Appendix

Resource constellations and institutional logics shape network structures of the organic seed niche innovation system

A. Population identification

We identified organic seed innovation system populations through two processes: An initial compilation of several stakeholder databases and a secondary snowball sampling process based on responses from the first round of data collection. For the initial process, we generated three databases with a total of 529 contacts. First, the USDA National Organic Program INTEGRITY database was manually reviewed to identify 390 seed producers (i.e. certified organic growers who produce crops for seed) who had valid email addresses and geographically identifiable operations. Second, 87 organic seed companies, based primarily but not entirely in the US, were identified by the national non-profit Organic Seed Alliance, who keep a database for their communication and research initiatives. Third, 52 organic seed researchers based in the US were identified by reviewing organic seed-related projects funded by major public and private organic grant funders (USDA -SARE, -OREI, -NIFA, OFRF, and Ceres Trust) and Web of Science publications over the last five years. This group included university, governmental, and non-profit researchers. Note that our initial population databases did not explicitly include governmental or non-governmental organizations, apart from those that were related to research.

For the second snowball process of identifying stakeholders, each survey included network questions about respondents' connections in the seed system. We used these responses to identify a snowball sample, from which there were an additional 227 seed system stakeholders, including 26 producers, 43 companies, 81 organizations, and 77 researchers (academic and governmental). While our initial database creation focused on US actors, the snowball process widened the scope of our respondents to include actors from other geographies. In total, we identified 756 actors in the organic seed innovation system.

B. Sample representativeness

The table below shows response rates by sector and location. Rows 2-5 include the response rates from actors based regionally in the United States (US). Row 6, USA, represents actors based in the US and operating at the national scale. Rows 7 an 8 represent all Canadian and other country respondents, respectively, and row 9 represents actors operating at the international scale.

Table S1: Sample representativeness across US regions and spatial scales

	Producer			Company			Researcher			Organization		
Location	n	N	% response	n	N	% response	n	N	% response	n	N	% response
Total	94	416	23	49	130	38	60	117	51	44	93	47
West	53	242	22	13	40	32	13	28	46	10	24	42
North Central	13	74	18	7	17	41	16	34	47	12	18	67
Northeast	9	39	23	7	10	70	8	14	57	3	12	25
South	11	38	29	2	7	29	21	38	55	7	11	64
USA	0	4	0	17	45	38	1	1	100	5	14	36
Canada	6	16	38	2	8	25	1	2	50	6	9	67
Other country	2	2	100	0	0	NA	0	0	NA	0	0	NA
International	0	1	0	1	3	33	0	0	NA	1	5	20

