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Online appendix for “Effectiveness of Connected Legislators”

Abstract

In this online appendix we present results omitted in the paper ”Effectiveness of Connected Legislators.”

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1 Proof of Proposition 1

The optimal level of effort l^i by a type $i = 1, ..., n$ solves the problem:

$$\max_{l_i} \left\{ A_i + \varphi \left(\sqrt{\textstyle\sum_{j=1}^n g_{i,j} E_j} \right) \cdot l_i - (l_i)^2 /2 \right\}, \tag{1}$$

Substituting the solution to this maximization in condition (2) in the paper, we obtain that the equilibrium levels of legislative efficiency for a type $i = 1, ..., T$ are given by:

$$E_i = A_i + \frac{\varphi^2}{2} \textstyle\sum_{j=1}^n g_{i,j} E_j. \tag{2}$$

These equations can be expressed in matrix form as:

$$\left[I - \frac{\varphi^2}{2} G \right] \cdot \mathbf{E} = \mathbf{A} \tag{3}$$

where $E = (E^1(G, A), ..., E^T(G, A))'$ is the vector of legislative effectiveness $E^i(G, A)$ solving (3), and $A = (A^1, ..., A^T)'$ is the vector of types' characteristics. It is easy to show that given Assumption 1, E_i are uniquely defined with:

$$(E^1(G, \mathbf{A}), ..., E^T(G, \mathbf{A}))' = \left[I - \left(\varphi^2/2 \right) \cdot G \right]^{-1} \mathbf{A}.$$

The vector $[I - \frac{\varphi^2}{2} \cdot G]^{-1} A$ coincides with the vector of weighted Bonacich centralities $b(\varphi^2/2, G, A) = (b_1(\varphi^2/2, G, A), ..., b_n(\varphi^2/2, G, A))$ with weights $A = (A^1, ..., A^T)'$, a well know concept in sociology and economics (see Ballester et al. [2006] for instance). We therefore have that there is a unique equilibrium in which legislator i's legislative effectiveness is equal to $b_i(\varphi^2/2, G, A)$. ■

2 Additional results from Section 4

2.1 Marginal effects of individual characteristics on effectiveness

In Table A1, Panel (b) we show the magnitudes of the marginal effect of a change in x_{ik} for y_i, based on the estimates in Column (3) of Table 2. We report the mean, standard deviation, minimum and maximum values. Panel (a) shows the OLS marginal effects, which can be compared to the mean values in Panel (b). In comparing the OLS estimates with the average effects of the model with network effects, we can see that the OLS estimates overestimate the effects of almost all of the legislators' characteristics. The OLS estimates are even higher than the maximum estimate from the model with network effects. For example, the OLS estimates suggest that being a committee chair is associated with an increase of 1.97 LES score points. This is higher than what is estimated in the network model with the strongest externalities (17% lower in magnitude). Thus, this evidence suggests that the effects of the politicians' characteristics are capturing network effects.

2.2 Robustness Checks

In model (7) there is a slight overlap in the data generating process of the dependent variable (LES), and the measure used to control for legislators' ideology (DW-nominate score). Specifically, the overlap comes from roughly ten percent of the bills introduced in each Congress that arrive at the voting stage. The ones that become law are considered in the LAW component of the LES score. At the same time, the roll call votes on these bills represent a portion of the votes used to estimate the dw-nominate score. In our first robustness check, we thus estimate model (7) when removing DW-nominate score. We rely on the variable capturing party membership to control for ideology. The results of this exercise are presented in Column (1) of Table A2. Estimates are qualitatively unchanged with respect to Table 2: the externality remain positive and statistically significant. Next, we introduce in model (7) dummies for all the Congressional committees (21 dummies) in the specification. Committees are an important institutional feature of the legislative process and have been shown to be an important determinant of social connections (see, for example, Caldeira et al. [1987], Caldeira et al. [1993] and Arnold et al. [2000]).[1] As shown in Table A2, column (2), the estimates barely change, confirming the robustness of the results. Interestingly, the importance of unobserved factors remains statistically different from zero, signaling that unobserved factors that simultaneously affect politicians' legislative activity and patterns of cosponsorships are not the same for all members of a given committee. We conclude our set of robustness checks by adding in the control set of the Congress member's previous legislative experience. This is one of the nine factors indicated by Volden and Wiseman [2009] as drivers of legislative effectiveness. The Legislative Effectiveness Project dataset, however,

