Georgia State University Law Review

Volume 24
Issue 4 *Summer 2008*

Article 7

March 2012

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HOMOGENEITY OF DEGREE IN COMPLEX SOCIAL NETWORKS AS A COLLECTIVE GOOD

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INTRODUCTION

Cooperation has played a prominent role in the evolution of many species, from the simplest single-celled organisms[1] to fish,[2] from birds[3] to canines[4] and felines,[5] and from non-human primates[6] to

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1. *See generally* SCOTT A. BOORMAN & PAUL R. LEVITT, THE GENETICS OF ALTRUISM (1980); Bernard J. Crespi, *The Evolution of Social Behavior in Microorganisms*, 16 TRENDS ECOLOGY & EVOLUTION 178 (2001); Gregory J. Velicer et al., *Developmental Cheating in the Social Bacterium* Myxococcus Xanthus, 404 NATURE 598 (2000); Gregory J. Velicer, *Evolution of Cooperation: Does Selfishness Restraint Lie Within?* 15 CURRENT BIOLOGY 173 (2005); Gregory J. Velicer, *Social Strife in the Microbial World*, 11 TRENDS MICROBIOLOGY 330 (2003); Gregory J. Velicer & Kristina L. Stredwick, *Experimental Social Evolution with* Myxococcus Xanthus, 81 ANTONIE VAN LEEUWENHOEK 155 (2002).

2. *See generally* LEE ALAN DUGATKIN, COOPERATION AMONG ANIMALS: AN EVOLUTIONARY PERSPECTIVE (1997); Sarah F. Brosnan et al., *Observational Learning and Predator Inspection in Guppies (*Poecilia Reticulata*)*, 109 ETHOLOGY 823 (2003); Lee Alan Dugatkin, *Dynamics of the Tit For Tat Strategy During Predator Inspection in the Guppy (*Poecilia Reticulata*)*, 29 BEHAV. ECOLOGY & SOCIOBIOLOGY 127 (1991); Lee Alan Dugatkin, *Tendency to Inspect Predators Predicts Mortality Risk in the Guppy,* Poecilia Reticulata. 3 BEHAV. ECOLOGY 124 (1992); Manfred Milinski, *Tit for Tat in Sticklebacks and the Evolution of Cooperation*, 325 NATURE 433 (1987).

3. *See generally* CHARLES R. BROWN & MARY BOMBERGER BROWN, COLONIALITY IN THE CLIFF SWALLOW: THE EFFECT OF GROUP SIZE ON SOCIAL BEHAVIOR (1996); John Faaborg et al.,

humans,[7] where cooperation may have had the most evolutionary significance.[8] And yet, the evolution of cooperation among self-regarding individuals remains a formidable challenge currently addressed by highly multi-disciplinary efforts that include scientists from anthropology, biology, computer science, ecology, economics, physics, political science, psychology, mathematics, sociology and numerous other fields.[9] The puzzles posed by cooperative behavior take many forms, but at their root, all involve social dilemmas – circumstances in which individual interests are at odds with common interests. More precisely, individuals are faced with a choice between selfish behavior and prosocial, cooperative behavior where the latter imposes more cost or offers less benefit than the former. While all individuals are strictly better off being selfish, regardless of what other individuals choose to do, all individuals would be best off if enough individuals behaved cooperatively. Thus, the dilemma.[10] The study of these types of problems has largely been driven by the

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Confirmation of Cooperative Polyandry in the Galapagos Hawk (Buteo Galapagoensis), 36 BEHAV. ECOLOGY & SOCIOBIOLOGY. 83 (1995).