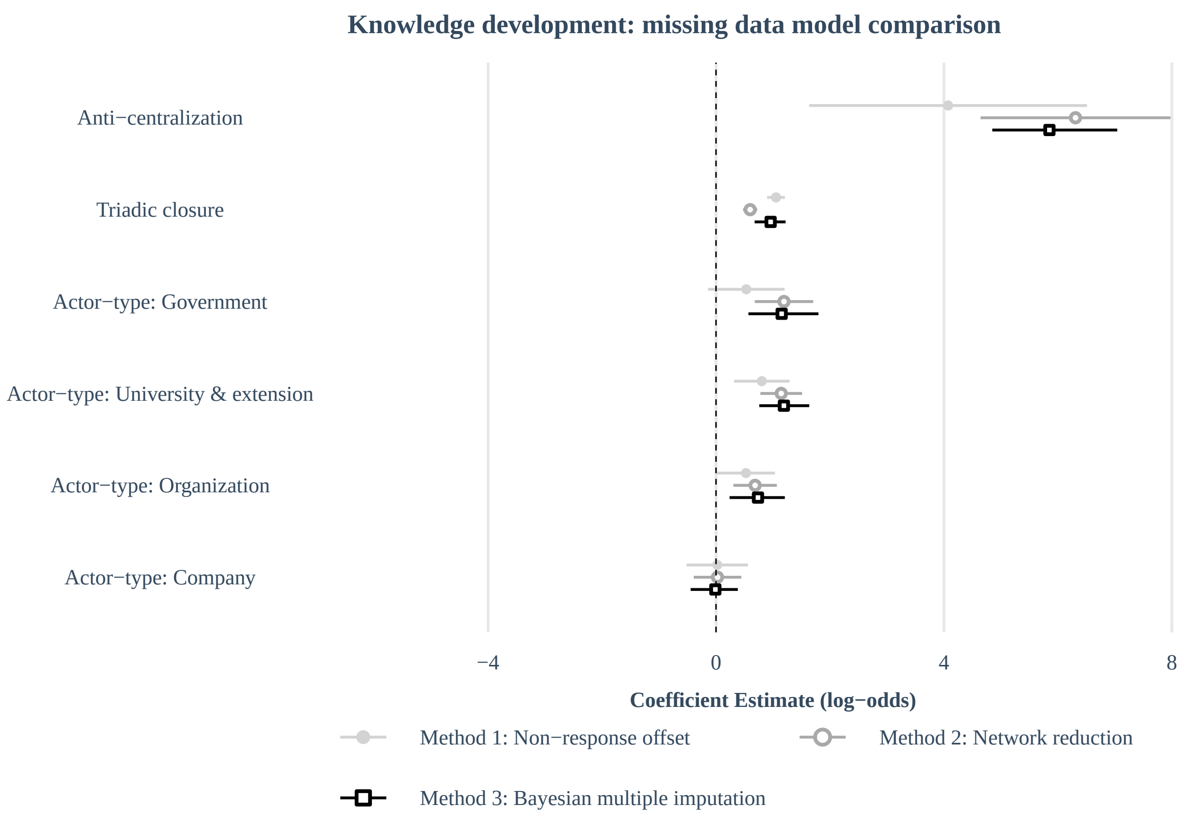
C. Comparing missing data approaches

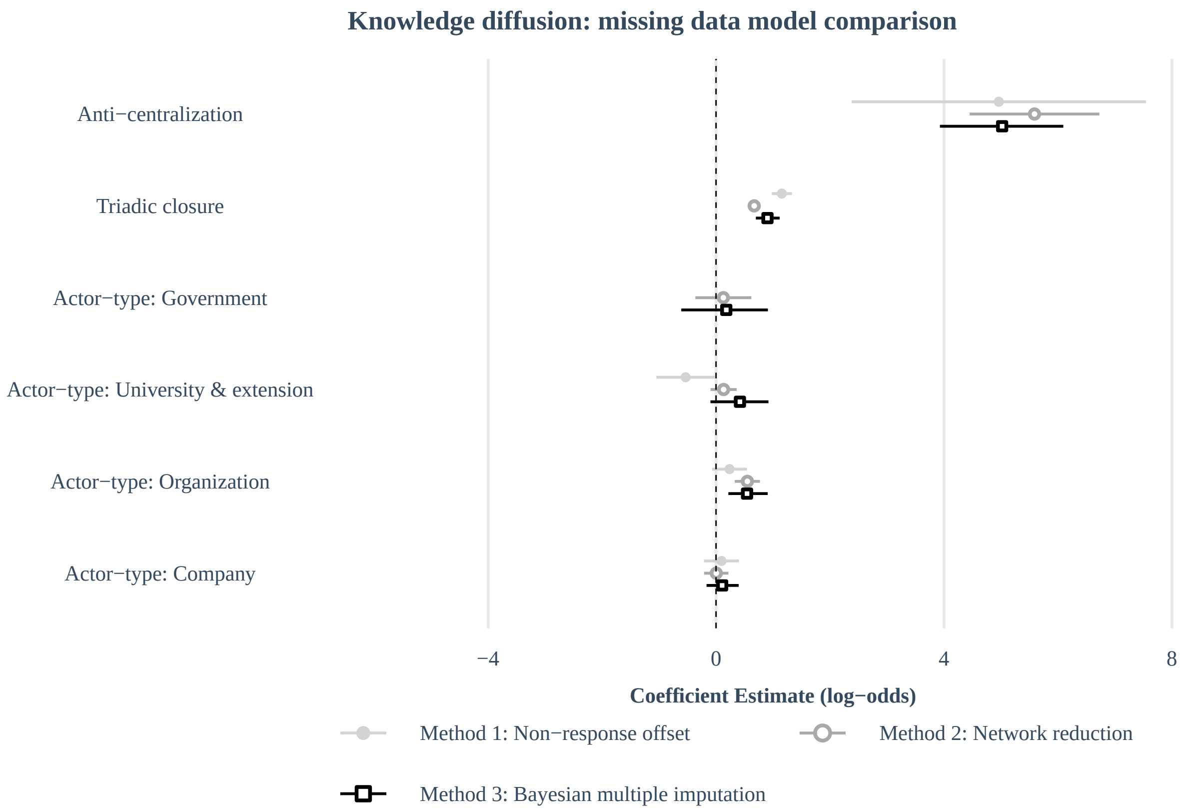
Given that we are modeling only a sample of the organic seed network, we need to take measures for dealing with missing data (Robins et al. 2004). There are several ways that network analysts deal with missing network data when networks are constructed with survey data (Krause et al. 2020). We review three approaches, described below:

