6 Methodological Appendix: Alternative Specifications and Diagnostics

6.1 Alternative Specification

Table 2: Alternative Specification

	Dependent variable:		
	Communication	Social	Info-seeking
	(1)	(2)	(3)
Edges (Intercept)	-5.691^{***}	-6.186^{***}	-5.367^{***}
	(0.196)	(0.237)	(0.534)
Δ Mandates	-0.017	-0.084	-0.101
	(0.040)	(0.052)	(0.122)
Δ Ideology	-0.482^{**}	-0.122	-1.359^{**}
	(0.193)	(0.224)	(0.612)
Same Education	0.213	0.235	0.457
	(0.132)	(0.158)	(0.334)
Same Floor	0.754^{***}	1.286^{***}	0.763^{**}
	(0.158)	(0.158)	(0.386)
Both Non-leadership	-0.550^{***}	-0.270^{*}	-0.976^{***}
	(0.132)	(0.155)	(0.338)
Both Leadership	0.556^{***}	0.417^{*}	0.846^{**}
	(0.166)	(0.214)	(0.398)
Same State	2.219^{***}	2.143^{***}	1.061^{**}
	(0.130)	(0.155)	(0.431)
Same Party	2.192^{***}	2.155^{***}	2.592^{***}
	(0.143)	(0.169)	(0.385)
Transitive Ties	0.731^{***}	0.913^{***}	0.647
	(0.135)	(0.156)	(0.406)
Akaike Inf. Crit.	2,788.852	1,974.222	472.202
Bayesian Inf. Crit.	2,873.528	2,057.574	538.418
N	35,156	30,800	5,500
Note:			*p<0.1; **p<0.05; ***p<0.01

6.2 Models with Imputation of Missing Edges

Table 3: Main Model with Imputation

	Dependent variable:		
	Communication	Social	Info-seeking
	(1)	(2)	(3)
Edges (Intercept)	−5.513***	−5.673***	−4.846***
	(0.094)	(0.108)	(0.190)
Δ Age	−0.013***	−0.020***	−0.016*
	(0.004)	(0.005)	(0.008)
Same Education	0.109	0.108	0.015
	(0.074)	(0.086)	(0.142)
Same Floor	0.660***	1.258***	0.648***
	(0.094)	(0.087)	(0.188)
Both Non-leadership	−0.356***	−0.179**	−0.718***
	(0.075)	(0.083)	(0.158)
Both Leadership.	0.489***	0.355***	0.448**
	(0.105)	(0.125)	(0.181)
Same State	2.011***	2.095***	1.664***
	(0.083)	(0.091)	(0.170)
Same Party	2.161***	1.826***	2.331***
	(0.084)	(0.083)	(0.175)
Transitive Ties	0.459***	0.549***	0.259*
	(0.090)	(0.095)	(0.156)
Akaike Inf. Crit.	7,945.312	6,522.415	1,985.739
Bayesian Inf. Crit.	8,029.399	6,605.983	2,053.579
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4: Alternative Specification with Imputation

	Dependent variable:		
	Communication	Social	Info-seeking
	(1)	(2)	(3)
Edges (Intercept)	-5.382^{***}	-5.642^{***}	-4.504^{***}
	(0.117)	(0.131)	(0.230)
Δ Mandates	-0.037	-0.045^{*}	0.030
	(0.025)	(0.027)	(0.049)
Δ Ideology	-0.473^{***}	-0.386^{***}	-0.840^{***}
	(0.118)	(0.130)	(0.234)
Same Education	0.152^{*}	0.162^{*}	-0.033
	(0.078)	(0.091)	(0.142)
Same Floor	0.649^{***}	1.220^{***}	0.577^{***}
	(0.099)	(0.097)	(0.194)
Both Non-leadership	-0.310^{***}	-0.196^{**}	-0.805^{***}
	(0.080)	(0.090)	(0.162)
Both Leadership.	0.487^{***}	0.324^{**}	0.404^{**}
	(0.107)	(0.128)	(0.183)
Same State	2.032^{***}	2.130^{***}	1.651^{***}
	(0.087)	(0.099)	(0.181)
Same Party	1.990^{***}	1.762^{***}	1.994^{***}
	(0.097)	(0.105)	(0.202)
Transitive Ties	0.508^{***}	0.581^{***}	0.315^{*}
	(0.097)	(0.106)	(0.175)
N	74,072	67,408	13,425
Akaike Inf. Crit.	7,088.003	5,580.581	1,924.670
Bayesian Inf. Crit.	7,180.131	5,671.766	1,999.718