4. *See generally* SCOTT CREEL & NANCY MARUSHA CREEL, THE AFRICAN WILD DOG: BEHAVIOR, ECOLOGY, AND CONSERVATION (2002); J. C. Fentress, Jenny Ryon, Peter J. McLeod, & G. Zvika Havkin, *A Multidimensional Approach to Agonistic Behavior in Wolves, in* MAN AND WOLF: ADVANCES, ISSUES AND PROBLEMS IN CAPTIVE WOLF RESEARCH 253 (Harry Frank ed., 1986) ; Franck Courchampa & David W. Macdonald, *Crucial Importance of Pack Size in the African Wild Dog* Lycaon Pictus, 4 ANIMAL CONSERVATION 169 (2001).

5. *See generally* TIMOTHY M. CARO, CHEETAHS OF THE SERENGETI PLAINS: GROUP LIVING IN AN ASOCIAL SPECIES (1994); Craig Packer & Anne E. Pusey, *Cooperation and Competition Within Coalitions of Male Lions: Kin Selection or Game Theory?* 296 NATURE 740 (1982).

6. *See generally* FRANS B. M. DE WAAL, CHIMPANZEE POLITICS (1982); FRANS B. M. DE WAAL, GOOD NATURED: THE ORIGINS OF RIGHT AND WRONG IN HUMANS AND OTHER ANIMALS (1996); ALEXANDER HARCOURT & FRANS B. M. DE WAAL, COALITIONS AND ALLIANCES IN HUMANS AND OTHER ANIMALS (1992); Sarah F. Brosnan & Frans B. M. de Waal, *A Proximate Perspective on Reciprocal Altruism*, 13 HUM. NATURE 129 (2003).

7. *See generally* Ernst Fehr & Urs Fischbacher, *The Nature of Human Altruism*, 425 NATURE 785 (2003); Dominic Johnson et al., *The Puzzle of Human Cooperation*, 421 NATURE 911 (2003); Elinor Ostrom et al., *Revisiting the Commons: Local Lessons, Global Challenges*, 284 SCIENCE 278 (1999).

8. PETER HAMMERSTEIN, GENETIC AND CULTURAL EVOLUTION OF COOPERATION (2003).

9. *Id.*

10. *See generally* Robyn M. Dawes & David M. Messick, *Social Dilemmas*, 35 INT'L J. PSYCHIATRY 111 (2000); N. M. Gotts et al., *Agent-Based Simulation in the Study of Social Dilemmas*, 19 ARTIFICIAL INTELLIGENCE REV. 3 (2003).

application of evolutionary game theory[11] and due to their importance as generalized models of many important socio-economic situations,[12] iconic games such as the Prisoner's Dilemma have been widely employed as metaphors for the dilemma.[13]

At the same time, the study of networks, complex systems, and nonlinear dynamics has pervaded all of science,[14] offering insight into such diverse concerns as the architecture of the Internet,[15] the topology of food webs,[16] and the metabolic network of the bacterium *Escherichia coli.*[17] Indeed, E.O. Wilson, who once characterized the evolution of cooperation as one of the greatest challenges for modern biology,[18] more recently made a more emphatic appeal for research on complex systems.[19]

> The greatest challenge today, not just in cell biology and ecology, but in all of science, is the accurate and complete description of complex systems. Scientists have broken down

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11. For a historical development of evolutionary game theory, *see generally* HERBERT GINTIS, GAME THEORY EVOLVING (2000); JOSEF HOFBAUER & KARL SIGMUND, EVOLUTIONARY GAMES AND POPULATION DYNAMICS (1998); JOHN MAYNARD SMITH, EVOLUTION AND THE THEORY OF GAMES (1982); JOHN VON NEUMANN & OSKAR MORGENSTERN, THEORY OF GAMES AND ECONOMIC BEHAVIOR (1944); William D. Hamilton, *Extraordinary Sex Ratios*, 156 SCIENCE 477 (1967); John Maynard Smith & George R. Price, *The Logic of Animal Conflict*, 246 NATURE 15 (1993); Robert L. Trivers, *The Evolution of Reciprocal Altruism*, 46 Q. REV. BIOL. 34 (1971).