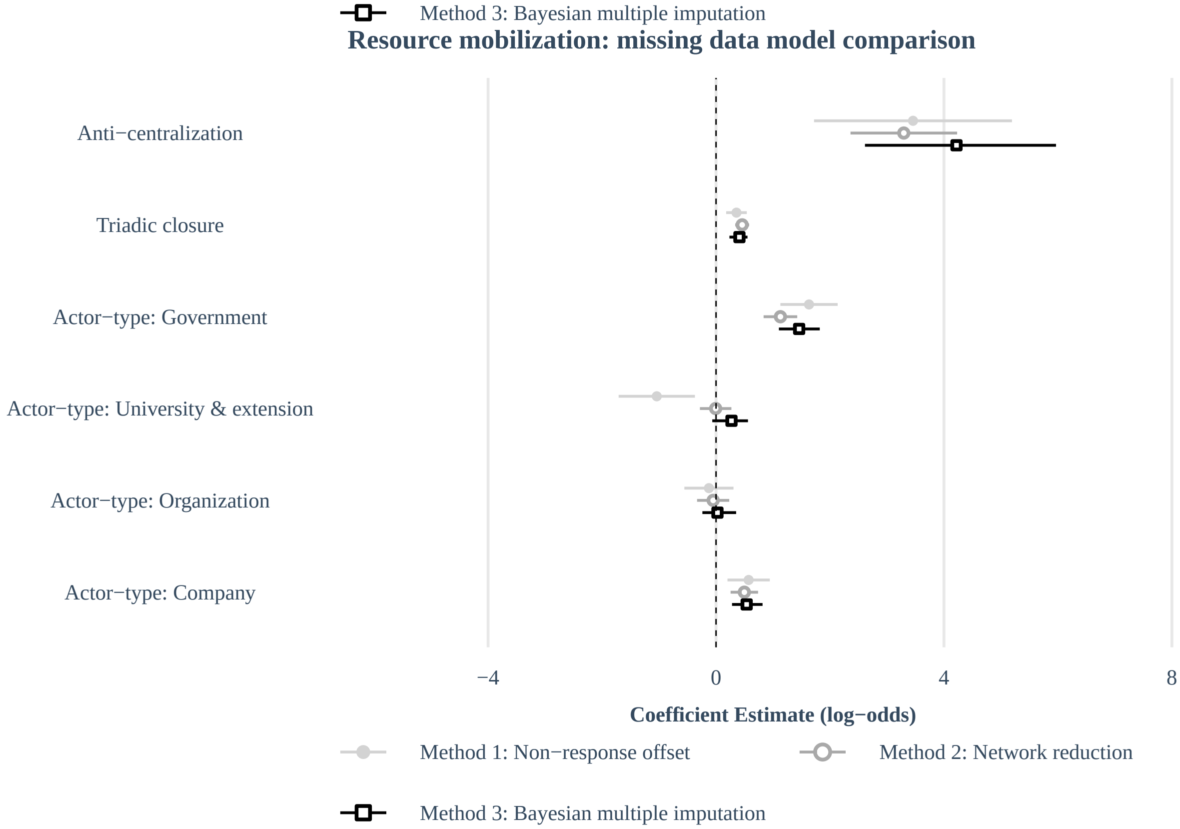
- **Method 1: Non-response offset** Maintain the network as reported by the survey sample (alters and egos), but account for non-response/missing-ness using sampling controls. This approach is commonly used in network studies for collaborative governance networks (e.g. Scott & Greer 2019; Levy & Lubell 2018).
- **Method 2: Network reduction** Reduce the network to only those who respond to a survey, the idea being that then you have a *sample of a full network*, where the structure is not biased towards core-periphery by alter non-respondents. This approach is also commonly used in network studies for collaborative governance networks (Angst & Brandenberger, 2022; Pozzi et al., 2024).
- **Method 3: Bayesian multiple imputation** Maintain the network as reported by the survey sample (alters and egos), but account for non-response/missing-ness using multiple imputation of ties with the `bergmM` function in the `Bergm` package (Caimo et al., 2022). This is a relatively new approach proposed by network methodologists and found to be highly robust (Krause et al. 2020; Xu et al. 2022).

