences on salient contemporary issues (Cook, 2017; Kim *et al.*, 2021; Payson *et al.*, 2022). State legislators' tweets are also regularly covered in the traditional news media.[1] In this paper, we describe the network, which we collected in 2020, among every state legislator on Twitter. We analyze the factors that are associated with tie formation—in terms of following, retweets, and mentions—among legislators. Consistently, among tie types, we find that within-state ties are more likely to be formed among those who are in the same party, same chamber, and are the same gender. The factors associated with cross-state tie formation are different from those that are associated with within-state tie formation, and vary across the types of networks. We find that homophily in identity variables—gender and race—are more likely to explain cross-state ties in these networks as opposed to party or state variables.

1. Digital networks in law and policymaking

Interstate networks are important to subnational policymaking processes. Network concepts have long played important roles in the study of policy diffusion. Walker (1969) describes the spread of policies across states as flowing through trees—a special case of a network (Xu *et al.*, 2016)—that connect regional hierarchies of states. Gray (1973) presents a mathematical model of the spread of policy that is based on networked contagion. Mintrom and Vergari (1998) demonstrate the importance of policymakers' involvement with cross-state education policy networks. However, few available data sources provide researchers with a comprehensive picture of communication ties between individual policymakers.

Complementing the formal and institutional interactions among legislators that are conventionally used to study legislative networks (Kirkland and Gross, 2014), Twitter presents a more fluid and multidimensional look at connections among legislators (Barberá, 2015; Garimella and Weber, 2017). With few exceptions, nearly all research addressing legislative behavior on Twitter has focused on the US Congress. Cook (2017) comprehensively collected account information on politicians serving in the 50 state legislatures in the US. They collected data in 2015 to analyze trends in Twitter adoption, and found that 65.1 percent of state legislators had Twitter accounts. Kim *et al.* (2021) collected state legislators' Twitter accounts in 2020, and found that this percentage had grown to 72.8.

1.1 Modeling state legislators' online networks

We study three separate networks in which the units (nodes) are individual legislator accounts. First, in the follower network, there is a directed tie from a legislator i's account to j, if i follows j. Second, in the retweet network, there is a directed link from legislator i's account to j if i retweets or mentions j at least once. In the retweet network, we weight the ties as the number of times legislator i retweets j. In the mention network, the tie from i to j is represented by the number of times legislator account i mentions legislator account j in the tweets that legislator i posted. We collected all legislator accounts that were active in the beginning of June 2020. We then collected all tweets posted by the legislators' accounts, and their follower networks, monthly between June 2020 and August 2020. Due to the COVID-19 pandemic, this is an unusual timeline to study. Partisanship was a dominant feature of political elites' online communications during this period (Green *et al.*, 2020). State legislators were, relatively speaking, highly active during this early period of the pandemic (see the online appendix for more on this). We formed the networks based on the data collected during this time interval.

Using network analysis, we analyze covariate effects and account for network dependence (e.g., a friend's friend is a friend; see Dorff and Ward, 2013). Ignoring dependence may bias estimates

[1]Searches for "state rep(representative) tweeted," "state senator tweeted," or "state legislator tweeted" in the Nexis Uni news database turned up over 100 unique results (on 8/30/2022).

and standard errors. Various tools for inferential network analysis exist (Cranmer *et al.*, 2020). We estimate relationships through logistic regression for following, and ordinary least squares for retweets and mentions. The directed dyad is the unit of analysis, with the dependent variable representing the network tie. Independent variables reflect either node (e.g., the political party of the potential tie sender) or dyad-level information (e.g., same-party indicator). We use p-values calculated with quadratic assignment procedure (QAP), which are robust to network dependence (Dekker *et al.*, 2007; Butts, 2022).

2. Independent variables

In specifying the set of covariates that we expect to be associated with ties, we consider eight sets of variables—state, party, chamber, professionalism of the legislatures, geographic relationships between states, legislator gender, and legislator race. For each variable, we estimate node-level sender and receiver effects, dyadic similarity effects, and interactions to determine the effects when legislators serve in different states. In modeling directed networks, it is considered a best practice to include at least three terms for each independent variable—a sender effect, receiver effect, and a homophily/similarity effect (Robins, 2011). Including the node-level sender and receiver effects controls for node-level patterns in identifying dyadic effects. Without the node-level variables, dyadic patterns could be spurious, attributable to unmodeled node-level patterns. Since there are well-known challenges in terms of the statistical power to detect interaction effects (Aguinis and Stone-Romero, 1997), and some regions of the networks we are studying are particularly sparse, in the online appendix we present descriptive distributions of the network variables, along with the breakdown of the within-state and within-party covariates. We also conduct an extensive simulation study to assess our power to detect the effects in our model. We find that the power is sufficiently high for all of the variables for which we find statistically significant effects.