12. Marco Tomassini et al., Social Dilemmas and Cooperation in Complex Networks (Dec. 22, 2006) (unpublished manuscript, *available at* http://arxiv.org/PS_cache/physics/pdf/0612/0612225v1.pdf).

13. *See generally* ROBERT AXELROD, THE EVOLUTION OF COOPERATION (1984); MAYNARD SMITH, THEORY OF GAMES, *supra* note 11; ROBERT SUGDEN, THE ECONOMICS OF RIGHTS, CO-OPERATION AND WELFARE (1986); Robert Axelrod & William D. Hamilton, *The Evolution of Cooperation*, 211 SCIENCE 1390 (1981); Michael Doebeli & Christoph Hauert, *Models of Cooperation Based on the Prisoner's Dilemma and the Snowdrift Game*, 8 ECOLOGY LETTERS 748 (2005); Martin A. Nowak & Robert M. May, *Evolutionary Games and Spatial Chaos*, 359 NATURE 826 (1992); Martin A. Nowak & Karl Sigmund, *Evolutionary Dynamics of Biological Games*, 303 SCIENCE 793 (2004); Martin A. Nowak & Karl Sigmund, *Tit for Tat in Heterogeneous Populations*, 355 NATURE 250 (1992).

14. Steven H. Strogatz, *Exploring Complex Networks*, 410 NATURE 268 (2001).

15. Michalis Faloutsos et al., *On Power-Law Relationships of the Internet Topology*, 29 COMPUTER COMM. REV. 251 (1999).

16. Richard J. Williams & Neo D. Martinez, *Simple Rules Yield Complex Food Webs*, 404 NATURE 180 (2000).

17. H. Jeong et al., *The Large-Scale Organization of Metabolic Networks*, 407 NATURE 651 (2000).

18. E. O. WILSON, SOCIOBIOLOGY: THE NEW SYNTHESIS (Twenty-fifth Anniversary Edition, 2000).

19. E. O. WILSON, CONSILIENCE 85 (1998).

> many kinds of systems. They think they know most of the elements and forces. The next task is to reassemble them, at least in mathematical models that capture the key properties of the entire ensembles.[20]

The application of complex systems tools and network analysis methodologies to the study of social dilemmas represents a very new, but extremely promising means of shedding light on the quandary of cooperation.[21]

Early simulation studies of the evolution of cooperation were based on the notion that all agents competed with all other agents, including themselves, in a round robin style tournament that pitted various interaction strategies against all others.[22] Later studies demonstrated that when evolutionary dynamics were at play, the evolution of cooperation depended on what philosopher Bryan Skyrms called "correlated association,"[23] that is, that it was at least slightly more likely that agents would interact with a subpopulation of agents of their own kind, in strategic terms. This correlated association can be accomplished in many ways, including reputational mechanisms, signaling mechanisms, and spatiality.

20. *Id.*

21. Guillermo Abramson & Marcelo Kuperman, *Social Games in a Social Network*, 63 PHYSICAL REV. LETTERS E 030901 (2001); Brian Skyrms & Robin Pemantle, *A Dynamic Model of Social Network Formation*, 97 PROC. NAT'L ACAD. SCI. USA 9340 (2000); Feng Fu et al., *Evolutionary Prisoner's Dilemma on Heterogeneous Newman-Watts Small-World Network*, 56 EUR. PHYSICAL J. B 367 (2007); Nobuyuki Hanaki et al., *Cooperation in Evolving Social Networks*, 53 MGMT. SCI. 1036 (2007); Erez Lieberman et al., *Evolutionary Dynamics on Graphs*, 433 NATURE 312 (2005); Hisashi Ohtsuki Onocomma, et al., *A Simple Rule for the Evolution of Cooperation on Graphs and Social Networks*, 441 NATURE 502 (2006); Francisco C. Santos & Jorge M. Pacheco, *Scale-Free Networks Provide a Unifying Framework for the Emergence of Cooperation*, 95 PHYSICAL. REV. LETTERS 098104 (2005); Francisco C. Santos et al., *Cooperation Prevails When Individuals Adjust Their Social Ties*, 2 PLOS COMPUTATIONAL BIOLOGY 1284 (2006); Francisco C. Santos et al., *Evolutionary Dynamics of Social Dilemmas in Structured Heterogeneous Populations*, 103 PROC. NAT'L ACAD. SCI. USA, 3490 (2006); Francisco C. Santos et al., *Graph Topology Plays a Determinant Role in the Evolution of Cooperation*, 273 PROC. ROYAL SOC'Y B 51 (2005); Yorgy Szabo & Gabor Fath, *Evolutionary Games on Graphs*, 446 PHYSICS REP. 97 (2007); Tomassini, *supra* note 12 . For an excellent and quite thorough review of the use of agent based simulations in the study of social dilemmas, see Gotts, *supra* note 10.