We compare three different models to provide the reader with an understanding of the different approaches for working with missing network data. Throughout these comparisons we set a decay value for geometrically weighted parameters (gwdegree and gwesp) to 0.1 and 0.8, respectively, for consistency across comparisons.

The coefficient estimates across the three different modeling approaches suggest that even across networks of different sizes (i.e. respondent only in Method 2 and ego-alter in Methods 1 and 3), and different approaches for missing data, the general understanding of results remains consistent.




Knowledge diffusion: missing data model comparison
Anti−centralization
Triadic closure
Actor−type: Government
Actor−type: University & extension
Actor−type: Organization
Actor−type: Company
−4
0
4
8
Coefficient Estimate (log−odds)
Method 1: Non−response offset
Method 2: Network reduction
Method 3: Bayesian multiple imputation


Resource mobilization: missing data model comparison
Anti−centralization
Triadic closure
Actor−type: Government
Actor−type: University & extension
Actor−type: Organization
Actor−type: Company
−4
0
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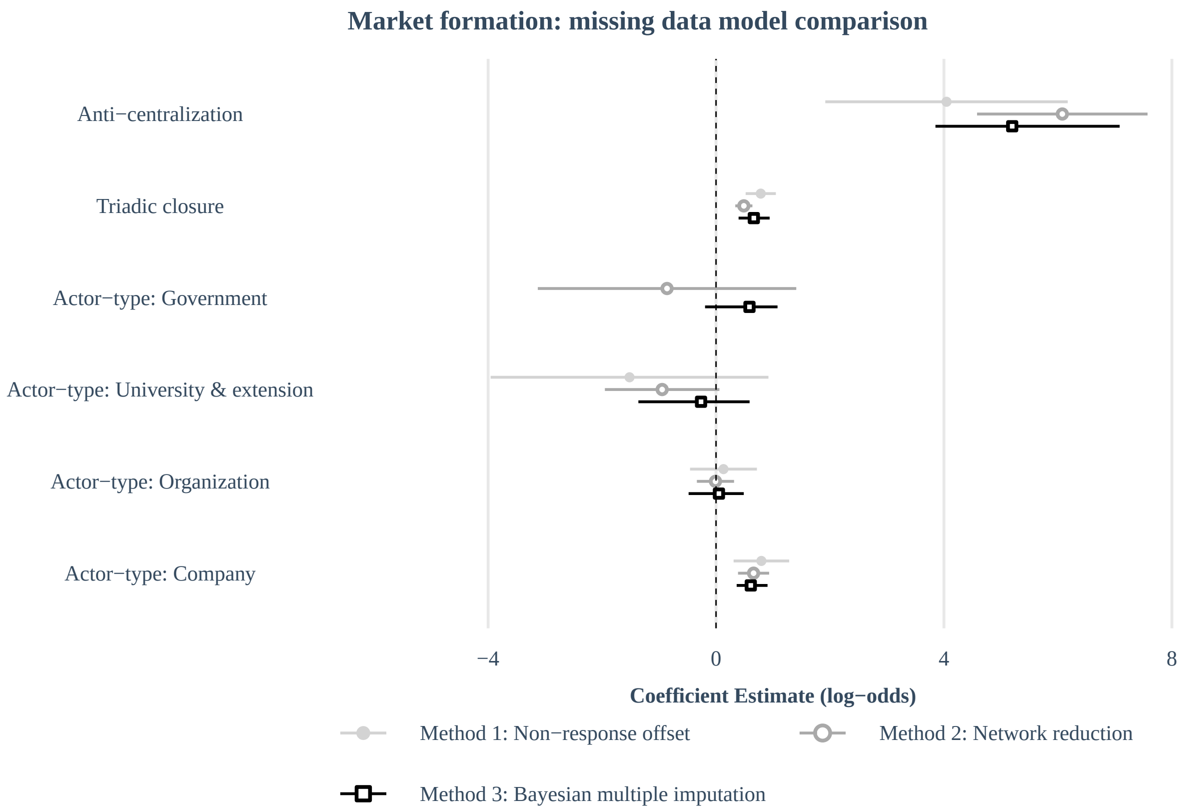
8
Coefficient Estimate (log−odds)
Method 1: Non−response offset
Method 2: Network reduction
Method 3: Bayesian multiple imputation