[1] Caldeira et al. [1993] find that representatives who share committee assignments are more likely to identify one another as a "friend" or "respected legislator," and that the probability of social bonds increases with the number of shared assignments. As noted by Caldeira et al. [1993], "the business of the legislature largely happens in its committees and subcommittees, where legislators become familiar with and take a measure of colleagues in a task-oriented environment. Legislators on the same committees or subcommittees share substantive interests and common workloads, so they have good reasons for establishing a relationship" (p. 12).

does not report this information for about 20% of the politicians in our sample. Therefore, we did not include it in our previous analysis to preserve the sample size. In Columns (3) and (4) of Table A2 we report the estimation results of model (7) when it is run on the subsample of Congress members for which this information is available. Previous legislative effectiveness is captured using a dummy taking value one whether a legislator has previously served in the state legislature (and 0 otherwise) and its interaction with the state's level of professionalism (see, e.g. Squire [1992]). Table A2, column (3) shows that our results hold true, and the point estimates are very close in magnitude to the ones in Table 2, Columns (2) and (3) in the paper. Columns (4) of Table A2 show the results with committee dummies. Again, the estimates of the externality remain positive and statistically significant, indicating that our evidence of network effects is not driven by common shocks at the level of the committee. Finally, our analysis is based on least square regressions with weights inversely proportional to the variance of the observations (legislators) in each state. This is done to give each data point its proper amount of influence over the parameter estimates in order to get the most precise parameter estimates possible. The size of the weight indicates the precision of the information contained in the associated observation, so that each data point receives its proper amount of influence over the parameter estimates. In the last column of Table A2 we show our estimation results when removing the weights. It shows that our evidence remain qualitatively unchanged.

2.3 Comparison with other centrality measures

It is useful to compare the predictions of our model with the predictions we would have obtained if we attempted to establish the importance of network centrality using standard measures that are not backed by a theoretical analysis. There are two issues to discuss. The first is the effect of the traditional measures when endogeneity issues are taken into account. The second is how our analysis would change if we included these variables in our estimation.

Table A3 presents OLS estimates of the relationship between politicians' legislative effectiveness and Degree, Betweenness, Closeness and Eigenvalue centralities.[2] The estimates of all effects of the control variables that are statistically significant have the expected signs (the same as in

[2] Degree centrality counts the total number of direct connections. Closeness centrality measures the length of the average shortest path passing between a node and each other node. Betweenness is equal to the number of shortest paths from all nodes to each other that passes through that node. Eigenvalue centrality of agent i is the ith component of the eigenvector associated to the highest eigenvalue of G. See Jackson [2008] for an introduction and detailed description of these measures.

Table 2), and it appears that a high connectedness score in the network of cosponsorship has a positive and significant impact in advancing agenda items [Columns (1), (3), (5), and (7)]. This is consistent with Fowler [2006], who studied the relation between centrality measures in the network of cosponsorship, and the number of amendments passed by each legislator in each Congress. However, when controlling for the unobserved factors related to agent's connectivity following our estimation strategy,[3] centrality measures are no longer significantly different from zero [Columns (2), (4), (6), and (8)]. More importantly, when those centrality measures are included in a regression where network effects are modeled as predicted by the theory [Column (9)], they lose statistical significance: only the measure of network externality supported by Proposition 1, ϕ, seems to matter. Table A4 show the ranking of legislators according to the different centrality measures. We present the top ten politicians according to different centrality measures in each of our Congresses together with their score in terms of legislative success (LES score). The rankings confirm that while the top ten politicians by Bonacich centrality are associated with very high LES scores, this is not always the case for the rankings in terms of other measures. For example, looking at the first Congress in our data (the 109th Congress), Democrat Representative Bob Filner (California's 51st congressional district from 1993 to 2012) or Republican Representative Joe Wilson (in office since 2001 for South Carolina's 2nd district) are ranked very high in terms of betweeness (respectively one and seven) but do not appear to be very successful (as measured by the LES score).