Note: *p<0.1; **p<0.05; ***p<0.01

6.3 Main Model without MCMC

Table 5: Main Model without MCMC

	Dependent variable:		
	Communication	Social	Info-seeking
	(1)	(2)	(3)
Edges (Intercept)	-5.720^{***}	-6.021^{***}	-5.761^{***}
	(0.169)	(0.198)	(0.456)
Δ Age	-0.022^{***}	-0.035^{***}	-0.063^{***}
	(0.007)	(0.009)	(0.023)
Same Education	0.165	0.157	0.633^{*}
	(0.134)	(0.158)	(0.351)
Same Floor	0.790^{***}	1.420^{***}	0.789^{**}
	(0.155)	(0.154)	(0.392)
Both Non-leadership	-0.661^{***}	-0.228	-0.793^{**}
	(0.130)	(0.148)	(0.340)
Both Leadership.	0.507^{***}	0.373	0.817^{**}
	(0.169)	(0.227)	(0.403)
Same State	2.239^{***}	2.163^{***}	1.011^{**}
	(0.126)	(0.145)	(0.448)
Same Party	2.302^{***}	2.000^{***}	2.972^{***}
	(0.124)	(0.144)	(0.340)
Transitive Ties	0.798^{***}	1.169^{***}	0.431
	(0.082)	(0.113)	(0.288)
Akaike Inf. Crit.	3,003.027	2,221.103	466.086
Bayesian Inf. Crit.	3,080.261	2,297.597	525.680
N	39402	36290	5550
Note:			*p<0.1; **p<0.05; ***p<0.01

6.4 Main Model without Back-filling

Table 6: Model without back-filling

	Dependent variable:		
	Communication	Social	Info-seeking
	(1)	(2)	(3)
Edges (Intercept)	−6.072***	−6.281***	−5.742***
	(0.229)	(0.270)	(0.447)
Δ Age	−0.023**	−0.026**	−0.063***
	(0.010)	(0.011)	(0.022)
Same Education	0.340*	0.181	0.600*
	(0.177)	(0.210)	(0.337)
Same Floor	0.640***	1.576***	0.793**
	(0.212)	(0.199)	(0.390)
Both Non-leadership	−0.472***	−0.376*	−0.808**
	(0.171)	(0.203)	(0.337)
Both Leadership.	0.758***	0.727***	0.838**
	(0.219)	(0.267)	(0.397)
Same State	2.322***	2.411***	0.989**
	(0.174)	(0.198)	(0.434)
Same Party	2.480***	2.168***	2.960***
	(0.169)	(0.194)	(0.342)
Transitive Ties	0.373*	0.533**	0.570
	(0.196)	(0.252)	(0.414)
Akaike Inf. Crit.	1,724.199	1,218.254	466.722
Bayesian Inf. Crit.	1,797.038	1,289.522	526.316
N	24,180	20,306	5,500
Note:			*p<0.1; **p<0.05; ***p<0.01

7 Selection Bias

Table 7: Logit Model of Response to Network Survey

	Dependent variable:
	Responded
Age	0.005
	(0.009)
Education - High School	−0.223
	(0.558)
Education - Advanced Ed.	−0.479
	(0.391)
Education - Above College	−1.017*
	(0.613)
Experience	−0.030
	(0.061)
Leadership	0.172
	(0.196)
Constant	−0.199
	(0.603)
Observations	515
Log Likelihood	−345.258
Akaike Inf. Crit.	704.516
Note:	*p<0.1; **p<0.05; ***p<0.01

7.1 Imputation on Exponential Random Graph Models

The network survey was not responded to by all members of the Brazilian Congress. The network survey covers roughly 45 percent of members of Congress, which means that 55 percent of the Congress has missing outgoing ties (but not incoming ties). Because the survey routine did not rely on self-supplied biographical data, there is no missingness in the covariates for the main models. This situation makes it possible to use the same model that is used to estimate tie formation to impute missing edges in the data.

To deal with the problem of absent edges, in some supplementary models missing edges are imputed using techniques that are native to the ERGM framework (**?**). In this process, the likelihood of the observed data is maximized under the proposed model, and it is assumed that there is no unobserved information governing the missingness process. In other words, the missing edges are assumed to be drawn from the same distribution as the observed data, and the information contained in the missing edges is ignorable. The missing edges are then imputed during the same Markov Chain Monte Carlo in which the parameters are estimated. Given that so far the data have exhibited no statistically discernible patterns of missingness, the ignorability assumption is plausible, though there is no way to know in practice (Gelman and Hill 2007). The likelihood of a respondent taking the survey does not vary with any of the observable biographical traits available in the data. More technical details about model-based imputation can be found in **?**.