Market formation: missing data model comparison
Anti−centralization
Triadic closure
Actor−type: Government
Actor−type: University & extension
Actor−type: Organization
Actor−type: Company
−4
0
4
8
Coefficient Estimate (log−odds)
Method 1: Non−response offset
Method 2: Network reduction
Method 3: Bayesian multiple imputation

D. Network correlations

Table S2: Matrix correlations

	Knowledge development	Knowledge diffusion	Resource Mobilization
Knowledge diffusion	0.41		
Resource Mobilization	0.18	0.31	
Market formation	0.16	0.39	0.29

E. Full model results

Table S3: Full model results

Term	Knowledge development		Knowledge diffusion		Resource mobilization		Market formation	
	Estimate	CI	Estimate	CI	Estimate	CI	Estimate	CI
Anti-centralization	5.85*	4.85,7.04	5.02*	3.93,6.09	4.22*	2.61,5.97	5.2*	3.85,7.08
Triadic closure	0.96*	0.68,1.22	0.9*	0.7,1.12	0.41*	0.24,0.55	0.66*	0.4,0.94
Actor-type: Government	1.15*	0.57,1.8	0.18	-0.61,0.91	1.46*	1.1,1.82	0.59	-0.19,1.08
Actor-type: University & extension	1.19*	0.76,1.64	0.42	-0.1,0.92	0.27	-0.07,0.56	-0.26	-1.36,0.59
Actor-type: Organization	0.74*	0.24,1.21	0.54*	0.22,0.91	0.02	-0.24,0.35	0.05	-0.48,0.49
Actor-type: Company	-0.01	-0.45,0.38	0.11	-0.17,0.4	0.54*	0.28,0.82	0.61*	0.36,0.9
Regional homophily: Northeast	2.47*	1.48,3.44	3.1*	2.44,3.6	1.71*	1.14,2.52	2.77*	1.37,4.51
Regional homophily: South	2.26*	1.56,2.85	2.78*	2.33,3.27	1.72*	1.13,2.24	2.47*	1.74,3.34
Regional homophily: North Central	2.17*	1.73,2.89	2.78*	2.2,3.19	2.15*	1.26,3.07	2.54*	1.5,3.45
Regional homophily: West	1.85*	1.24,2.61	2.33*	1.71,3.14	1.76*	1.33,2.25	1.26*	0.59,1.86
National homophily: US National	-0.14	-2.43,1.18	-1.32	-2.92,0.27	-2.29*	-3.22,-1.5	0.09	-0.47,0.63
Scale: National/International (vs. Regional)	1.24*	0.7,1.8	1.47*	0.87,2.1	1.7*	1.29,2.1	0.91*	0.24,1.47
Survey non-respondent	-2.55*	-3.03,-1.73	-2.02*	-2.33,-1.59	-1.59*	-1.96,-1.28	-2.25*	-2.55,-1.71
Edges	-7.09*	-7.71,-6.43	-6.69*	-7.05,-6.27	-6.22*	-6.67,-5.76	-5.87*	-6.71,-5.37

