Network Transmission of State Court Precedent

Taran Samarth

December 14, 2022

Introduction

Literature Review

State court precedent is only controlling within each state: what New Jersey's supreme court decides has no immediate implications for Pennsylvania's judicial institutions. But, as the body of state and federal judicial decisions has grown, judges within each state looking to justify their arguments have looked towards other states' high courts for persuasive authority. Interstate precedent can guide judges when cases interact with laws which are similarly implemented in several states (for example, the Uniform Prudent Management of Industrial Funds Act, enacted in all states but Pennsylvania). Moreover, external state court precedent helps buttress decisions reached on other grounds (Walsh, 1997) and give judges authority to legitimate the introduction of new doctrines or rights into their state's legal tradition (Denniston, 2014).

What explains the transmission and citation of state court decisions across borders? Hinkle and Nelson (2016) propose two hypotheses: the proximity hypothesis, and the prestige hypothesis. Legislatively, interstate policy diffusion is more common when states are proximal in ideology and geography (Mallinson, 2021), in part due to shared information environments. Geographically and ideologically proximate citizens are exposed to similar political media, and nearby legislators are more likely to be exposed to policy updates in each other's states. Similarly, as state judges look to buttress conclusions that they have already reached, Hinkle and Nelson (2016) argue that cognitive biases direct them to first cite similar states where they expect to find support somewhere in their precedential regime. States that share federal circuits—which formed of nearby states—would also be expected to cite each other for legal reasons. Decisions in each circuit court are controlling on courts below, such that if the same federal questions arise in state high courts within the same circuit, they would have particular reason to cite each other's approaches to addressing similar questions under the same legal environments. Finally, state courts with ideologically proximate constituents may look to see how judges in similar political conditions tackled legal questions, especially if those judges are elected to office.

Proximity hypothesis: A state supreme court will cite more precedents from a sister supreme court that is more proximate to itself in terms of ideology, geography, and institutional features.

The prestige hypothesis observes that legitimation by citation is more persuasive when less-prestigious courts can "cite up" the ladder (Denniston, 2014, e.g.,). More resourced and professionalized judiciaries can be seen as producing "better" (more researched, persuasive, and valid) decisions. Courts that take on larger caseloads and have a more substantial body of precedent may tackle legal questions before other states, making their cases more likely to be cited when the same questions arise elsewhere.

Prestige hypothesis: A state supreme court will cite more precedents from a sister supreme court that is more prestigious.

Caldeira (1988) shows that prestige, professionalism, proximity, shared state court opinion reporters, and cultural linkage between state dyads explains the strength of citation ties in 1975 decisions. Repeating this analysis over decisions and citations in 2010 with updated measures of professionalism, Hinkle and Nelson (2016) show that prestige and proximity remain influential: state courts cite another more often when the cited court has high professionalism, high legal capital, high population, is in the same reporter region, shares a cultural linkage with the home state, and has an ideologically similar population.

Neither study, however, accounts for network dependencies (both use regression models with the number of citations from state i of state j as the outcome variable). While the two studies essentially address assortativity, neither accounts for transitivity—that state court i cites state court k more often when one of i's favored courts j also cites k—or reciprocity—that state court j cites state court i more often if i cites j. And these have intuitive reasons for likely occurring in the network. If judges in state i takes precedential cues from state court j for reasons of prestige or proximity, then the states j deems worthy of citation should cue to i's judges that those other states are worth citing. And states should be more likely to reciprocate ties, controlling for proximity and prestige: if state i cites state j, then the underlying reason that there are similar legal questions arising in both states may indicate to state j that state i is worth citing. Consequently, reciprocity and transitivity should occur in the network, but are unaccounted for in previous studies.

Reciprocity hypothesis: A state supreme court i will cite more precedents from a sister supreme court j when that sister court j cites the home court i.

Transitivity hypothesis: A state supreme court i will cite more precedents from a third sister supreme court k when a second sister court j that is often cited by court i cites the home court i.

Data and Methods

In this paper, I replicate the analysis produced in Hinkle and Nelson (2016), only using all state high court decisions from 2010.[1] While the network effects of interest are best studied over time—state courts may only start reciprocating ties or sending transitive ties after they have been established for a year or two (such that they have time to take notice)—the base tendencies are still likely present in a single-year analysis. Given theoretical reasons for network effects that could interfere with the study's fundamental conclusions about prestige and proximity, the analysis in Hinkle and Nelson (2016) is ripe for a network approach.

Replication of Table 1, Model 1 in Hinkle and Nelson (2016)

[Table 1 about here.]

I first visualize the network and describe centralities, reciprocity, and assortativity within the network. To account for reciprocity, transitivity, popularity (the propensity for states to be cited externally), and activity (the propensity for states to cite externally) in the replicated model, I model the strength of weighted directed citation ties (the number of times state i cited state j in 2010) using exponential random graph and additive and multiplicative effects models Minhas, Hoff and Ward (2019)(ERGM and AMEN, respectively). I control for the same covariate effects used in Hinkle and Nelson (2016), and I describe continuous covariates in histograms in Figure 1.[2]

[1] Model 1 from Hinkle and Nelson (2016) is successfully replicated in Table 1.

[2] With the lone exception of regional reporters, as I forgot to include them and the ERGMs take too long to repeat the analysis now!