7.2 Convergence of MCMC Chain

A variety of diagnostics exist to examine the convergence properties of an MCMC chain. The diagnostics I conducted indicated that all chains achieved good mixing and convergence was satisfactory. In practice, the goal of MCMC diagnostics is to establish that the chain has reached a stationary state that is independent from its starting point and has adequately 'mixed' throughout the parameter space. Many diagnostics exist, from the Raftery-Lewis test to the Geweke statistic. The Geweke statistic is given automatically within the ERGM framework, and tests for differences in means between two non-overlapping windows of the Markov chain. The significance of the test statistic indicates that the windows are correlated beyond random chance, and conveys to the analyst that more burn-in may be necessary to produce a steady-state in the chain. Another set of statistics worth examining are the autocorrelation statistics across sampled intervals in the chain. This set of statistics provides the correlations among adjacent samples from the chain. High autocorrelations indicate inefficient or slow mixing in the chain, such that adjacent samples are highly similar. On the other hand, low values indicate more efficient mixing in the parameter space.

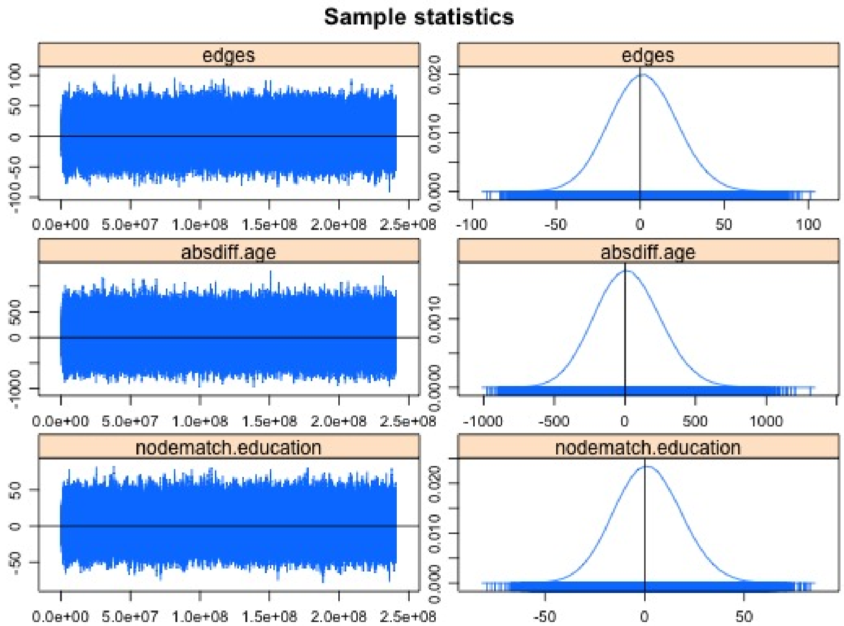

Figure 7: MCMC Diagnostics - Communication Network with No Imputation

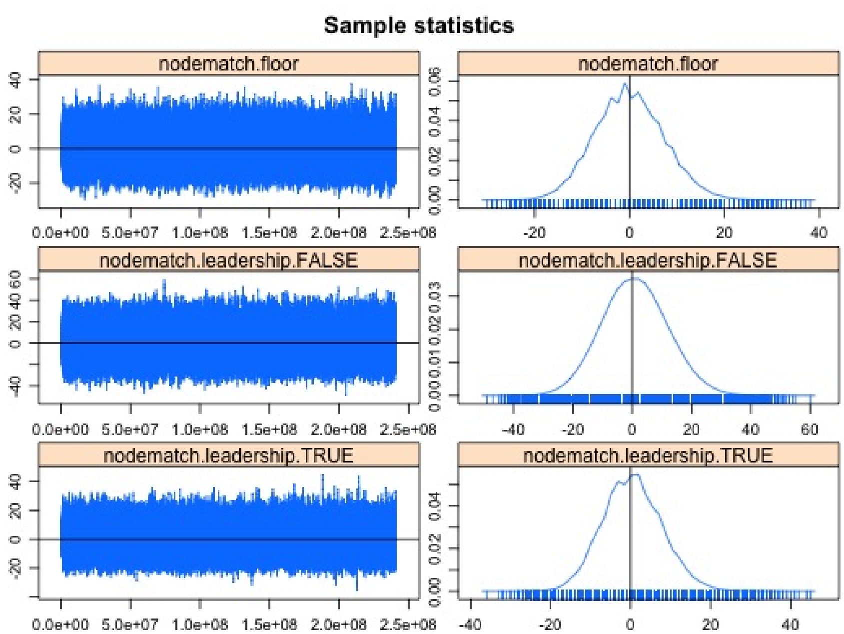

Figure 8: MCMC Diagnostics - Communication Network with No Imputation