2.1 Legislator similarity

Social networks usually contain a preponderance of within-category ties and exhibits what is called "homophilly." Under homophily, nodes are more likely to form a link with one another because they share certain attributes. On the ideological side, we consider if two legislators belonging to the same party influences the presence of links between them (Harbridge, 2015; Russell, 2018). We expect legislators to prefer to listen to, interact with, and promote those who share their party identities.

Attributes related to the identity of legislators may also influence who they follow and communicate with. We consider the effect of belonging to the same gender and race. Research shows that gender and race are important variables which can help explain many different social ties (Joyner and Kao, 2000; McPherson *et al.*, 2001). The research on identity-based homophily in legislative networks has results across the spectrum—with some studies demonstrating the presence of it (Fischer *et al.*, 2019; Davis *et al.*, 2022) while others showing the lack of it (Baller, 2017) or that it depends on the context (Bratton and Rouse, 2011; Cook, 2011).

We also consider other environmental/social settings in which legislators interact, such as serving in the same state and the same legislative chamber. Because these factors determine the contexts in which legislators collaborate and interact online, we expect that shared environments lead to greater interaction and communication online.

The last variable we incorporate into the model is legislative professionalism, which captures the capacity of legislators (and their staffs) to engage in communications work, and the general breadth of activities in which legislators can be expected to engage at any given time (Squire, 2007). The professionalism of a legislature determines the type of career legislators have in the legislature, the scope of legislative problems they can address within a fixed period of time,

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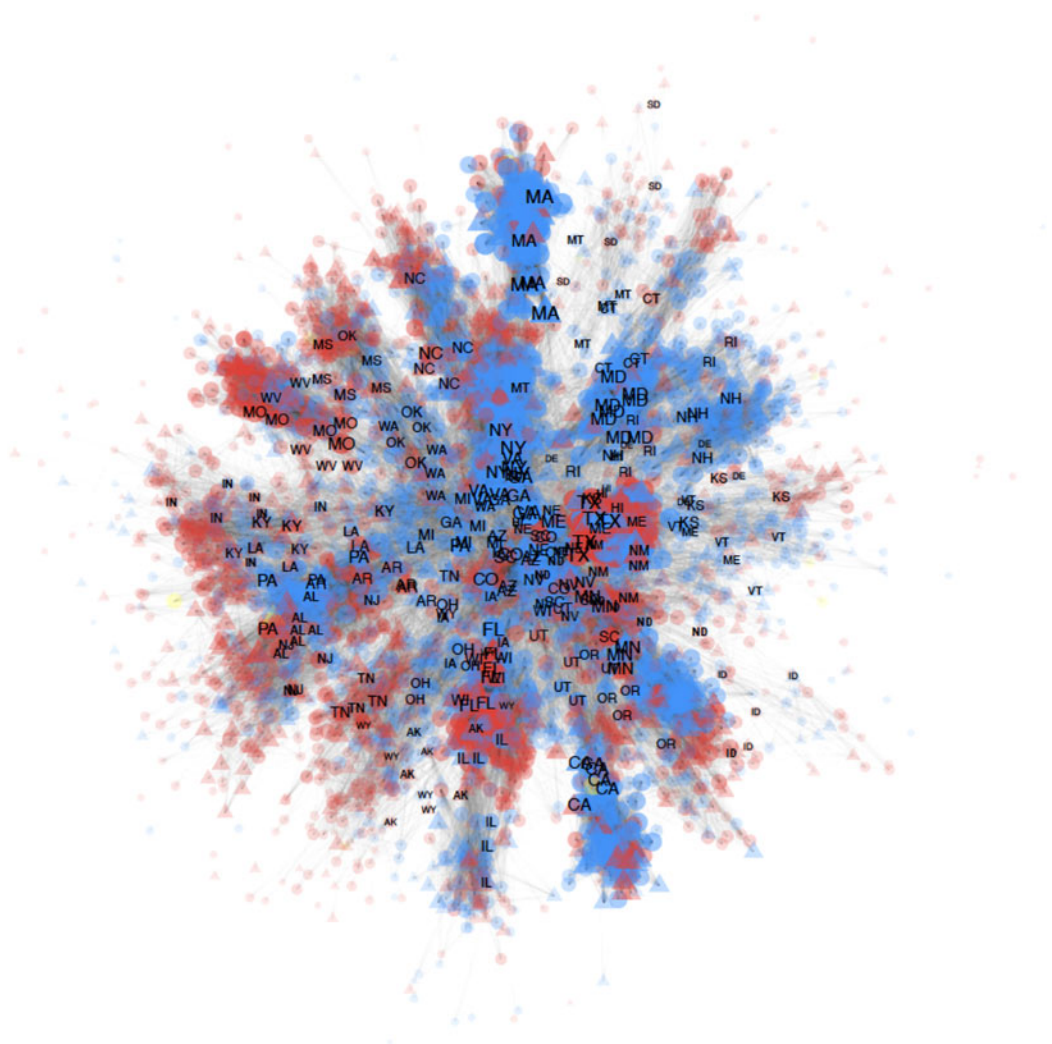

Figure 1. Inter-legislator follower network.

and the resources at their disposal in carrying out their work. Legislators have the most in common, in terms of their official roles, with others from legislatures with similar levels of professionalism. For example, one of the features that factors into measures of legislative professionalism is the amount of time the legislature is in session. Some, less professionalized legislatures, are in session for three months or less, whereas some more professionalized legislatures are in session nearly year round. We expect legislators to be more likely to form online connections with those from legislatures with similar levels of professionalism.