* Credible intervals do not cross over zero

F. BERGM fit

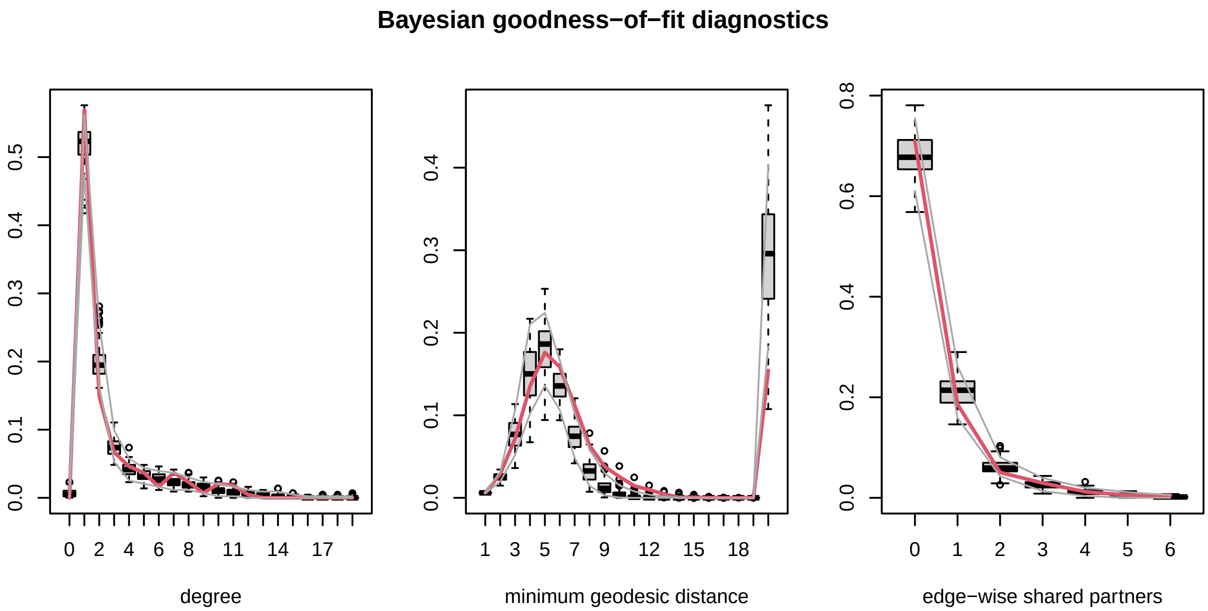


Figure S1: BGOF Knowledge development

Bayesian goodness−of−fit diagnostics

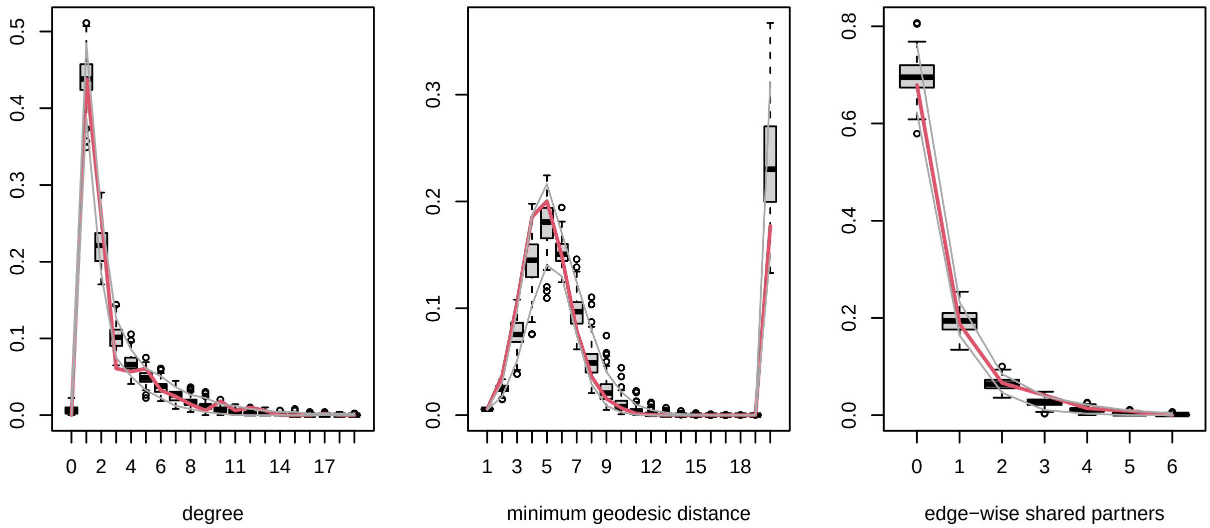


Figure S2: BGOF Knowledge diffusion