22. Known as a "mean field" simulation. Axelrod's early tournaments were archetypal. *See* AXELROD, EVOLUTION OF COOPERATION, *supra* note 13.

23. BRYAN SKYRMS, EVOLUTION OF THE SOCIAL CONTRACT (1996); BRYAN SKYRMS, THE STAG HUNT AND THE EVOLUTION OF SOCIAL STRUCTURE (2004).

Following the common sense notion that geography might play a role in the evolution of cooperation, many simulation studies have employed spatiality, placing agents on a two-dimensional grid.[24] (See Figure One.) Side effects of this typology include an artificial limitation on the number of neighbors, or social connections (known as "degree" in network analysis parlance) and a concurrent limitation on the possible differences in levels of connections between individual agents (known as "heterogeneity of degree").

In this study, we join those that employ complex systems tools and network analysis methodologies[25] to leave the artificiality of the two-dimensional toroidal architecture behind in favor of network architectures offering a full range of degree and heterogeneity of degree, facilitating a more generalized study of the evolution of prosocial behavior. (See Figure Two.) In what follows, we begin by formally specifying the models under study and providing a detailed description of the simulations. We then explain our results, focusing principally on the conclusion that heterogeneity of degree negatively influences the evolution of cooperation and that this effect is independent from other factors such as average degree.

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24. Where this two-dimensional grid is "non-bordered," that is, the top wraps to the bottom and the left side wraps to the right side, the typology is called a torus.

25. *See supra* note 21.