[Figure 1 about here.]

Network Description

I show the network of citations from Hinkle and Nelson (2016) in Figure 2 with edges weighted per the number of citations sent in each dyad. The network is visually dense: 77% of possible ties exist.

[Figure 2 about here.]

To explore the structural dynamics of the network, I examine centrality (degree, strength, and eigenvector), reciprocity, and assortativity (degree and covariate—the latter of which I explore more fully in the inferential models).

Centrality

I examine three forms of centrality: degree centrality, strength centrality, and eigenvector centrality. Degree centrality counts how many nodes each node is connected to, while strength centrality sums the edge weights (citation counts) for those ties. Thus, degree centrality shows how well-connected nodes are, while strength centrality shows how active nodes are across all of their ties. Eigenvector centrality measures how strongly-connected each node is to other strongly-connected nodes. The top ten state courts for each metric are shown in Table 2. The most central nodes per the eigenvector and in-degree centrality measures overlap heavily. For the most part, the courts who get cited largely do not do much of the out-of-state citing: only three of the most in-degree central courts are among the top ten out-degree central courts, while only one of the most in-strength central courts is among the top ten out-strength central courts. This is consistent with expectations: the states that have lots of precedent that would get cited by other states have internal precedential regimes, and thus do not need to reach beyond their borders to the degree that other states reach into theirs. Indeed, the number of existing precedents is negatively associated with out-degree ($r = -.23$) and out-strength ($r = -.21$) centrality, while it is positively associated with in-degree ($r = .31$) and in-strength ($r = .30$) centrality. Controlling for existing precedent, the top ten states by weighted in-strength include several more states with small precedential regimes (Alaska, Wyoming, and Idaho, particularly), and controlling for 2010 caseload, the top ten states by weighted out-strength include only about half of the unweighted top ten states by out-strength. Thus, the propensity to send and receive citations is unsurprisingly influenced by how many opportunities to cite existed in 2010 and how much was available to be cited.

[Table 2 about here.]

Reciprocity

Using the ρ definition of reciprocity for weighted networks, I find that the network displays a weak degree of reciprocity ($\rho = .13$). The slight tendency for state courts to reciprocate citation tie strength–that is, cite another court that tends to cite it as often–is interesting, as that suggests that state courts mutually construct (to a small degree) precedential regimes that rely on each other. However, this tendency is likely conditional on some homophily–state courts in the same circuit, for example, likely reciprocate tie strength, since they are subject to the same federal precedent and thus have reason to cite other state courts' interpretation of circuit rulings.

Assortativity

Assortativity can help identify whether or not such circuit homophily or other forms of homophily are the case. I compute the assortativity coefficients by circuit, court ideology, citizen ideology, and in/out-strengths, as shown in Table 3. All strength assortativity coefficients are negative, showing that nodes with similar out-strengths and in-strengths are not any more likely to connect than dissimilar ones. While the coefficients for circuit and court ideology homophily are small, the coefficient for citizen ideology is larger (and, with jackknife $SE = .03$, significant), showing that state courts are more likely to be tied when their constituents are ideologically similar. The lack of homophily within circuits and by court ideology are very surprising, given that the straightforward theoretical intuitions for both (and evidence from Hinkle and Nelson (2016) for circuit homophily).

[Table 3 about here.]

Network Modeling

The descriptive analysis points towards a few network dynamics: that state court citation depends on the opportunities to cite (caseload) and be cited (legal capital) externally; state courts have a slight tendency to reciprocate citations; that preferential attachment by popularity and activity are not present in the network; and that state courts with ideologically homophilous citizens are more likely to cite each other. A more rigorous test of this behavior can be provided through inferential models that can account for the wide spread of nodal and edge covariates at play in the proximity and prestige hypotheses. I estimate three models over the data to account for these dependencies, alongside the same covariates (excluding reporter region, interactions between circuit homophily and contiguity, and population differences) from Hinkle and Nelson (2016): two count ERGMs (one that accounts for popularity and one that accounts for activity) and one AMEN model (which accounts for network dependencies). Theoretically, AMEN accounts for all first-, second-, and third-order dependencies without need for specification through latent variable estimation (**?**). ERGMs require that network terms be explicitly specified, so I include the following network terms:

- **sum**: The sum of the weights of all network ties
- **nonzero**: The count of all non-zero ties in the network
- **mutual**: A parameter ($\sum_{(i,j)\in\mathbf{Y}} \min(y_{i,j}, y_{j,i})$) estimating the probability of $y_{j,i}$ given $y_{i,j}$. This is a test of the *reciprocity hypothesis*.
- **CMP**: A parameter controlling for under/overdispersion, since the ERGMs use a Poisson distribution as the reference.
- **transitiveweights**: A conservative parameter estimating closure of weighted two-stars in the network, using the minimum strength of the two-path i and j form and the maximum strength of all two-paths starting at i and ending at j. This is a test of the *transitivity hypothesis*.
- **nodeicovar/nodeocovar**: Parameters estimating the degree of heterogeneity in popularity (nodeicovar) and activity (nodeocovar) across the nodes.