2.2 Sender and receiver effects

In addition to similarity measures, for each variable that is naturally defined at the node level, we include effects to assess whether the respective variable is associated with legislators' tendencies to send and receive ties. These effects are important in effectively identifying the similarity effects involving the same variables, and are interesting in their own regard. Further, given that

Table 1. Top 10 legislators with the highest in-degree centrality

Follower network			
Danica Roem	Virginia	D	H
Brian P. Kavanagh	New York	D	S
Robert DeLeo	Massachusetts	D	H
Eric Lesser	Massachusetts	D	S
Nily Rozic	New York	D	H
Mary Gonzalez	Texas	D	H
Shevrin Jones	Florida	D	H
Rafael Anchia	Texas	D	H
Four Price	Texas	R	H
Carl Heastie	New York	D	H
Mentions network			
Danica Roem	Virginia	D	H
Anna Eskamani	Florida	D	H
Robert DeLeo	Massachusetts	D	H
Carl Heastie	New York	D	H
Karen Spilka	Massachusetts	D	S
Andrea Stewart-Cousins	New York	D	S
Jamie Eldridge	Massachusetts	D	S
Dennis Bonnen	Texas	R	H
Mary Gonzalez	Texas	D	H
Shevrin Jones	Florida	D	H
Retweets network			
Danica Roem	Virginia	D	H
Melissa Hortman	Minnesota	D	H
Nily Rozic	New York	D	H
Joe Moody	Texas	D	H
Elijah Haahr	Missouri	R	H
Leslie Herod	Colorado	D	H
Brad Hoylman	New York	D	S
Jeff Leach	Texas	R	H
Shelly L. Hettleman	Maryland	D	S
Marc Korman	Maryland	D	H

politicians often seek information from others to guide their own decisions, sending a tie in the network may also be conceptualized as cue taking behavior. For example, politicians from third/independent parties may be motivated to send ties to Democratic and Republican legislators with more resources in the hope of gathering more information. Additionally, because Democratic legislators are more active on Twitter (Kim *et al.*, 2021), they may be more likely to send and receive ties.

2.3 Interactions

An important feature of the networks we study is the ability to observe ties between both same-state and different-state legislators. To understand what drives cross-state ties, relative to within-state ties we test whether partisan, chamber, and identity effects are stronger within or across states. We do this by interacting the variables that measure party, chamber, and identity-based similarity with an indicator for whether the two legislators serve in the same state. It is likely that legislators use online platforms to monitor the communications and occasionally interact with members of the opposite party. However, the incentive to engage with members of the opposite party is stronger when it comes to legislators in the same state, as it is necessary to work with other legislators from the same state. In contrast, legislators may connect with others outside their state to gather information, for example, to learn policy ideas. We expect that legislators will be more likely to form connections with like legislators from other states—seeking to emulate what similar policymakers are doing elsewhere. Thus, we hypothesize that homophily based on party and identity will be stronger across states than within states.

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Table 2. Top 10 legislators with the highest out-degree centrality

Follower network			
Brian P. Kavanagh	New York	D	S
Mary Gonzalez	Texas	D	H
Eric Lesser	Massachusetts	D	S
Shevrin Jones	Florida	D	H
Alfred C. Carr Jr.	Maryland	D	H
Alan D. Clemmons	South Carolina	R	H
Victoria Neave	Texas	D	H
Sheryl Cole	Texas	D	H
Lori Ehrlich	Massachusetts	D	H
Sarah Davis	Texas	R	H
Mentions network			
Tram Nguyen	Massachusetts	D	H
Alan D. Clemmons	South Carolina	R	H
Brian P. Kavanagh	New York	D	S
Tami Gouveia	Massachusetts	D	H
Michelle Ciccolo	Massachusetts	D	H
Drew Springer Jr.	Texas	R	H
Christine Barber	Massachusetts	D	H
Carolyn Dykema	Massachusetts	D	H
Leslie Herod	Colorado	D	H
Cesar Blanco	Texas	D	H
Retweets network			
Cheryl Youakim	Minnesota	D	H
Leon Lillie	Minnesota	D	H
Chris Eaton	Minnesota	D	S
Lucy Weber	New Hampshire	D	H
Melissa Hortman	Minnesota	D	H
Fue Lee	Minnesota	D	H
Jason Isaacson	Minnesota	D	S
Susan Kent	Minnesota	D	S
Marjorie Porter	New Hampshire	D	H
Joelle Martin	New Hampshire	D	H