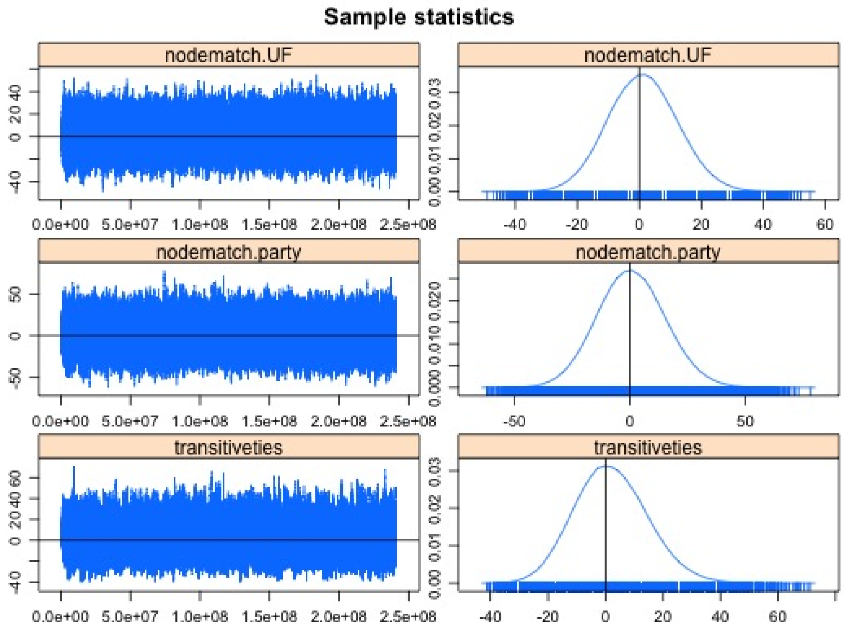

Figure 9: MCMC Diagnostics - Communication Network with No Imputation

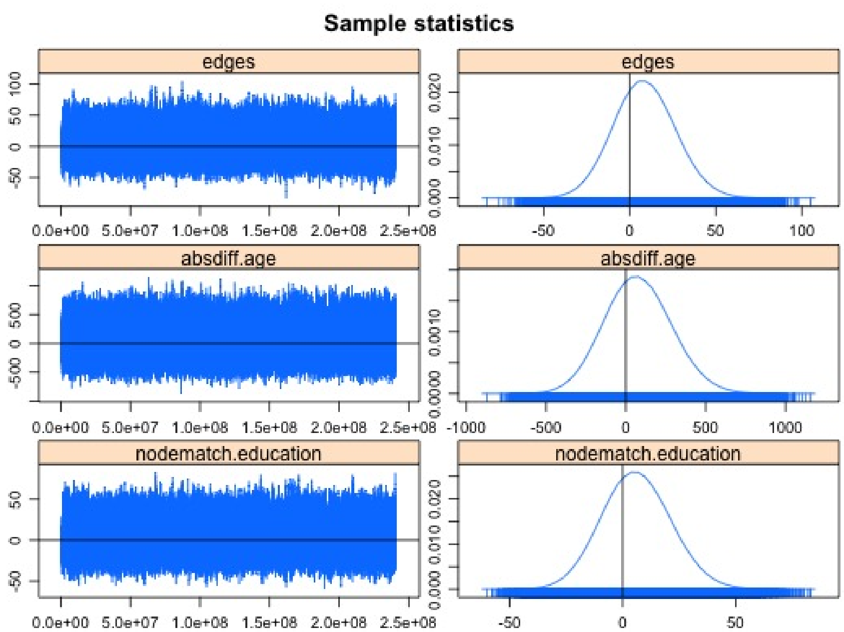

Figure 10: MCMC Diagnostics - Social Network with No Imputation

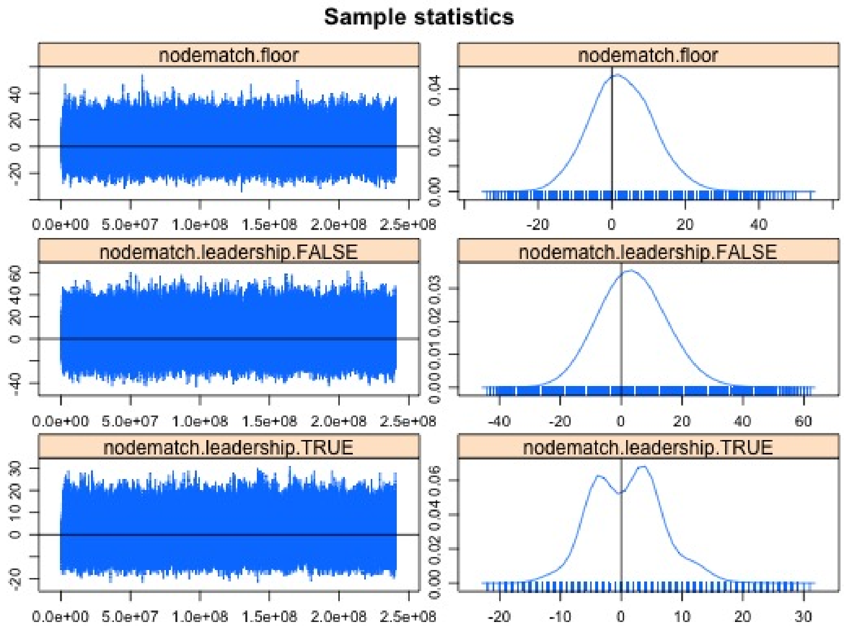

Figure 11: MCMC Diagnostics - Social Network with No Imputation

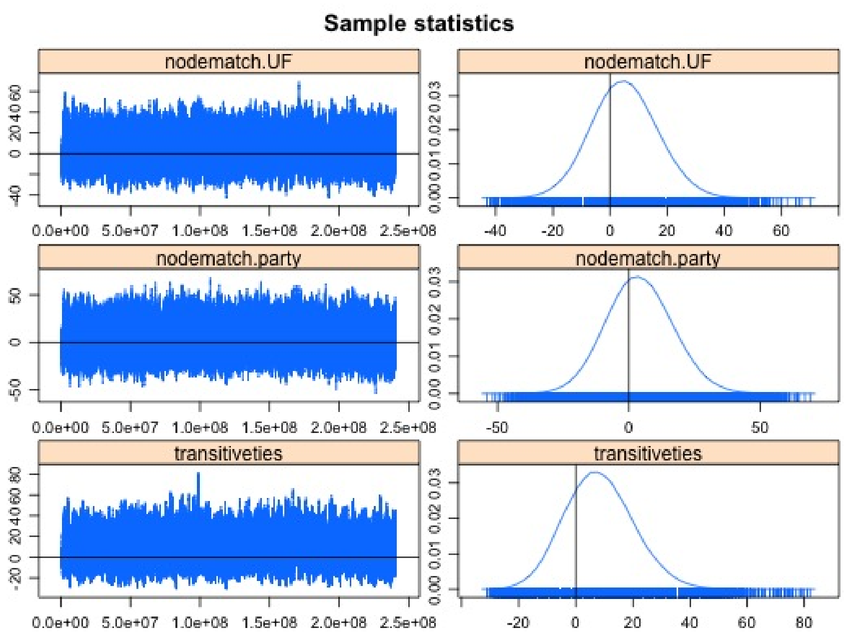

Figure 12: MCMC Diagnostics - Social Network with No Imputation

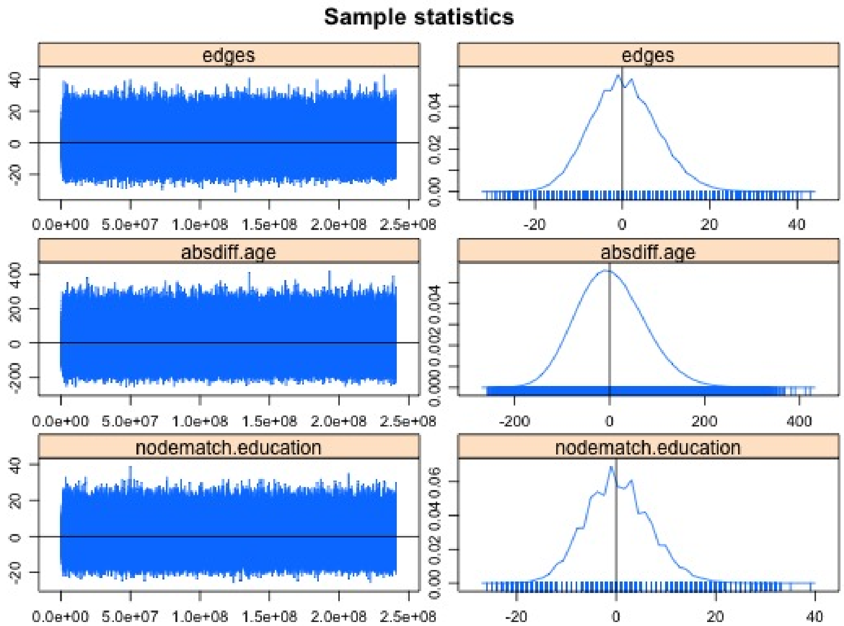

Figure 13: MCMC Diagnostics - Info Network with No Imputation

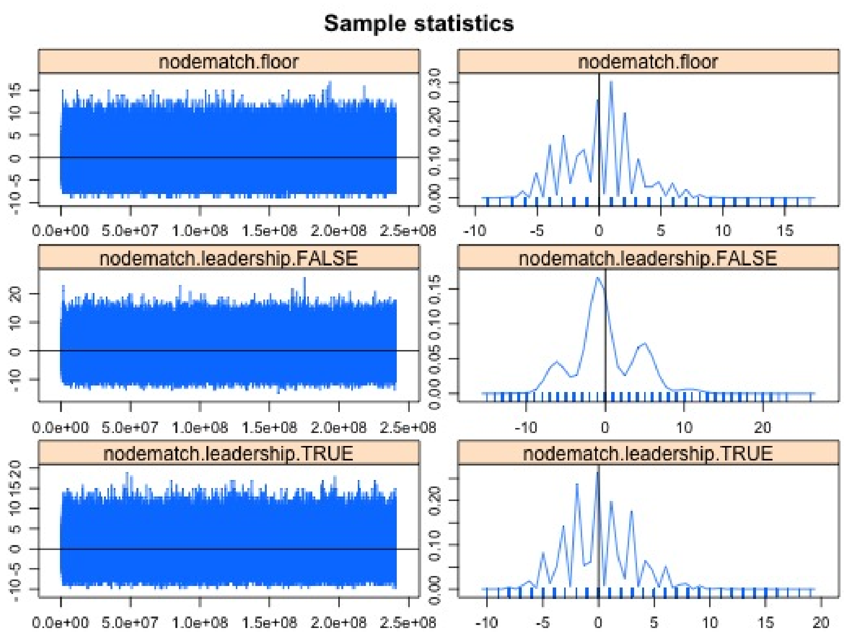

Figure 14: MCMC Diagnostics - Info Network with No Imputation

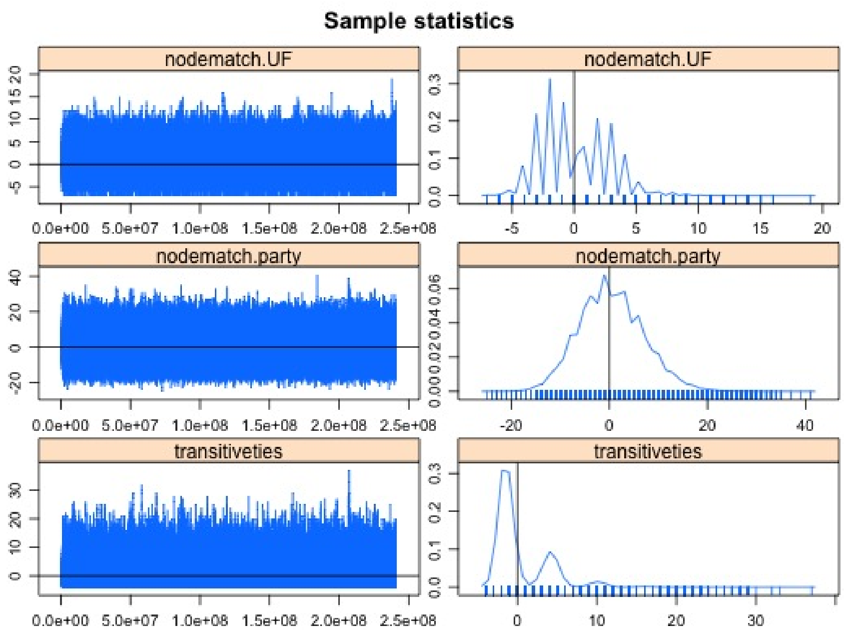

Figure 15: MCMC Diagnostics - Info Network with No Imputation

7.3 Goodness of Fit

The goodness of fit from the imputed model is a poor comparison because missing values are not natively imputed when assessing goodness of fit statistics. However, because we are to assume that there is no additional information within the missing edges, and the model we have with or without imputation is nearly identical. Thus, we can assess the degree to which the model computed by listwise-deletion model is able to generate networks with similar properties as our observed networks. The models faithfully generate many properties of the observed networks. In these graphs, the dark line represents observed statistics from the data, while the boxplots represent simulations from the fitted models.