I estimate the normal AMEN model with two latent dimensions and 100000 iterations of the Markov chain with 1000 burn-in iterations.[3] The ERGMs are specified identically, except one includes a nodeocovar term and another includes a nodeicovar term as the inclusion of both led to degeneracy. MCMC convergence plots are provided for AMEN in Figure 3 and the ERGMs in Figures 4 and 5.

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

[3] A more appropriate implementation could use a Poisson distribution as the reference for the AMEN model, but this has no native implementation in the package.

I report the results of the models, alongside to the coefficient results of the model in Hinkle and Nelson (2016), in Table 4. A few findings are consistent across all four estimations: citizen ideological distance is associated with weaker ties; cultural linkage (share of people in state i born in state j) is associated with stronger ties; citational propensity (total cites excluding $y_{i,j}$) is associated with stronger ties; and contiguity and circuit homophily are associated with stronger ties. These results are evidence for the proximity hypothesis: states that are geographically, ideologically, and culturally proximal with a state i are more likely to be cited.

Notable, however, are the deviations across the models. The ERGMs identify multiple sender and receiver effects, but none are identified by AMEN. Courts with more legal capital and courts that are more professional are more likely to be cited, per the ERGMs and the original negative binomial regression, but not per the AMEN. Similarly, all but the AMEN show that elected courts are less likely to be cited. The deviations withdraw support for the prestige hypothesis presented in Hinkle and Nelson (2016) if we take the AMEN model to be the best approach to estimating covariate effects and network dependencies in the citation network. The ERGM terms are evidence that network dependencies are relevant to modeling the network: ties are more likely to be reciprocated (in support of the reciprocity hypothesis), although there is noimmediate evidence for transitivity in the network. In the two separate ERGMs, the receiver and sender heterogeneity terms are positive and significant, implying the presence of substantive receiver and sender effects. Consequently, the presence of network effects indicates that the negative binomial regression from Hinkle and Nelson (2016) ignored relevant dependencies that AMEN and ERGMs can variably account for.

[Table 4 about here.]

To compare the fit of the models and decide which to trust, I take Minhas, Hoff, and Ward's (2018) approach to modeling the network parameters for ERGM by calculating the parameters across 1,000 networks simulated from the model. The mean parameter estimates (and associated 95% and 90% prediction intervals in black and grey, respectively) are shown in Figure 6. The horizontal lines are the actual values of each parameter in the observed network. Evidently, the AMEN specification fares slightly better than the ERGM specification. All models are able to estimate the row mean standard deviations (sender effects) and dyadic correlation well. The two ERGMs (and not AMEN) estimate one measure of triadic dependency (cycle.dep) well, while none are able to capture the second measure of triadic dependency (trans.dep). AMEN accurately captures the variance in the receiver means, while the receiver ERGM is close and the sender ERGM is unable to fit it well. Consequently, since AMEN models the degree of popularity best and there is little transitivity to capture (although the ERGMs appear to do it better), AMEN appears to estimate the relevant network dependencies best—and its results for covariate effects then hold the most water.

but with room for improvement: the actual parameter values are within the 95% prediction intervals of the AMEN estimates for column and row mean standard deviations and within-dyad correlations. The ERGM estimates and associated intervals only capture one measure of triadic dependency (cycle.dep) and the column mean standard deviations. Neither accurately models the second measure of triadic dependency (trans.dep).

[Figure 6 about here.]

Conclusion

Dataset

Uploaded to Github repo (obtained from the SPPQ dataverse).

Network Descriptive Statistics

References

Caldeira, Gregory A. 1988. "Legal precedent: Structures of communication between state supreme courts." *Social Networks* 10(1):29–55.

Denniston, Mark W. 2014. *Dialogue among state supreme courts: advancing state constitutionalism.* El Paso, [Texas]: LFB Scholarly Publishing LLC.

Hinkle, Rachael K. and Michael J. Nelson. 2016. "The Transmission of Legal Precedent among State Supreme Courts in the Twenty-First Century." *State Politics & Policy Quarterly* 16(4):391–410. Publisher: SAGE Publications Inc.

Mallinson, Daniel J. 2021. "Who Are Your Neighbors? The Role of Ideology and Decline of Geographic Proximity in the Diffusion of Policy Innovations." *Policy Studies Journal* 49(1):67–88.

Minhas, Shahryar, Peter D. Hoff and Michael D. Ward. 2019. "Inferential Approaches for Network Analysis: AMEN for Latent Factor Models." *Political Analysis* 27(2):208–222.

Walsh, David J. 1997. "On the Meaning and Pattern of Legal Citations: Evidence from State Wrongful Discharge Precedent Cases." *Law & Society Review* 31(2):337–361. Publisher: [Wiley, Law and Society Association].