3. Data

Our sample includes all state legislators who were serving in June 2020. We manually collected legislators' accounts by searching Twitter, Google, official legislative websites, and using the archive of accounts from Cook (2017). For each account we found, we hand-checked it to confirm that it was a valid account associated with the respective legislator. We also cross-checked the hand-collected handles with information on Ballotpedia, following Kim *et al.* (2021). We only included accounts that had posted at least one tweet in the last year. In the end, we were able to identify 4109 legislator accounts. For these accounts, we then collected information on independent variables we include in our model. The state, party, and chamber of the legislators were collected from Ballotpedia, the Aggregate State Legislator Shor-McCarty Ideology Data (Shor, 2020), and the OpenStates dataset (https://openstates.org/).[2]

We collected information on race from the Candidate Characteristics Cooperative (C3) 2018 Data (Fraga *et al.*, 2021), Rutgers Center for American Women and Politics (CAWP),[3] and through manual searches for those who were not present in either of these datasets. We collected information on gender from Ballotpedia, and through manual search. We found only one legislator who identified as non-binary and removed them from the analysis to avoid the issue of perfect separation. For state legislatures' professionalism, we used the first dimension from Bowen and Greene (2014).

[2]We do not use Shor-McCarty Ideology scores because scores are not available for many of the recently elected legislators in our data.

[3]See https://cawpdata.rutgers.edu/women-elected-officials/race-ethnicity.

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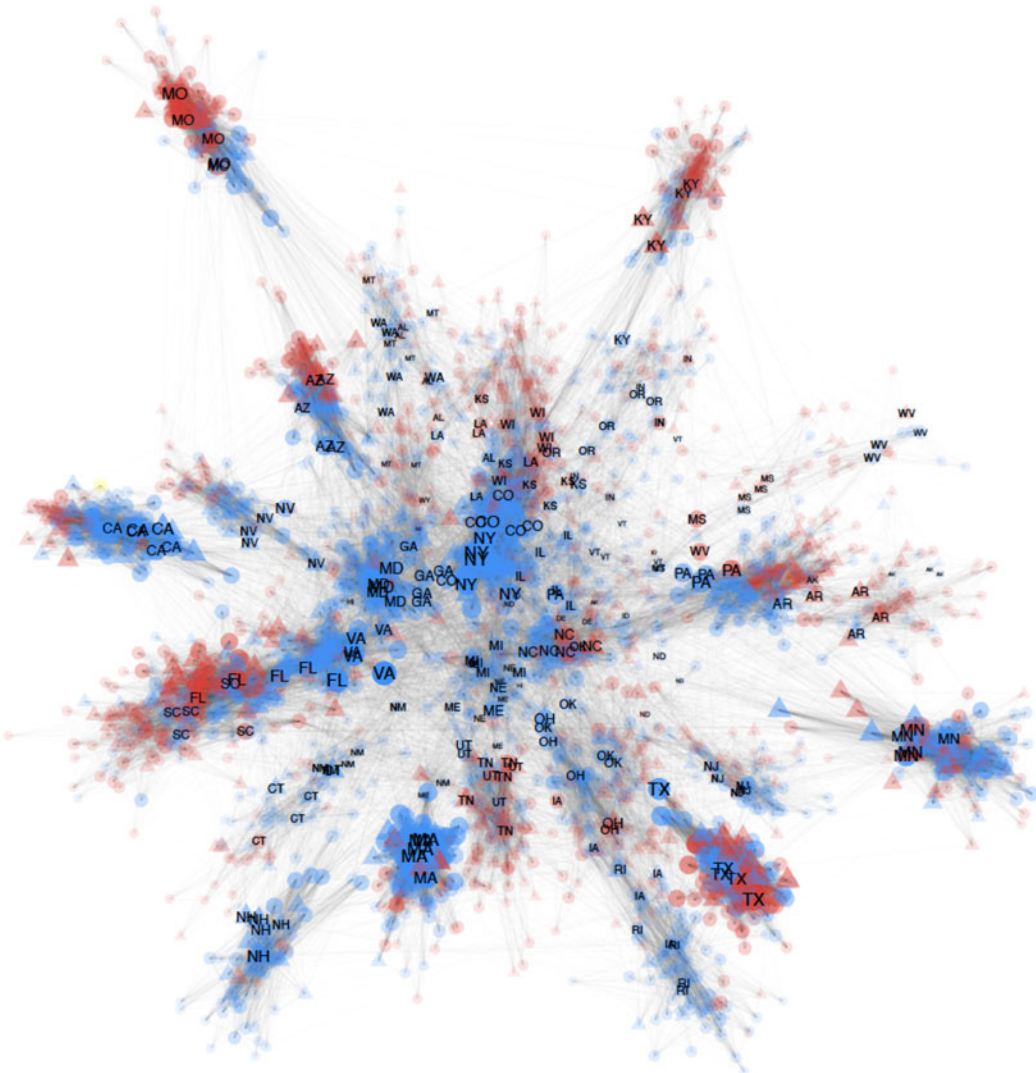

Figure 2. Inter-legislator mentions network.