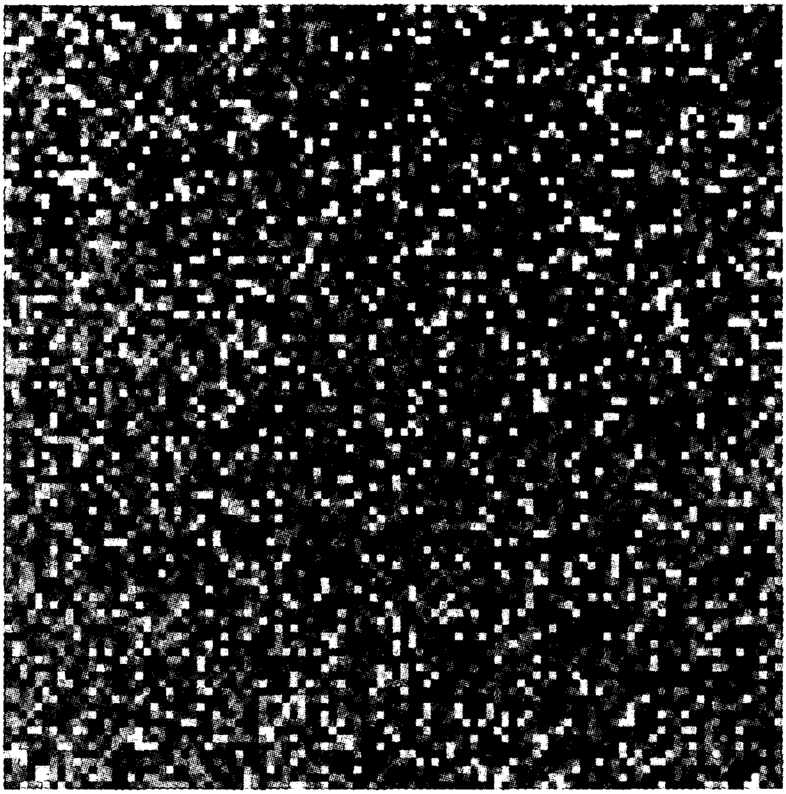


Figure One: A torus – a two-dimensional, non-bordered space. (full color diagram available at: http://www.gregorytoddjones.com/publications.htm).

Finally, we briefly discuss the consequences of these results in the broader context of institutional design efforts that may bring about increased levels of cooperation and maximize social welfare. We suggest that the promotion of homogeneity of degree may properly be viewed as a collective good.

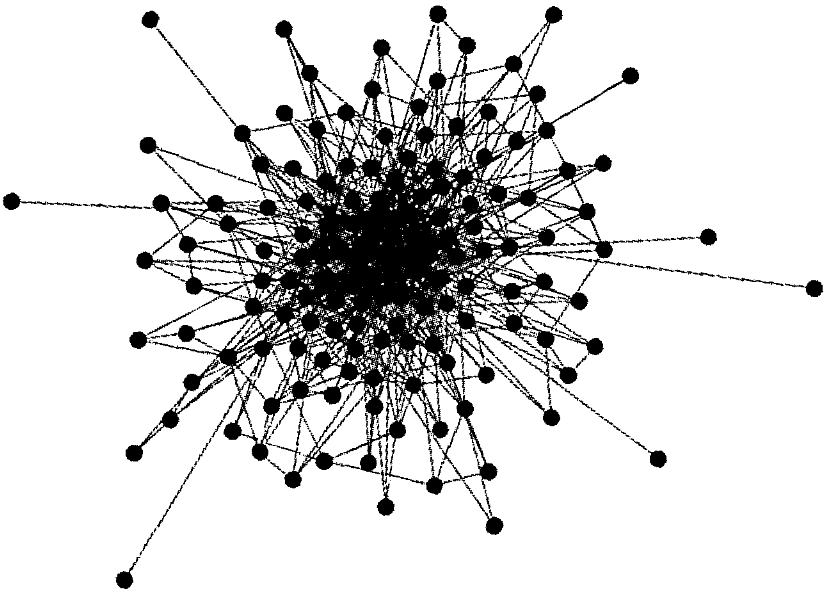


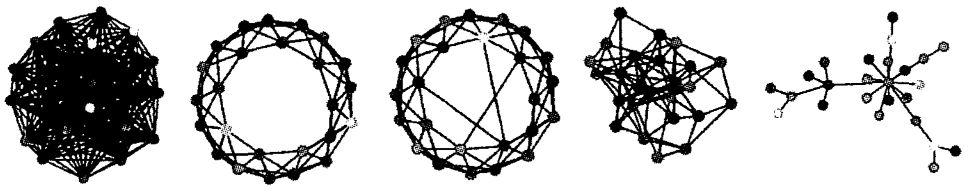
Figure Two: A complex network in which each agent has N – 1 possible connections, a full range of degree and heterogeneity of degree. (full color diagram available at: http://www.gregorytoddjones.com/publications.htm).

MODELS AND SIMULATIONS

We examine a population of N players, each engaging in a repeated prisoner's dilemma game with a neighborhood of other players defined by particular network architectures.[26] The set of players with whom player i interacts in period t is denoted by $\Omega_{i,t}$. In each generation, which is comprised of g games, each player accumulates an adaptive score based upon a standard payoff matrix described in more detail below. At the end of each generation, each player

26. For an introduction to the significance of network architecture, see Xiao Fan Wang & Guanrong Chen, *Complex Networks: Small-World, Scale-Free and Beyond*, IEEE CIRCUITS AND SYSTEMS MAGAZINE 6 (2003). See Figure Three.

observes the payoffs and strategies of each neighbor and stochastically updates[27] their strategy with probability $\rho \in [0,1]$ by imitating the strategy of the neighbor with the highest adaptive score (including themselves). Ties in high scores are broken at random.