List of Figures

Figure 1: Continuous Node Covariate Distributions

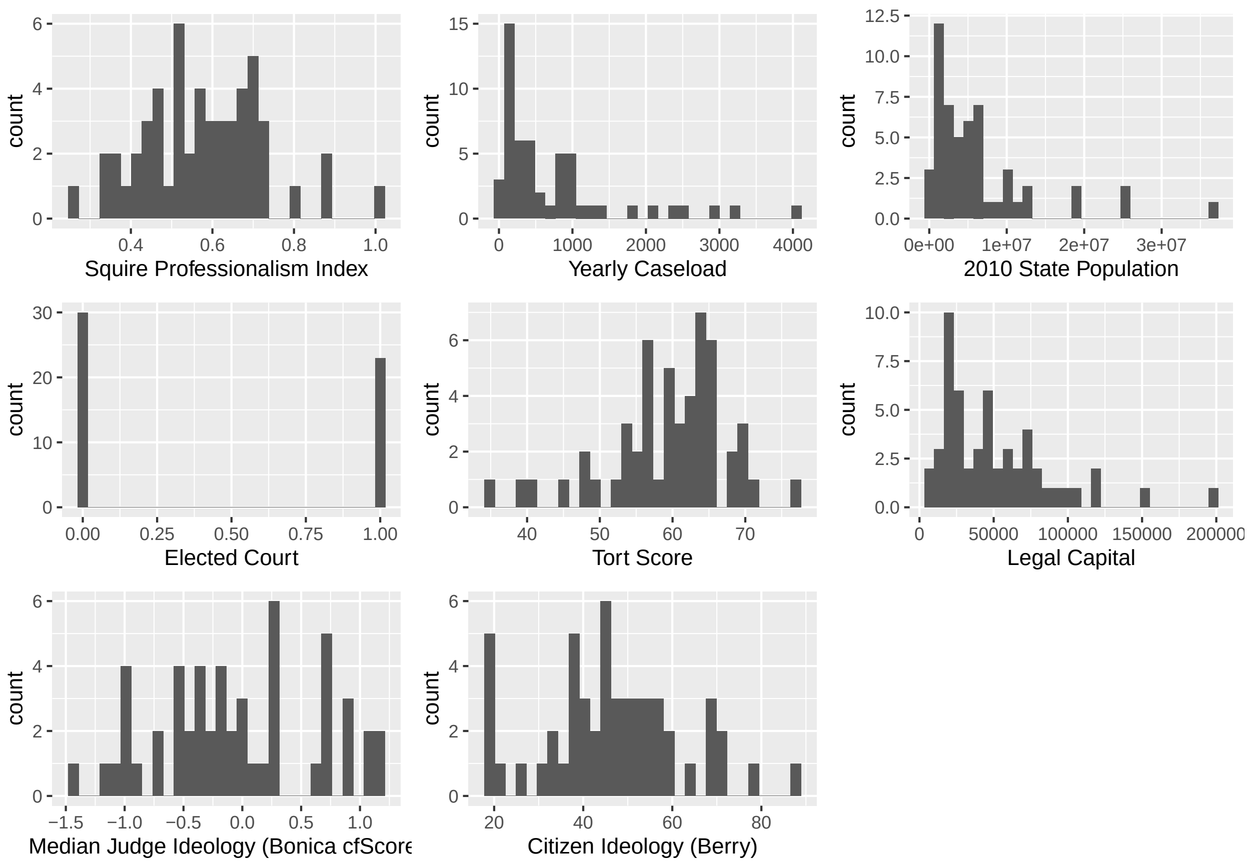


Figure 2: 2010 State Court External Citation Network

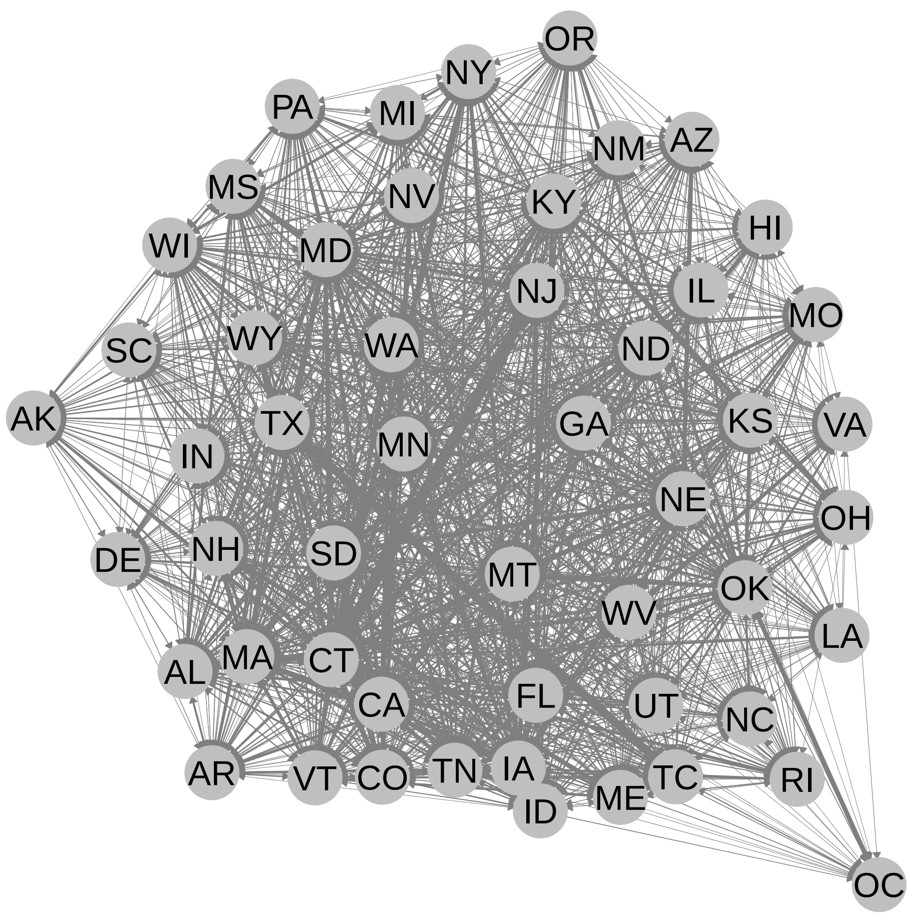


Figure 3: AMEN Convergence

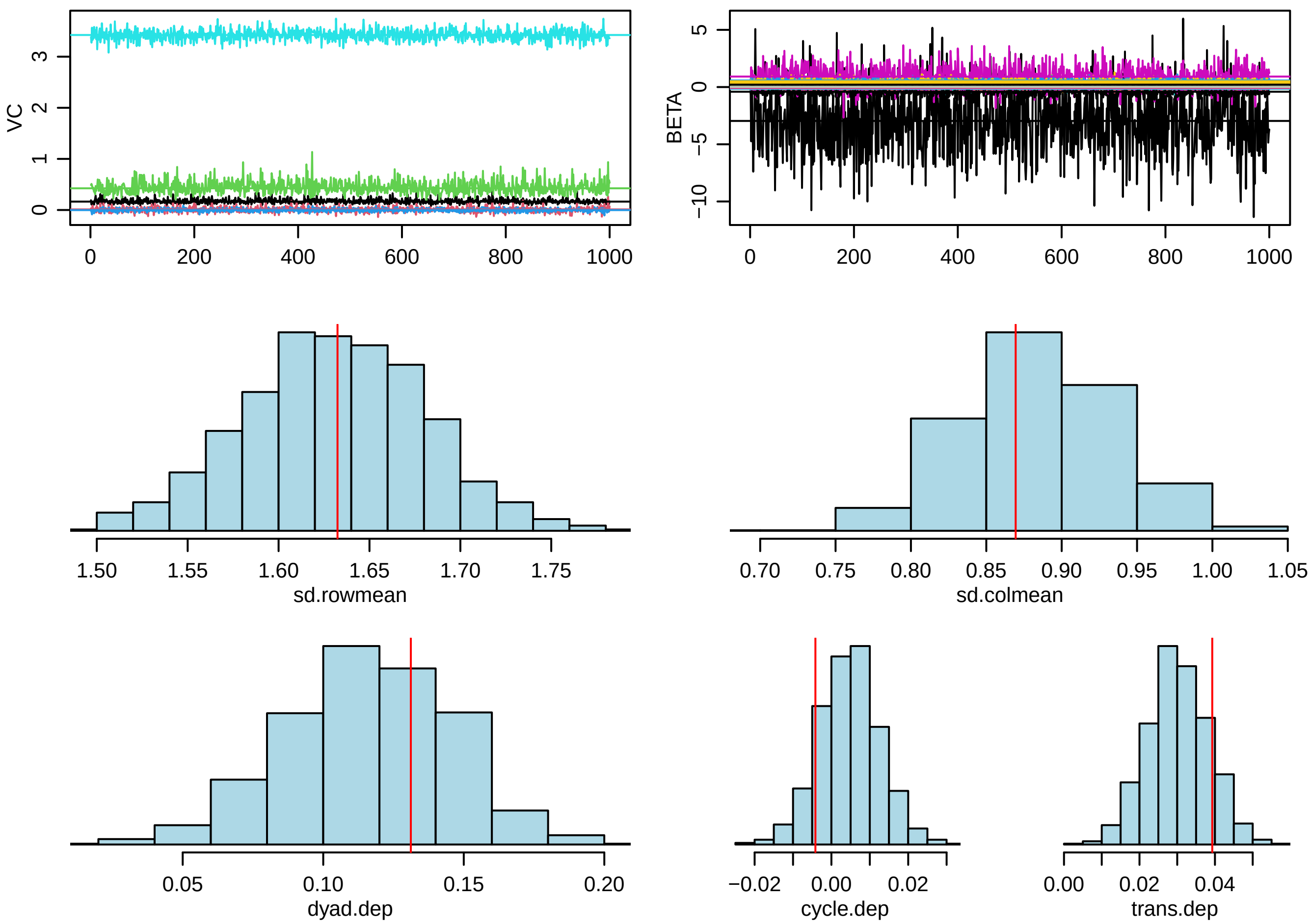


Figure 4: ERGM (icovar) Convergence

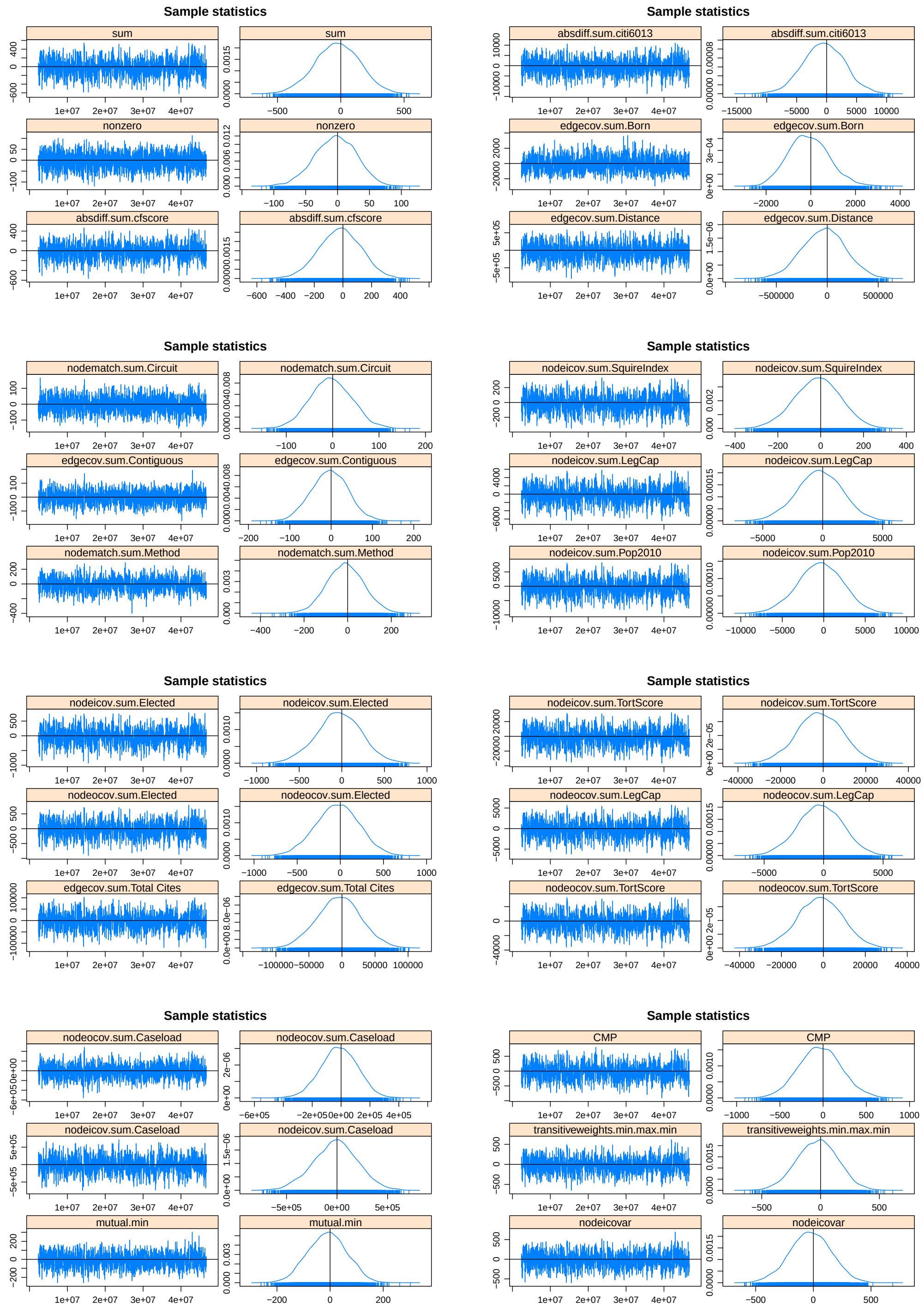


Figure 5: ERGM (ocovar) Convergence