We created tie and node-level attributes using the above information. For every pair of legislators, we constructed "similarity" variables. This results in a 4108 × 4108 matrix for each variable. We use binary indicators for state, party, chamber, race, and gender, where 1 indicates that legislators i and j belong to the same group (e.g., same state) and 0 otherwise. We use absolute difference in the state legislatures' professionalism scores to define professionalism difference between every pair of legislator—0 indicates the professionalism scores are the same for legislators i and j. For contiguity we use 2 to indicate that legislators i and j belong to the same state, 1 to indicate that a pair of legislators belong to different states but where state boundaries touch, and 0 to indicate that legislators i and j belong to different states with no boundary contact. Node-level variables follow the same logic.

4. Descriptive analysis

There are 4108 legislators in our analysis (56 percent of the 7383 overall who were serving at this time (Kim *et al.*, 2021)): 2244 Democrats (54.6 percent), 1853 Republicans (45.1 percent), and 11

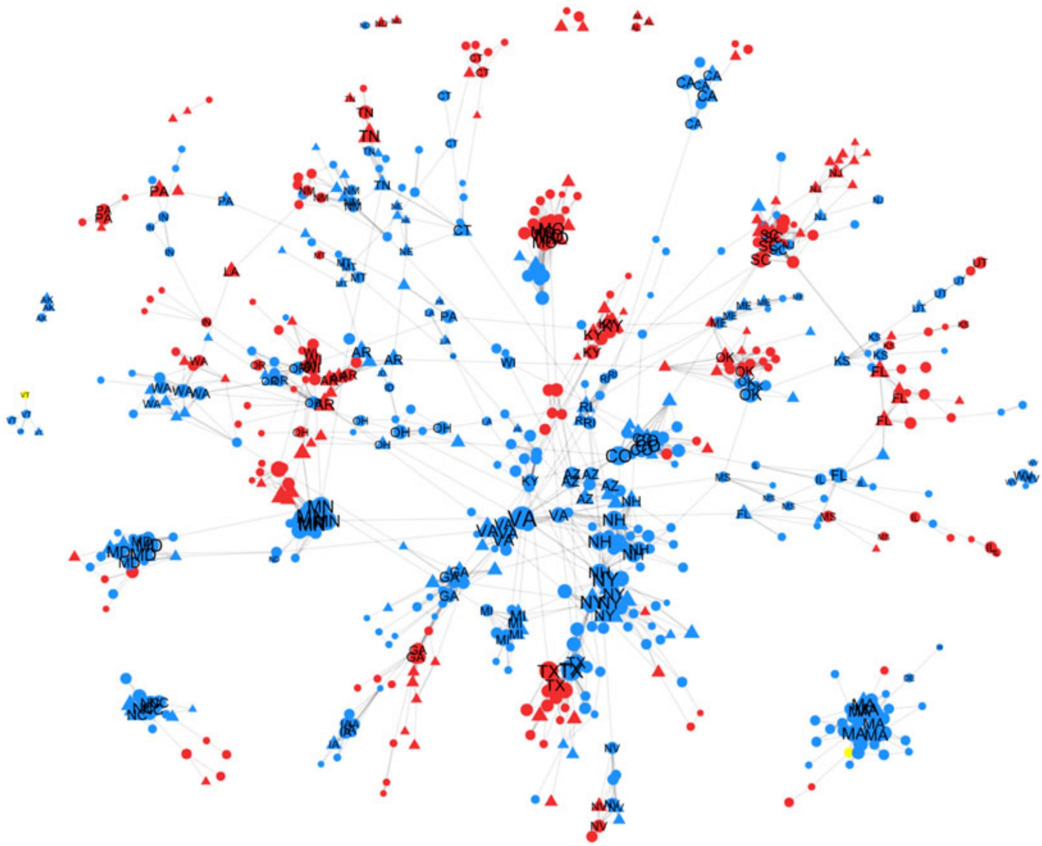

Figure 3. Inter-legislator retweet network.

Independents. Democrats are over-represented in these data due to their higher degree of activity on Twitter. This imbalance results in an approximate ten-percentage-point shift in the distribution of parties relative to the population of state legislators, of which in 2020 52 percent were Republicans and 46 percent were Democrats (Kim *et al.*, 2021). Due to the partisan imbalance, we emphasize that our results can be interpreted in the context of state lawmakers who choose to be active on Twitter, but are not directly applicable to the overall population of state legislators. Below we present visualizations of our networks, along with associated descriptive statistics.