(a) (b) (c) (d) (e)

Figure Three: Schematic illustration of various network architectures, all with 25 nodes, roughly in ascending order of heterogeneity. (a) Fully connected network. (b) Ring lattice with all nodes connected to its neighbors out to some range *k* (here *k* = 3).(c) Small world network starting with ring lattice and adding shortcut links between random pairs of nodes. (d) Random network constructed with connection probability, *p* = .15. (e) Scale-free network constructed by attaching nodes at random to previously existing nodes, where the probability of attachment is proportional to the degree of the target node, i.e., "the rich get richer." (full color diagram available at: http://www.gregorytoddjones.com/publications.htm).

Strategic Dynamics

For each period *t*, players choose to either cooperate (*C*) or defect (*D*) with each of its neighbors $\Omega_{i,t}$ and the strategic decision for each neighbor is independent of the decisions with regard to other

27. Note that where $\rho < 1$, updates are asynchronous. *See* Bernardo A. Huberman & Natalie S. Glance, *Evolutionary Games and Computer Simulations*, 90 PROC. NAT'L ACAD. SCI. USA 7716 (1993).

neighbors, that is, a player can choose to cooperate with some neighbors and defect with others.[28] Each neighbor $j \in \Omega_{i,t}$ faces a symmetrical decision giving rise to a standard payoff matrix.

i, j	***C***	***D***
C	*R, R*	*S, T*
D	*T, S*	*P,P*

Where $\pi(s_i, s_j)$ is the payoff for player *i* choosing strategy s_i when neighbor *j* chooses strategy s_j,

$$\pi(C,C) = R,\ \pi(C,D) = S,\ \pi(D,C) = T,\text{ and } \pi(D,D) = P.$$

In keeping with the standard structure of a social dilemma, $T > R > P > S$, which makes defection a dominant strategy, that is, defection results in a higher payoff as compared to cooperation, regardless of what strategy the opponent neighbor chooses, and $2R > (T + S)$, which insures that mutual cooperation is preferred over all other strategy sets in the sense that it produces maximum aggregate outcomes. The unique equilibrium for the game, mutual defection, thus leads to a Pareto-suboptimal solution.

For each generation, each player accumulates an adaptive score for *g* games for all neighbors. Following the logic that the maintenance of networks with more neighbors would involve more cost than networks with fewer neighbors, we reduce adaptive scores by $\theta(k)$, the total cost of interaction with a network of *k* neighbors. Thus, the net payoff for each player *i* accumulated in a time period *t* is

$$\Pi_{i,t} = \sum_{j \in \Omega_{i,t}} \pi(s_{i,t}, s_{j,t}) - \theta(k_{i,t}),$$

where $\theta(k)$ is an increasing function of k with the specific form $\theta(k) = ck^{\alpha}$, where $\alpha \geq 1$ and $0 \leq c \leq P$.[29]

28. *But see* Hanaki, *supra* note 21.

29. *See* Hanaki, *supra* note 21.

Imitation Dynamic

After each generation, each player examines the accumulated adaptive scores of each of its neighbors, $\Omega_{i,t}$, and its own accumulated adaptive score, and either adopts by imitation the strategy of the most successful neighbor, or keeps it own strategy if it has been most successful, to be employed in the next generation, formally

$$s_{i,t+1} = \arg\max_{j \in \Omega_{i,t}} \Pi_{j,t}(s_{j,t}), \Pi_{i,t}(s_{i,t}) .$$

If more than one player in the neighborhood shares the highest accumulated adaptive score, ties are broken at random.