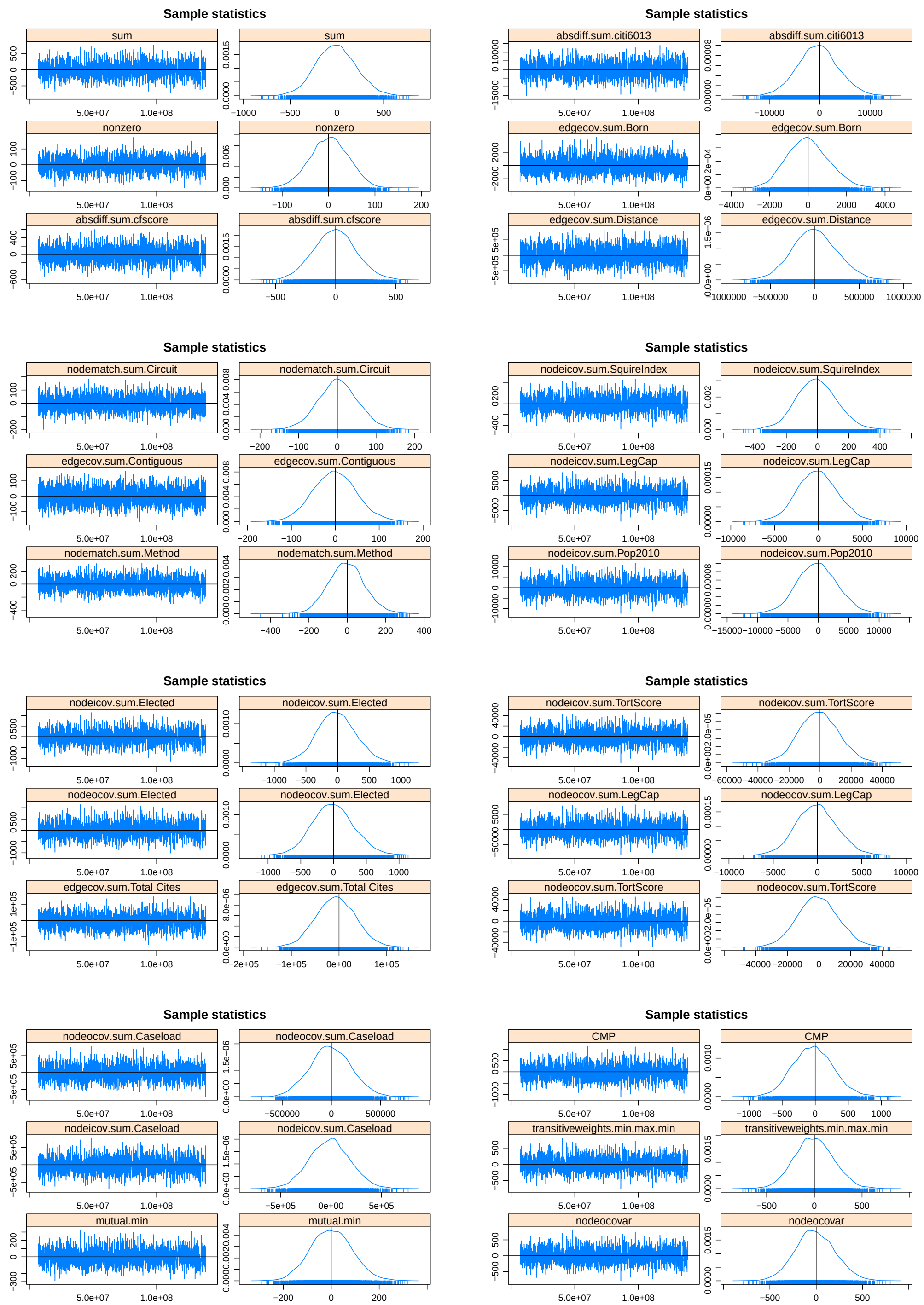
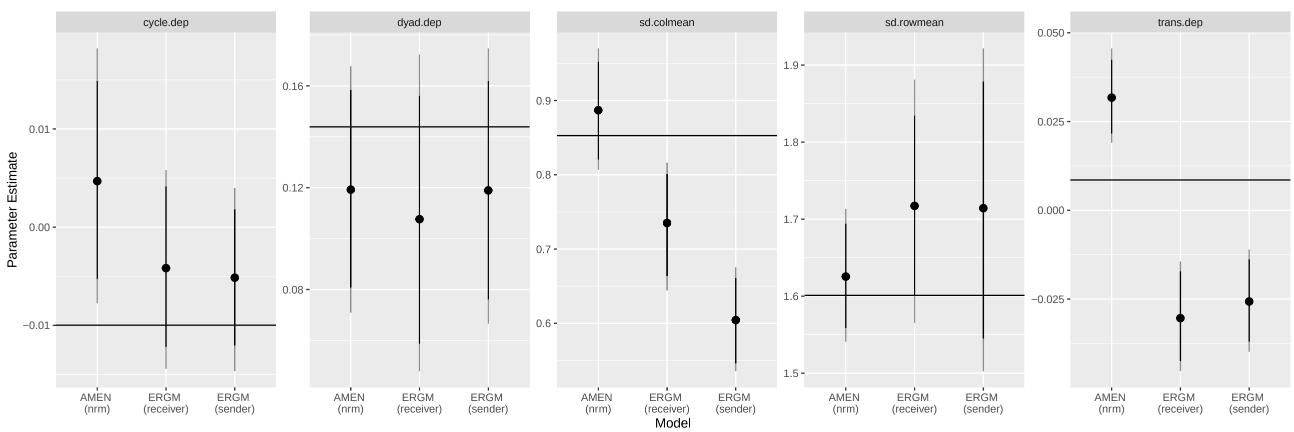


Figure 6: Goodness-of-Fit Comparison



List of Tables

Table 1: Model 1 (All cases)

	weight
ID Distance: Courts	0.022
	(0.031)
ID Distance: Citizens	-0.007^{***}
	(0.001)
Cultural linkage	0.032^{***}
	(0.005)
Distance	-0.005^{**}
	(0.002)
Pop. difference	-0.004
	(0.003)
Same West region only	0.246^{***}
	(0.058)
Same federal circuit only	0.206^{*}
	(0.110)
Contiguous only	-0.030
	(0.096)
Same West and circuit	0.349^{***}
	(0.094)
Same West and contiguous	0.559^{***}
	(0.102)
Same circuit and contiguous	0.407^{***}
	(0.141)
Same West, circuit, and contiguous	0.576^{***}
	(0.089)
Same selection method	-0.052
	(0.038)
Cited ct: legal professionalism	0.373^{**}
	(0.151)
Cited ct: Legal capital	0.030^{***}
	(0.005)
Cited ct: Population	0.008^{**}
	(0.004)
Cited ct: Elected	-0.200^{***}
	(0.039)
Citing ct: Elected	0.059^{*}
	(0.036)
Cited ct: Louisiana	-0.493^{***}
	(0.150)
Citing ct: Louisiana	-0.646^{***}
	(0.190)
Total cites difference	0.006^{***}
	(0.0002)
Cited ct: Tort score	0.003
	(0.003)
Constant	-0.470^{**}
	(0.207)
N	2,652
Log Likelihood	$-4{,}895.884$
θ	4.130^{***} (0.315)
AIC	9,837.769