4.1 Follower network

The follower network, visualized in Figure 1, is a directed, unweighted network with 159 346 edges. The nodes in the network plots are colored with Democrats in blue, Republicans in red, and Independents in yellow. Only 6.4 percent of the ties are cross-state and 21.5 percent of the ties are cross party. We see that the network is organized largely according to state and party clusters.

Tables 1 and 2 list the top 10 legislators who have the highest in and out degree centrality (i.e., receive and send the most ties, respectively). The most active legislators are nearly all Democrats, and most come from large states.

4.2 Mentions network

The mentions network, depicted in Figure 2 is a directed, weighted graph with 111 592 edges. Only 5.7 percent of the ties are across state and 23.0 percent of these ties cross party lines.

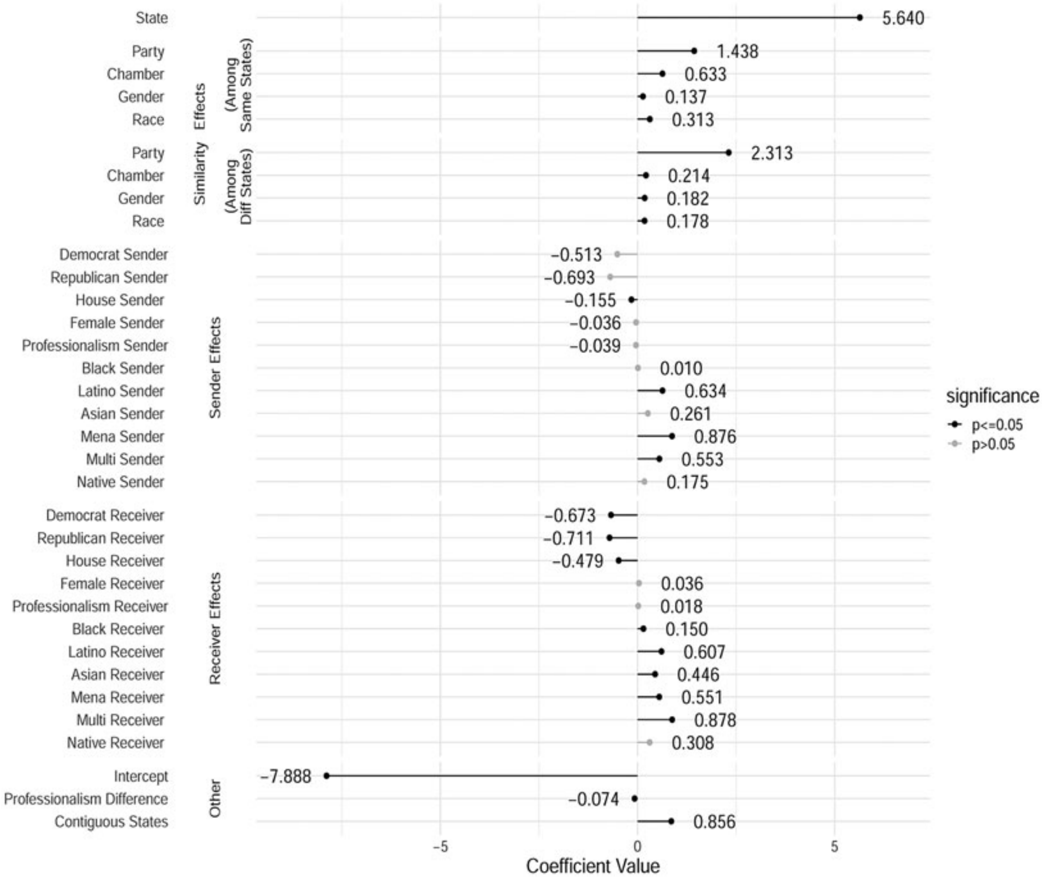

Figure 4. QAP results for the follower network.

4.3 Retweet network

The retweet network is also a directed and weighted network where a link exists between two legislators if one of them retweets the other (Figure 3). If legislator i retweets a tweet by legislator j then a link exists from i → j. The weights are equal to the number of times i retweets j. In total, 3.8 percent of the retweets are cross-state and 9.5 percent cross party lines.

5. Modeling results

We first review the results for the followers network (Figure 4). Many of the effects we estimate need to be interpreted in the context of interaction. Specifically, we analyze how similarity in party, chamber, gender, and race of legislators are related to the connections (dyads) formed between legislators within the same state and across different states.