2.4 Analysis of heterogeneity

To study the effect of individual characteristics on social spillovers, let us generalize equation (2) in the paper to allow j's usefulness to depend on her/his characteristics:

$$E_i = A_i + \sqrt{\varphi_i \sum_j g_{i,j} \left(\eta_j \cdot E_j\right)} \cdot l_i \tag{4}$$

In (4) we allow for heterogeneity in social spillovers by splitting φ in $2n$ variables, $(\varphi_i)_{i=1}^n$ and $(\eta_j)_{j=1}^n$. The variable φ_i can be interpreted as measuring how legislator i's effectiveness is susceptible to the effectiveness of her/his socially connected peers: a legislator with a higher φ_i is able to better "use " all the other legislators whom he has befriended. The variable η_j, instead,

[3] For each centrality measure, in the first step, a politician's centrality score in the cosponsorship network is explained as a function of individual characteristics and the centrality measure in the alumni network. The residuals of this regression are then used as a selection correction term in the second step regression when the LES score is explained by the centrality score (and controls).

describes how legislator j's effectiveness is useful to her/his socially connected peers: a legislator j with a higher η_j is more "useful" to all the legislators who have befriended him.

Following essentially the same steps as in Section 2.2, we can derive the analog of (3) in the paper for this more general model, obtaining:

$$[I - \Phi \cdot G \cdot \Lambda] \cdot \mathbf{E} = \mathbf{A} \tag{5}$$

where Λ is a diagonal matrix with ith diagonal component equal to $\eta_i/\sqrt{2}$ and Φ is a diagonal matrix with ith diagonal element equal to $\varphi_i/\sqrt{2}$.

To bring (5) to the data, we assume:

$$\begin{aligned} \varphi_i &= \sqrt{2}(\theta_0 + Z_i' \boldsymbol{\theta}_1) \\ \eta_j &= \sqrt{2}(\gamma_0 + K_j' \boldsymbol{\gamma}_1) \end{aligned} \tag{6}$$

where $Z_i = (z_i^1, ..., z_i^k)$ is a vector of characteristics of j, θ_0, $\boldsymbol{\theta}_1 = (\theta^1, , ..., \theta^k)$ and γ_0, $\boldsymbol{\gamma}_1 = (\gamma^1, , ..., \gamma^k)$ are coefficients. To interpret (6), imagine that the lth component of $\boldsymbol{\theta}_1$ and $\boldsymbol{\gamma}_1$ is seniority. Then $\theta^l > 0$ (respectively, $\theta^l < 0$) means that the seniority of a legislator increases (resp., reduces) the ability of the legislator to "use " the effectiveness of her/his socially connected peers; $\gamma^l > 0$ (resp., $\gamma^l < 0$) means that seniority of a legislator increases (resp., reduces) the usefulness of the effectiveness a legislator to her/his socially connected peers.

Once we insert (6) in (5), the parameters of the model can be again jointly estimated using NLLS as in the estimation of (8) in the paper. The estimation of (5), in which we include the legislators' personal characteristics (the Z variables), are presented in Table 3 for a few characteristics. Table A5 shows the results for the remaining characteristics.

2.5 Analysis of the influence of parties

To allow for party effects, let us reorder the legislators in Congress r so that the first n_R are Republicans and the second $n_D = n - n_R$ are Democrats. The matrix G can now be divided into four submatrices. The top left $n_R \cdot n_R$ dimensional submatrix collects the interactions of Republicans with fellow Republicans; the bottom right $n_D \cdot n_D$ dimensional submatrix collects the interactions of Democrats with fellow Democrats; the top right $n_R \cdot n_D$ dimensional submatrix shows the influence of Democrats on Republicans (i.e. $g_{i,j,r}$ where j is Democrat and i Republican); and finally the bottom left $n_D \cdot n_R$ dimensional submatrix shows the influence of Republicans on Democrats (i.e. $g_{i,j,r}$ where j is Republican and i Democrat).

We can now decompose G_r in two $n \times n$ matrices G_r^* and G_r^{**} with $G_r = G_r^* + G_r^{**}$, where G_r^* is a matrix that has the same top left and bottom right components as G_r and it is zero otherwise and G_r^{**} is a matrix that has the same bottom left and top right components as G_r and it is zero otherwise. Given this, we can extend the basic model by assuming:

$$E_{i,r} = A_i + \sqrt{\varphi^* \sum_j g_{i,j,r}^* \cdot E_{j,r} + \varphi^{**} \sum_l g_{i,l,r}^{**} \cdot E_l} \cdot l_{i,r} \tag{7}$$

In (7) we are distinguishing between the effects of intraparty and interparty social connections, allowing them to be different. If the impact of i's effectiveness on a legislator of the same party is greater (resp. smaller), than that of a legislator of a different party, then we should see $\varphi^* > \varphi^{**}$ (resp., $\varphi^* < \varphi^{**}$). If we impose $\varphi^* = \varphi^{**}$, we are back at the baseline model (2).