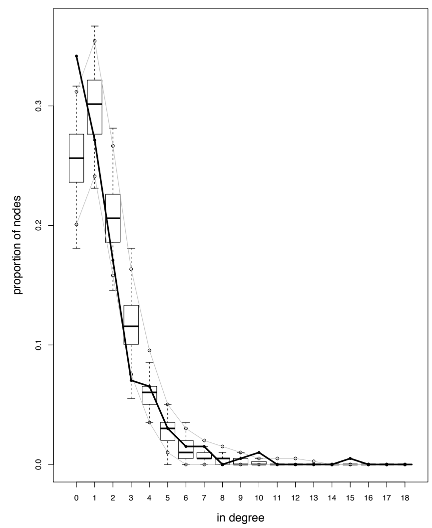

Figure 16: Goodness of Fit - Communication Network with No Imputation

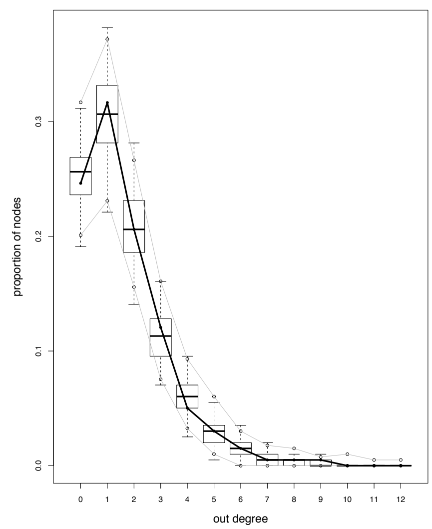

Figure 17: Goodness of Fit - Communication Network with No Imputation

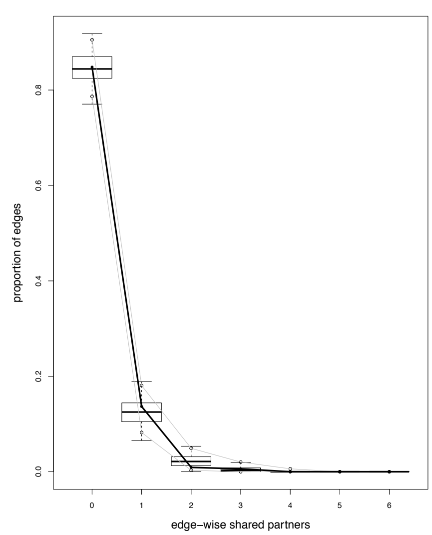

Figure 18: Goodness of Fit - Communication Network with No Imputation

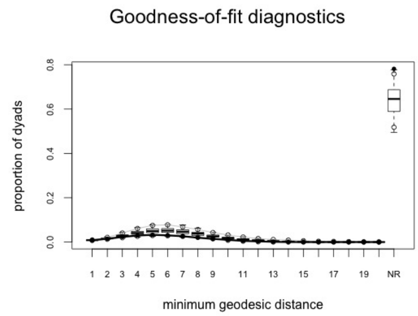

Figure 19: Goodness of Fit - Communication Network with No Imputation

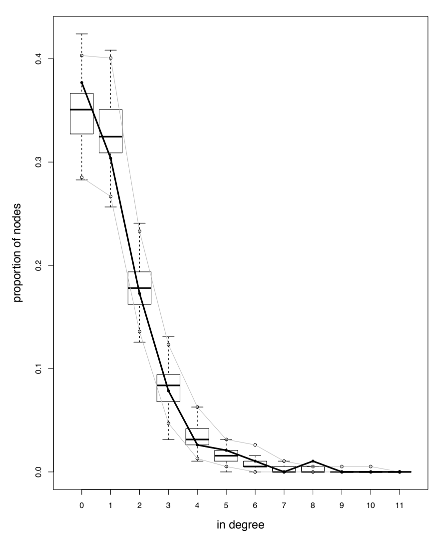

Figure 20: Goodness of Fit - Social Network with No Imputation

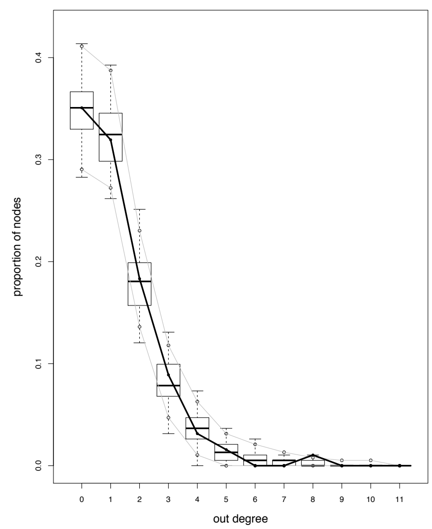

Figure 21: Goodness of Fit - Social Network with No Imputation