From the results, we see that if two legislators are from the same state, they are more likely to be tied than are legislators from different states, regardless of party, race, chamber, or gender. Legislators from the same party are more likely to follow each other, though this effect is stronger for legislators from different states than it is for legislators from the same state, as the Party (Among Diff State) coefficient of 2.313 is much larger than the Party (Among Same State) coefficient of 1.438. We find chamber, race, and

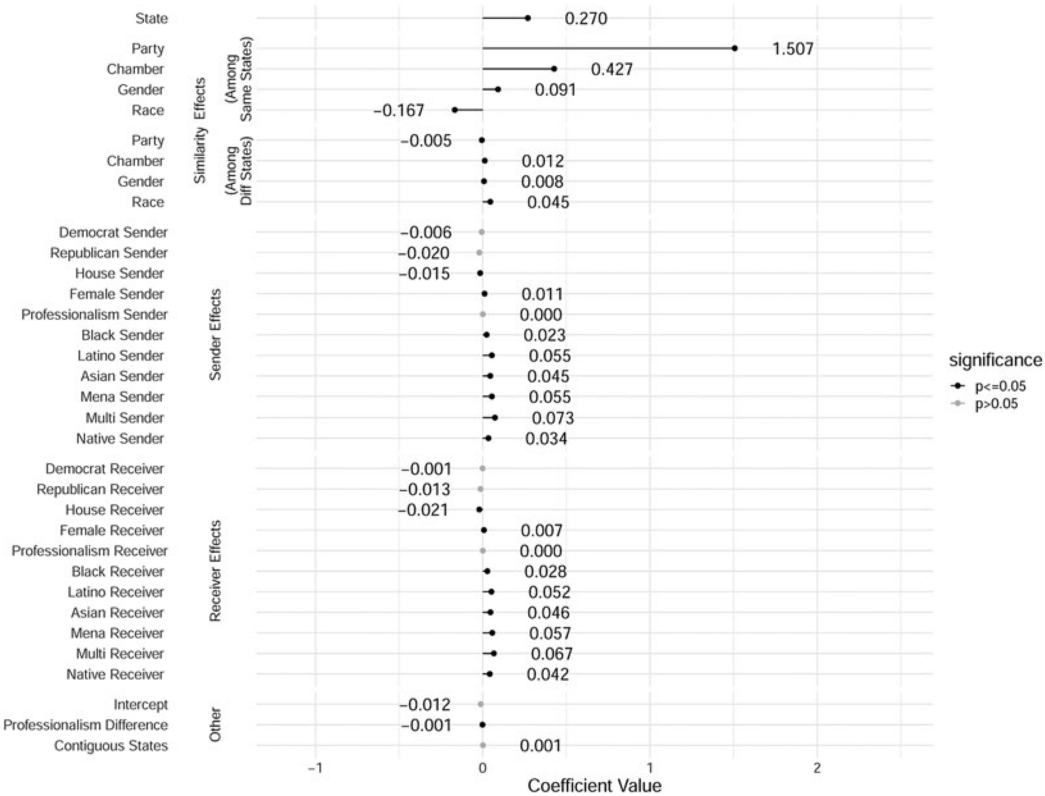

Figure 5. QAP results for the mentions network.

gender-based homophily in the follower network. Race and chamber-based homophily are significantly stronger in within-state ties.[4]

Considering terms that are not included in the interactions, two legislators are less likely to follow one another the larger the differences in the professionalism of their legislatures. Sender and Receiver effects of being a female (versus male) are not statistically significant. Democrats and Republicans are less likely to receive ties than are independents. Senators send and receive more ties than do house members. Non-white legislators are more likely to receive ties than white legislators (the effect for Native Americans is not significant). Legislators who are geographically close are more likely to follow one another.

Next we discuss results with the mentions network (Figure 5). Similar to the follower network, if two legislators are from the same state, same chamber, or of the same gender and race, they mention one another more. Pairs of legislators are also less likely to mention one another the larger the differences in their legislatures' professionalism scores. Further, Non-Republicans, senators, and non-white legislators mention others more and are also mentioned more compared to Republicans, members of lower chambers, and white legislators. Interestingly, unlike the follower network, two legislators from different states are more likely to mention one another if they are from different parties. Female legislators are more likely to mention and be mentioned than male legislators. Looking at the interacted terms, chamber and gender effects are stronger

[4]The p-values for the conditional effects of same party, chamber, race, and gender are calculated by estimating the model once with each variable interacted with a same-state indicator and once with each variable interacted with a different-state indicator. Since no covariance matrix is estimated with permutation methods, such as QAP, we cannot use the conventional formulas for conducting inference with interaction effects, as presented by Brambor *et al.* (2006).