Bayesian goodness−of−fit diagnostics

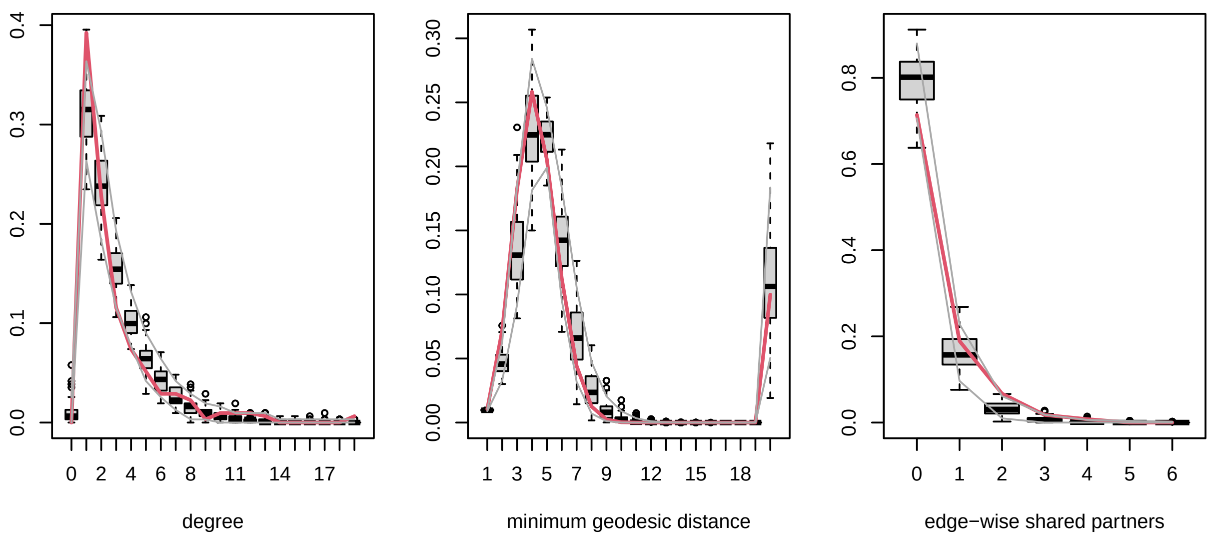


Figure S3: BGOF Resource mobilization

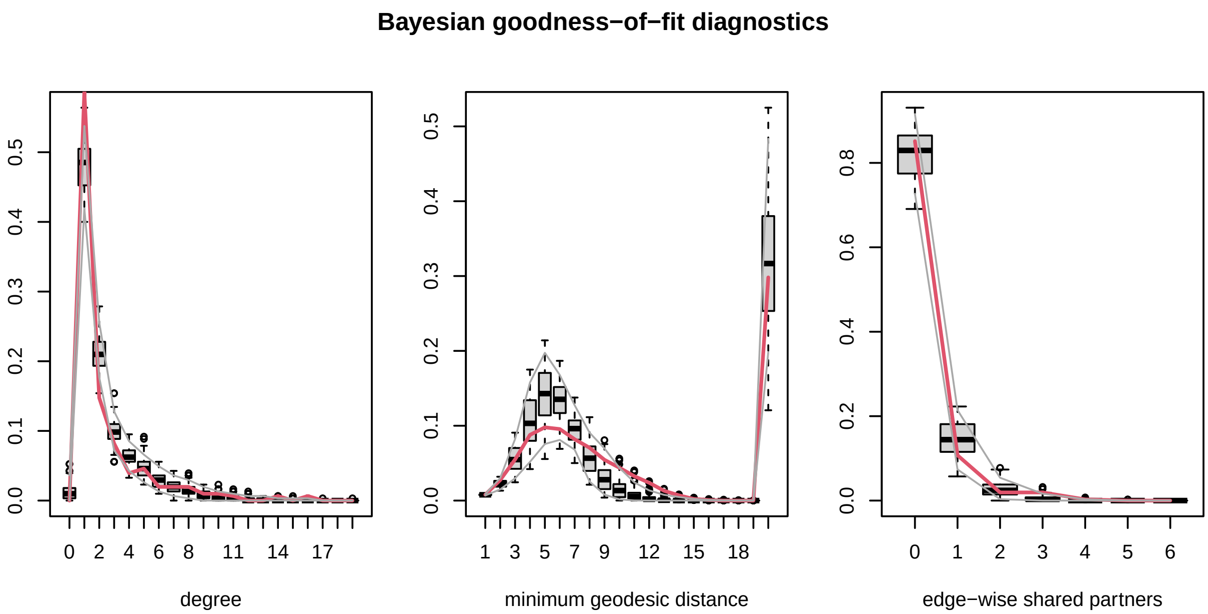


Figure S4: BGOF Market formation

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