Network measures

For each run of the simulation, which is comprised of a large number of generations sufficient to arrive at equilibrium in the strategy population, a number of variables are recorded: population, average degree, heterogeneity of degree, network architecture, and cooperation. Network architecture is recorded as lattice, small world, random, or scale-free (fully connected is a special case of lattice). Cooperation is measured as a ratio of player decisions to cooperate to the total number of cooperation/defection decisions. (See Table One.)

RESULTS

We ran the simulation as described above 1,000 times creating stochastic networks by drawing network architecture uniformly from lattice, small world, random, or scale-free; drawing population uniformly from a range of 10 to 100; and drawing average degree uniformly from a range of 2 to 10. Heterogeneity of degree ranged from 0 to 4 as a function largely of network architecture. Each run was for 1,000 generations with the cooperation ratio measured in the last 100.

Variable	Variable Type	Specification
Population: the number of players – constant throughout a given simulation run	Independent	N
Average Degree: the average number of social network connections across all players	Independent	$\bar{k} = \frac{1}{N}\sum_i k_i$
Heterogeneity: the standard deviation of average degree across all players	Independent	$\sigma = \sqrt{\sigma^2}$ where $\sigma^2 = \sum_{k=1}^{N-1}(k-\mu)^2 \cdot d(k)$ $\mu = \sum_{k=1}^{N-1} k \cdot d(k)$
Network Architecture	Independent	Indicator Variables
Cooperation	Dependent	The ratio of acts of cooperation to opportunities for cooperation.

Table One: Model Variable Specification

First, we regressed cooperation on population, average degree, heterogeneity of degree, and three indicator variables representing four network architectures: lattice (as the base case), small world, random, and scale free. (See Model One.) We included the indicator variables to capture any variation resulting from network architectural differences not captured by the other independent variables.

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Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	70.524	3.023		23.330	.000		
	SWDum	-.915	2.075	-.017	-.441	.660	.675	1.481
	RNDum	-60.740	5.802	-1.203	-10.468	.000	.080	12.445
	SFDum	-65.202	5.493	-1.291	-11.871	.000	.090	11.152
	Pop	.245	.028	.312	8.604	.000	.805	1.241
	Degree	-8.170	.348	-1.320	-23.450	.000	.335	2.986
	Hetero	31.847	3.272	1.164	9.733	.000	.074	13.485

a. Dependent Variable: Coop

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions						
				(Constant)	SWDum	RNDum	SFDum	Pop	Degree	Hetero
1	1	4.051	1.000	.00	.01	.00	.00	.01	.01	.00
	2	1.274	1.783	.00	.22	.01	.00	.00	.00	.01
	3	1.060	1.955	.00	.00	.02	.04	.00	.00	.00
	4	.324	3.538	.00	.63	.03	.01	.05	.09	.01
	5	.164	4.965	.03	.05	.02	.01	.34	.26	.03
	6	.112	6.007	.25	.05	.02	.01	.44	.00	.05
	7	.014	17.087	.72	.05	.91	.94	.16	.63	.91

a. Dependent Variable: Coop

Model One: Cooperation ("Coop") regressed on Population ("Pop"), Average Degree ("Degree"), Heterogeneity of Degree ("Hetero") and three indicator variables representing four network architectures, Lattice (base case), Small World ("SWDum"), Random ("RNDum"), and Scale Free ("SFDum").

We hypothesized that population size would have a positive effect on cooperation, and that both average degree and heterogeneity of degree would have a negative effect. While Model One bore out the first two hypotheses (population coefficient = .245, $p < .000$ and average degree coefficient = -8.170, $p < .000$), heterogeneity of degree showed a significant positive effect (heterogeneity of degree coefficient = 31.847, $p < .000$). However, collinearity diagnostics indicated that the two most heterogeneous network architectures were highly collinear with the heterogeneity of degree variable (variance proportions on dimension 7: random network = .91, scale-free network = .94, and heterogeneity of degree = .91). Further, the small-world network indicator variable failed to achieve statistical significance (p = .660). These results offered confidence that the indicator variables were not adding significantly additional explanatory power. Indeed, the collinearity made model coefficients uninterpretable.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	43.468	2.372		18.328	.000		
	Pop	.335	.035	.428	9.473	.000	.919	1.089
	Degree	-4.780	.279	-.772	-17.146	.000	.925	1.081
	Hetero	-4.208	1.204	-.154	-3.495	.001	.969	1.032