Starting from (7), we can easily derive:

$$E_{i,r} = A_i + \frac{1}{2}\left[\varphi^* \sum_j g_{i,j,r}^* \cdot E_{j,r} + \varphi^{**} \sum_l g_{i,l,r}^{**} \cdot E_{l,r}\right]. \tag{8}$$

In matrix form, it becomes:

$$\mathbf{E}_r = \left[I - \frac{1}{2}\left(\varphi^* G_r^* + \varphi^{**} G_r^{**}\right)\right]^{-1} \cdot \left[\alpha \cdot \mathbf{1} + X_r \boldsymbol{\beta} + \boldsymbol{\varepsilon}_r\right]. \tag{9}$$

Given the social network G_r, from which we can easily construct G_r^* and G_r^{**}, and the covariates X_r, we can now estimate (9) as before by NLLS. The results of this analysis are presented in column (1) of Table A6.

2.6 Analysis of the influence of weak and strong ties

The analysis of strong and weak ties mimics the approach of the previous section (2.3). The matrix G_r representing legislator connections in Congress r is decomposed in two matrices G_r^S and G_r^W with $G_r = G_r^S + G_r^W$. In this setting, G_r^W is a matrix registering weak tie connections between legislators. Its generic element $g_{i,j,r}^W$ indicates the fraction of bills that j co-sponsored to i is greater than zero if i and j forms a weak tie, and zero otherwise. By contrast, G_r^S keeps trace of the interactions between legislators linked by strong ties, with generic element $g_{i,j,r}^S$ greater than zero if i and j forms a strong tie, and zero otherwise. Given this, we can extend the basic model by assuming:

$$E_{i,r} = A_i + \sqrt{\varphi^W \sum_j g_{i,j,r}^W \cdot E_{j,r} + \varphi^S \sum_l g_{i,l,r}^S \cdot E_l} \cdot l_{i,r} \tag{10}$$

Similar to (7), equation (9) separates the effect of weak and strong ties, allowing them to be different. If the impact of weak ties on i's effectiveness is greater (resp. smaller) than that of a strong ties, then we should see $\varphi^W > \varphi^S$ (resp., $\varphi^W < \varphi^S$). Starting from (9), we obtain

$$E_{i,r} = A_i + \frac{1}{2}\left[\varphi^W \sum_j g^W_{i,j,r} \cdot E_{j,r} + \varphi^S \sum_l g^S_{i,l,r} \cdot E_{l,r}\right]. \tag{11}$$

In matrix form, it becomes:

$$\mathbf{E}_r = \left[I - \frac{1}{2}\left(\varphi^W G^W_r + \varphi^S G^S_r\right)\right]^{-1} \cdot [\alpha \cdot \mathbf{1} + X_r \boldsymbol{\beta} + \boldsymbol{\varepsilon}_r] \tag{12}$$

Given the social network G_r, from which we can construct G^W_r and G^S_r, and the covariates X_r, we can now estimate (9) as before by NLLS. The results of this exercise can be found in columns (2) and (3) of Table A6.

2.7 Analysis of the timing of interactions

In this section, we investigate whether network effects are more important in the early or late stages of the legislative process. We follow the classification presented by Volden and Wiseman [2009] who categorize bills as follows: bills proposed in the House of Representatives (BILL); bills that received any action in committee (AIC); and bills that received some action beyond the committee stage, distinguishing here between those that have passed (PASS) in the House, those that have not passed in the House (ABC), and those that have become law (LAW). The Legislative Effectiveness score (LES) that we used in the previous analysis is calculated by averaging the five indicators (BILL, AIC, ABC, PASS, LAW) and then normalizing so that the average LES takes a value of 1 in each Congress. (The fraction of bills in each category is weighted by the category's importance.)[4] We now perform the same analysis considering each class separately.