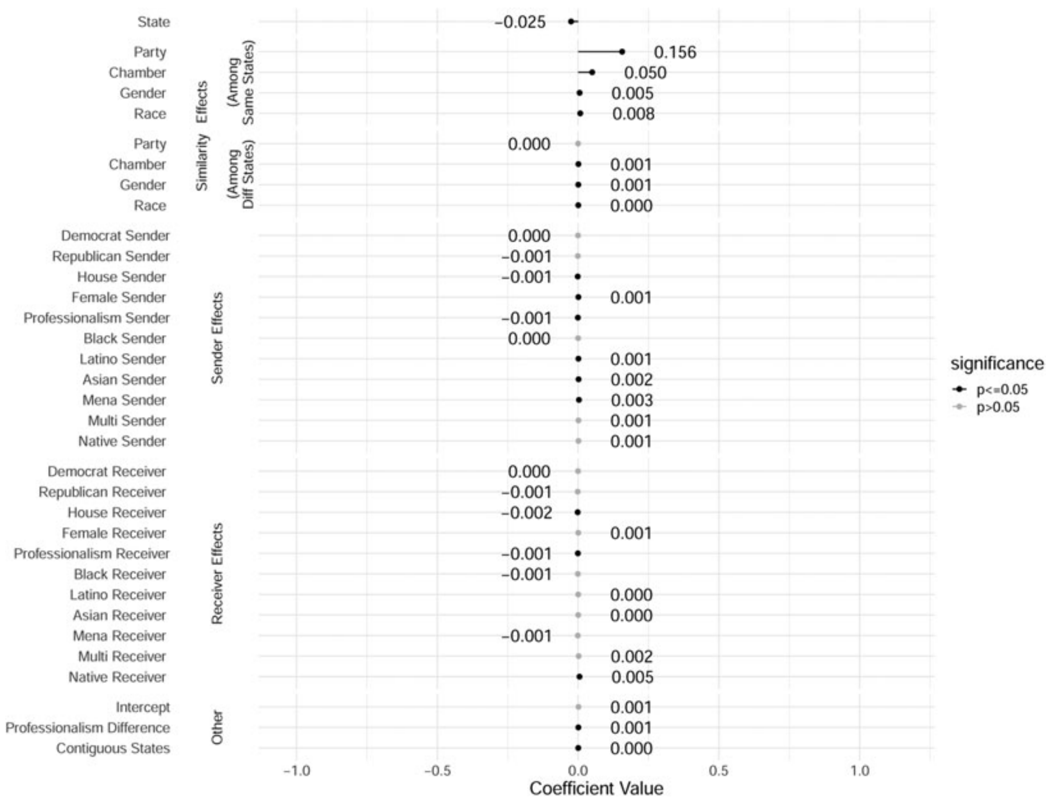

Figure 6. QAP results for the retweets network.

within states than across states; that is, legislators from the same chamber and gender mention one another more if they are from the same state. But unlike the follower network, party effects are stronger within states than across states, so legislators from the same party are more likely to mention one another if they are from the same state. Also, race effects are stronger across states than within states. The effect of geographic proximity between legislators is not significant.

The last network we analyzed is retweets (Figure 6). Two legislators from the same party, chamber, or who are of the same gender and race retweet each other more. But legislators from different states are more likely to retweet one another. Senators are more likely to send and receive retweets as compared to those serving in the lower chamber. Female legislators retweet and get retweeted more than male legislators. Sender and Receiver effects for non-whites is not significant. Partisan, chamber, and identity effects are stronger within states than across states. Legislators who are geographically nearer retweet one another more.

There are some consistencies (and inconsistencies) across networks that are worth noting. First, for legislators from different states, in two of the three networks legislators do not exhibit a preference for tying with legislators of the same party. Only in the followers network do we find significant partisan homophily in cross-state ties. In contrast, for legislators in the same state we find partisan homophily in each network. This pattern is consistent with a greater adherence to party lines in online discussions of within-state issues than in cross-state interactions. The greater prevalence of within-state partisan homophily in retweets and mentions may be due to the fact that these are easily observable active interactions, whereas following is relatively passive and difficult for others on the platform to observe.

Among legislators from different states, we do, however, find that legislators are more likely to tie with others of the same race and gender—indicating that identity factors play a major role in shaping cross-state connections.

6. Discussion

There is a complex, national-scale online network of state legislators. It is characterized by a core of Democrats with clusters organized by party and state. The Twitter networks that we introduce and analyze provide a unique view of state legislative behavior, as we can observe connections between lawmakers that cross state boundaries. In our analysis of the factors that are associated with tie formation, we find that in-state ties follow patterns that are commonly observed in legislative networks—legislators are more likely to tie with those in their own parties, and in the same chamber. When it comes to cross-state ties, only in follower relationships do we find partisan homophily. We do, however, see consistent homophily effects of gender and race in the formation of cross-state ties, suggesting the importance of demographic identity factors. Beyond specific findings, our contribution advances the concept and empirical understanding of a national network of state-level policymakers.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/psrm.2024.52. To obtain replication material for this article, https://doi.org/10.7910/DVN/IYDYOI

Acknowledgements. This research was supported by the National Science Foundation (Award Abstract Number: 2318460).

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Cite this article: Gopal I, Kim T, Nakka N, Boehmke FJ, Harden JJ and Desmarais BA (2024) The national network of US state legislators on Twitter. *Political Science Research and Methods* 1–13. https://doi.org/10.1017/psrm.2024.52