a. Dependent Variable: Coop

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	Pop	Degree	Hetero
1	1	3.247	1.000	.01	.02	.02	.03
	2	.429	2.750	.01	.02	.09	.93
	3	.220	3.843	.09	.21	.86	.03
	4	.104	5.580	.88	.75	.02	.01

a. Dependent Variable: Coop

Model Two: Cooperation ("Coop") regressed on Population ("Pop"), Average Degree ("Degree"), and Heterogeneity of Degree ("Hetero")

Subsequently, in Model Two, we removed the indicator variables and regressed cooperation on population, average degree, and heterogeneity of degree. (See Model Two.) In this more parsimonious model, population had a significant positive effect (population coefficient = .428, p < .000), average degree had a significant negative effect (average degree coefficient = -4.78, p < .000), and heterogeneity of degree had a significant negative effect (heterogeneity of degree coefficient = -4.208, p < .001). Additionally, collinearity diagnostics showed that each of the independent variables was loading highly on its own dimension (population variance proportion on dimension 4 = .75, average degree variance proportion on dimension 3 = .86, heterogeneity of degree variance proportion on dimension 2 = .93). Based on this evidence, we concluded that heterogeneity of degree has a significant *negative* effect on the evolution of cooperation and that this effect is *independent* of the negative effect of average degree.

DISCUSSION

In *Bowling Alone*,[30] Robert Putnam worries that the decline of social capital that he sees in the declining memberships in civic organizations may undermine the civil engagement that, according to him, is necessary for a strong democracy. The results of this study suggest that the problem may be more nuanced. It may not be, in fact, the mere magnitude of social connections but the nature of these connections that should concern us most. As Putnam points out, membership in local civic organizations has been replaced to some extent by mass membership organizations, and our results demonstrate that resulting increases in average degree may exert a negative influence on cooperative behavior that promotes social welfare. Putnam's work also suggests that local cohesiveness, or "clumpiness" may have a determinative effect. This is a network measure not included here, but planned for future studies.

Our most important finding in this study, however, is that inequality in social connectedness, heterogeneity of degree, has a negative effect on the evolution of prosocial behavior, and that this effect is independent of the negative effect of average degree. Paired with evidence that modern day social and technological networks are increasing in heterogeneity, exhibiting multi-peaked degree distributions[31] unlike the egalitarian, single-peak degree

30. Robert D. Putnam, *Bowling Alone: America's Declining Social Capital*, 6.1 J. DEMOCRACY 65 (1995). *See also* ROBERT D. PUTNAM, BOWLING ALONE: THE COLLAPSE AND REVIVAL OF AMERICAN COMMUNITY (2000).

31. Francisco C. Santos & Jorge M. Pacheco, *A New Route to the Evolution of Cooperation*, 19 J. EVOLUTIONARY BIOLOGY 726 (2006).

distributions[32] characteristic of the Pleistocene's environment of evolutionary adaptedness (EEA)[33] when our current social brains evolved, these findings should give us pause. Merely promoting the development of dense social networks may lead us down a path to social decline. More important may be the design of institutions that promote homogeneity in social connectedness – increasing homogeneity of degree produces network effects that increase overall social welfare. As such, homogeneity of degree is properly thought of as a collective good.

32. Satoshi Kanazawa, *Where Do Social Structures Come From?* 18 ADVANCES IN GROUP PROCESSES 161 (2001).
33. JOHN BOWLBY, ATTACHMENT (1969).