Table A7 collects the NLLS estimations of (2) when the LES score is decomposed in order to isolate the Congress members' effectiveness at different stages of the legislative process. In Column (1), the dependent variable measures the Congress members' effectiveness at the very early stages of the legislative, i.e. when effectiveness is calculated using only bills categorized as

[4] Volden and Wiseman [2009] categorize a bill's relevance in three groups: i) commemorative (C), ii) substantive and significant (SS), iii) substantive (S). A bill is deemed commemorative (C) when its subject is a provision for a renaming, a commemoration, the private relief of an individual, and the like. A bill is deemed substantive and significant (SS) if it had been the subject of an end-of-the-year write-up in the Congressional Quarterly Almanac. Finally, all other bills, and any "commemorative" bills that were also the subject of a CQ Almanac write-up are classified as substantive (S). Bills assigned to the substantive and significant category are counted 10 times more than those in the commemorative category, and twice as much as those in the substantive category.

BILL. In Column (2), the dependent variable is effectiveness computed using the bills in BILL and the bills deemed as AIC, thus capturing effectiveness at the next step in the legislative process. Finally, in Columns (3), the dependent variable is effectiveness of Congress members at the later stages of the legislative process. In this case, the dependent variable is calculated including all bills that received any action beyond the committee stage on the floor of the House (ABC, PASS, LAW). The three dependent variables (BILL, BILL+AIC, ABC+PASS+LAW) are normalized so that their average take a value of 1 in each Congress. As anticipated in the discussion in the paper, the results in Table A7 show that network effects are positive and significant for all stages of the legislative process.

3 On the ERGM analysis in Section 5

3.1 Specification

In the cosponsorship network used in the baseline analysis of Section 4, $g_{i,j}$ is equal to the total number of i's bills cosponsored by j: the matrix $G = (g_{i,j})_{i,j \in N}$ therefore describes a weighted network (i.e. it includes information on the intensity of connections), that is very dense, and that changes over time. It is however well known that ERGMs can be fitted when the network is sufficiently sparse, and it has a relatively small sample size – typically around 100 nodes (see, for instance Chatterjee et al. [2011], Handcock [2003a] and Schweinberger [2011] on this). State-of-the-art techniques, moreover, allow ERGMs to model either the formation of the intensive margin of the network in one temporal instance (binary and weighted ERGMs); or the temporal evolution of network structure, assuming that the panel is balanced and all connections have the same intensity (Separable Temporal ERGMs) (Krivitsky and Handcock, [2014]). To cope with these constraints on the use of ERGMs, in the analysis of Section 5 in the paper, we have followed the extant literature as follows. First, we have focused on the political network formed in a single legislature: the last of our dataset, the 113th legislature. This is the approach also used by Bratton and Rouse [2011], Cranmer and Desmarais [2011], Fischer and Sciarini [2015], who also focus the analysis of cosponsorship networks using one legislature. Second, we have used a network definition in which two Congress members i and j are connected if j cosponsored at least 5% of the bills sponsored by i, an approach also used by Cranmer and Desmarais [2011].

Regarding the specification of the ERGM, it should be noted that ERGMs require to include only variables explaining a significant number of connections in the network. We are therefore prevented from using the dummies "Majority Leader," "Minority Leader" and "Speaker of the House" given that connections to these types of politicians represent less than the 0.05% of all possible connections in the network. By including those characteristics, we would place a disproportionate probability on a too small set of outcomes, generating well-known problems of near degeneracy when fitting the model (Handcock [2003b], Snijders et al., [2006]). We allow for more complex structural effects, as captured by Geometric Weighted Edgewise Shared Partners (GWESP) and Geometric Weighted In-Degree (GWIDegree) [Hunter and Handcock, 2006]. GWESP is used to model transitivity effects (e.g. the propensity for i and j to have shared collaborators), while controlling for diminishing marginal effects of additional shared cosponsors. GWEsp therefore measures transitivity while accounting for the fact that there is a limit to the number of possible shared cosponsors that two Congress members can maintain, both for reason of time and for the limited number of Congress members interested in their political agenda. GWiDegree estimates the change in the likelihood given the degree of the nodes involved, but with marginally decreasing weighting as degree increases. It can be interpreted as a proxy of popularity effects in the network. In order to adequately model transitivity and popularity we have also included in the model variables capturing explicitly how the presence of certain ties may induce other ties to form. Specifically, we control for differences in legislators' characteristics (gender, race, and state), institutional position (party affiliation, seniority in Congress, and chairmanship), and ideology (distance to the median). Furthermore, we include a control for the presence of a link between two legislators in the alumni network and for the number of legislators' shared committees. All these controls are included because triangles of similar actors may be a by-product of homophilous/heterophilous dyadic selection processes (Snijders et al., [2006]): e.g. Congress members working in the same committee (homophily) may be more likely to form a triangle (transitivity effect).