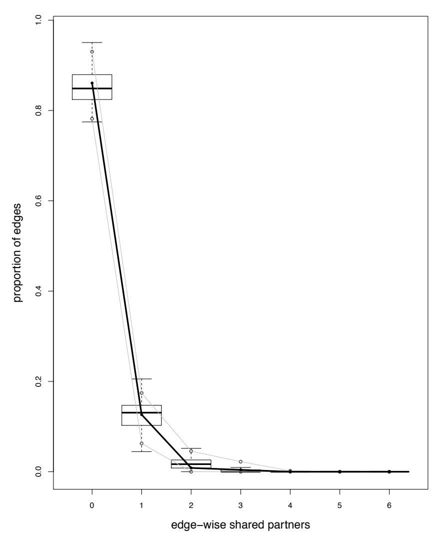

Figure 22: Goodness of Fit - Social Network with No Imputation

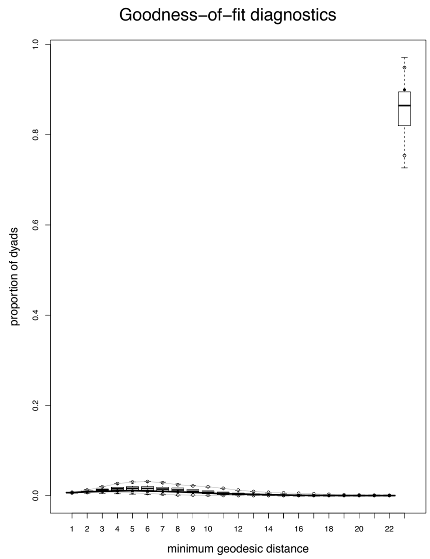

Figure 23: Goodness of Fit - Social Network with No Imputation

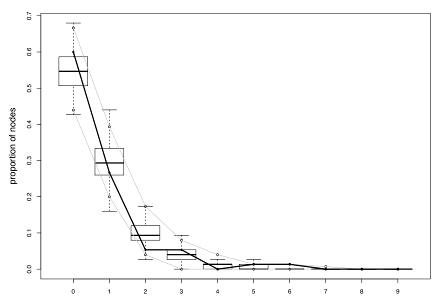

Figure 24: Goodness of Fit - Info Network with No Imputation

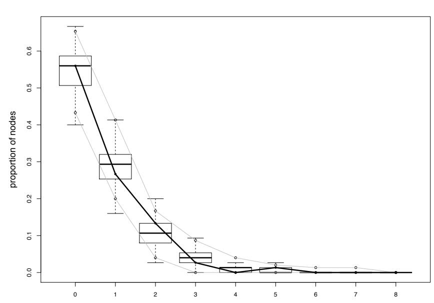

Figure 25: Goodness of Fit - Info Network with No Imputation

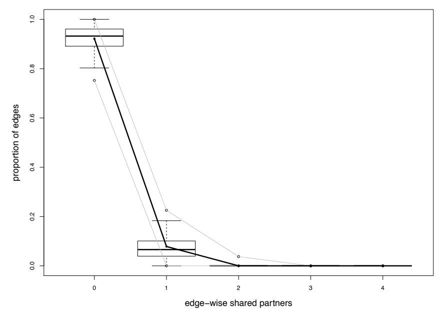

Figure 26: Goodness of Fit - Info Network with No Imputation

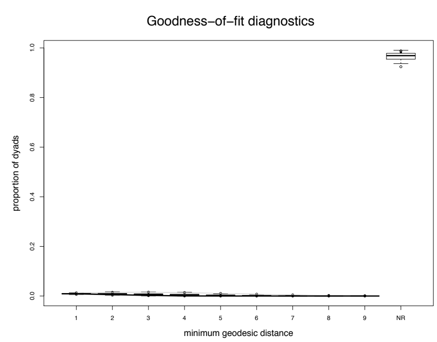

Figure 27: Goodness of Fit - Info Network with No Imputation