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Table 2: Most Central State Courts

In-Degree	Out-Degree	In-Strength	Out-Strength	In-Strength (Wtd.)	Out-Strength (Wtd.)	EV
MA	CT	CA	CT	AK	OK	CA
CA	IA	MA	OK	WY	TN	MA
CT	TN	NY	IA	AZ	IA	NY
NY	WV	NJ	MD	NH	NE	NJ
MD	AL	CO	TN	ID	TX	IA
NJ	ID	FL	NE	DE	WV	CO
KS	NE	IA	SD	CA	NH	FL
NH	KY	WA	KY	CO	ID	WA
WA	MD	MD	WV	TX	AZ	MN
AL	ND	MN	VT	UT	SD	AZ

Table 3: Assortativity Coefficients

Relationship	r
Strength (In, Out)	-0.021
Strength (Out, In)	-0.061
Strength (In, In)	-0.018
Strength (Out, Out)	-0.043
Court Ideology	0.013
Citizen Ideology	0.122
Circuit	0.033

Table 4: Network Model Results

	Hinkle and Nelson (2016)	AMEN	ERGM (ocovar)	ERGM (icovar)
Dyadic Proximity Effects				
ID Distance: Courts	0.022	-0.097	0.017	0.028
	(0.031)	(0.082)	(0.015)	(0.017)
ID Distance: Citizens	-0.007^{***}	-0.012^{**}	-0.001^{***}	-0.003^{***}
	(0.001)	(0.004)	(0.001)	(0.001)
Cultural linkage	0.032^{***}	0.211^{***}	0.009^{***}	0.011^{***}
	(0.005)	(0.016)	(0.001)	(0.011)
Distance	-0.005^{**}	-0.000^{***}	-0.000	-0.000
	(0.002)	(0.000)	(0.000)	(0.000)
Pop. difference	-0.004			
	(0.003)			
Same West region only	0.246^{***}			
	(0.058)			
Same federal circuit only	0.206^{*}			
	(0.110)			
Contiguous only	-0.030			
	(0.096)			
Same West and circuit	0.349^{***}			
	(0.094)			
Same West and contiguous	0.559^{***}			
	(0.102)			
Same circuit and contiguous	0.407^{***}			
	(0.141)			
Same West, circuit, and contiguous	0.576^{***}			
	(0.089)			
Contiguous		0.496^{**}	0.126^{***}	0.141^{***}
		(0.154)	(0.031)	(0.032)
Same circuit		0.566^{***}	0.184^{***}	0.192^{***}
		(0.157)	(0.030)	(0.031)
Same selection method	-0.052	-0.050	-0.005	-0.014
	(0.038)	(0.090)	(0.020)	(0.021)
Receiver Prestige Effects				
Cited ct: Legal professionalism	0.373^{**}	0.910	0.490^{***}	0.211^{***}
	(0.151)	(0.913)	(0.098)	(0.064)
Cited ct: Legal capital	0.030^{***}	0.330	0.205^{***}	0.074^{***}
	(0.005)	(0.261)	(0.028)	(0.019)
Cited ct: Population	0.008^{**}	0.046	-0.000	-0.006
	(0.004)	(0.159)	(0.016)	(0.010)
Cited ct: Tort score	0.003	0.011	0.004^{*}	0.001
	(0.003)	(0.015)	(0.001)	(0.001)
Sender Prestige Effects				
Citing ct: Legal capital		-0.160	-0.007	0.032
		(0.143)	(0.012)	(0.023)
Citing ct: Tort score		-0.002	0.000	0.001
		(0.009)	(0.001)	(0.001)
Nodal Controls				
Cited ct: Elected	-0.200^{***}	-0.404	-0.157^{***}	-0.076^{***}
	(0.039)	(0.266)	(0.024)	(0.018)
Citing ct: Elected	0.059^{*}	-0.064	-0.000	0.060^{*}
	(0.036)	(0.163)	(0.014)	(0.027)
Cited ct: Louisiana	-0.493^{***}			
	(0.150)			
Citing ct: Louisiana	-0.646^{***}			
	(0.190)			
Citing ct: Caseload		0.004	-0.000	-0.000^{***}
		(0.090)	(0.000)	(0.000)
Cited ct: Caseload		0.037	-0.000^{***}	-0.000
		(0.132)	(0.000)	(0.000)
Total cites excluding tie	0.006^{***}	0.017^{***}	0.001^{***}	0.003^{***}
	(0.000)	(0.001)	(0.000)	(0.000)
ERGM Terms				
Reciprocity			0.107^{**}	0.087^{*}
			(0.038)	(0.035)
Transitivity			-0.008	0.033
			(0.030)	(0.030)
sum			-3.374^{***}	-2.203^{***}
			(0.321)	(0.308)
nonzero			-0.714^{***}	-0.951^{***}
			(0.074)	(0.102)
CMP			0.917^{***}	0.752^{***}
			(0.037)	(0.037)
$\sqrt{\text{nodeocovar}}$			0.771^{***}	
			(0.037)	
$\sqrt{\text{nodeicovar}}$				0.626^{***}
				(0.050)
Constant	-0.470^{**}	-2.970		
	(0.207)	(2.765)		

*p < .1; **p < .05; ***p < .01