3.2 Evaluating the goodness of fit

To evaluate the goodness of fit of the ERGM specification, we use the Goodness of Fit heuristic methodology suggested in Hunter at al. [2008] (hence, GOF). To evaluate the fitness of the specification, the ERGM estimates are used to simulate new sets of connections for the nodes conditional on the density of the observed network, and obtain 100 new instances of the network.

A number of global characteristics of these simulations are then measured. The distribution of these characteristics in the observed network is compared with the same distributions in the sample of simulated networks in order to verify if the observed network can be considered as a typical realization from the generative model. Given the focus of our analysis on the importance of network centrality measures, we use degree centrality, betweenness centrality and eigenvector centrality as benchmark statistics. The GOF procedure accepts a network specification if, for each centrality measure, the frequency of its values in the observed network lies between the minimum and the maximum frequency observed in the simulated networks. The GOF test assesses the extent to which our ERGM specification incorporates all the fundamental drivers of connectivity in the network, and correctly replicates the structural features of the observed network (Hunter at al. [2008]).

3.3 Results

The ERGM estimation results and the results of the GOF tests are reported in Table A8, and Figure A1 respectively. Consider, for example, the top-left figure of Figure A1, which shows a boxplot of the proportions of nodes (y axis) with each given degree value (x axis) in the networks simulated from the estimated ERGM. Dotted lines indicate the minimum and the maximum values of the boxplots, while the bold line indicates the proportions of nodes observed in the actual cosponsorship network. We have verified that for all the network measures considered, the bold line lies generally well within the boxplots, showing that, on average, our generative models produce network statistics that are similar to the observed ones, and therefore successfully replicate the actually observed network characteristics. We conclude that the specification of the ERGM estimated provides a good fit of the observed cosponsorship network.

As we mentioned in Section 5, a concern that one may have is that in estimating the ERGM we are omitting some unobserved but relevant variable, a typical and unavoidable problem of ERGM analysis. A correction of this has been proposed by Box-Steffensmeier et al. [2018] who suggested a generalization of ERGM, the Frailty Exponential Random Graph Model (FERGM) and a test to verify if a FERGM performs better than an ERGM. We perform this test using the software routine provided by Morgan et al. [2018].

Before commenting on the finding, we should note two preliminary issues. The current state-of-the-art software used to implement FERGMs (Morgan et al., 2018) has two constraints: i)

FERGMs cannot be implemented when using a directed network, as in the case of co-sponsorship data; ii) when fitting the model, it is not possible to run a constrained estimation: i.e., assign non-zero probability only to distributions of networks with the same number of edges of the observed network. This is a common procedure used in the ERGM framework to decrease computational time and avoid phase transition, a well-known ERGM near-degeneracy issue arising when the network is extremely dense (see among others, Häggström and Jonasson, [1999]; Burda et al. [2004]; Park et al., [2004]), as for the case of co-sponsorship networks. For this reason, in order to estimate FERGMs, we were required to symmetrize connections in the co-sponsorship network, so that now, e.g., i is connected to j if i cosponsored j or vice versa. Moreover, since we had to remove the edge constraint on the estimation process, we were forced to include the number of edges in the network as an additional control in the model specification. In fact, when removing the edge constraint, the number of edges becomes the single most important statistics in the estimation process. This variable is used to create a baseline, a sort of ERGM intercept, indicating the average likelihood of connection between two nodes in the observed network. Conditional on this value, it is possible to correctly estimate any other local process underpinning the formation of the network. In our analysis, we find that there is no need to use FERGM. When comparing ERGM and FERGM using the procedure of Box-Steffensmeier et al. [2018] mentioned above, the former model reflects a 20.39% improvement in tie prediction relative to the latter model.

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