

Social Capital and Social Quilts: Network Patterns of Favor Exchange[†]

By MATTHEW O. JACKSON, TOMAS RODRIGUEZ-BARRAQUER, AND XU TAN*

We examine the informal exchange of favors in societies such that any two individuals interact too infrequently to sustain exchange, but such that the social pressure of the possible loss of multiple relationships can sustain exchange. Patterns of exchange that are locally enforceable and renegotiation-proof necessitate that all links are “supported”: any two individuals exchanging favors have a common friend. In symmetric settings, such robust networks are “social quilts”: tree-like unions of completely connected subnetworks. Examining favor exchange networks in 75 villages in rural India, we find high levels of support and identify characteristics that correlate with support. (JEL D85, O12, O18, Z13)

Human beings rely on cooperation with others for their survival and growth. Although some forms of cooperation and behavior are enforced by social, religious, legal, and political institutions that have emerged throughout history, much of development, growth, and basic day-to-day functioning relies on a society’s ability to “informally” encourage cooperative behavior. This sort of informal enforcement of cooperation ranges from basic forms of quid pro quo (or “tit for tat” in game theory parlance) to more elaborate forms of social norms and culture, all of which must function without enforceable contracts or laws.¹ Indeed, contracting costs are prohibitive for many day-to-day favors that people exchange, ranging from offering advice to a colleague, a small loan to a friend, or emergency help to an acquaintance. Such informal favor exchange and cooperative behaviors, in one form or another, underly much of the literature on social capital.

* Jackson: Department of Economics, Stanford University, 579 Serra Mall, Stanford, California 94305-6072, Santa Fe Institute, and the Canadian Institute for Advanced Research (e-mail: jacksonm@stanford.edu); Rodriguez-Barraquer: Department of Economics, European University Institute, Villa San Paolo, Via della Piazzuola 43, 50133 Firenze, Italy (e-mail: alcaparro@gmail.com); Tan: Department of Economics, Stanford University, 579 Serra Mall, Stanford, California 94305-6072 (e-mail: xutan@stanford.edu). We gratefully acknowledge financial support from the NSF under grants SES-0647867, SES-0752735, and SES-0961481. The data were gathered in collaboration with Abhijit Banerjee, Arun Chandrasekhar, and Esther Duflo, whom we thank for making the data analysis here possible. We are also grateful to the Abdul Latif Jameel Poverty Action Lab (J-PAL) and the Centre for Microfinance at the Institute for Financial Management and Research in Chennai (CMF at IFMR) for support and help in the data collection. We thank Scott Altman, Nicolas Carayol, Avner Grief, Ian Jewitt, Mihai Manea, Markus Mobius, Sudipta Sarangi, Giancarlo Spagnolo, and three anonymous referees for helpful comments and suggestions.

[†] To view additional materials, visit the article page at <http://dx.doi.org/10.1257/aer.102.5.1857>.

¹ In fact, the term “ostracism” (which has Greek origins based on a practice of banishments that originated in the Athenian democracy) has come to embody the idea of individuals cutting ties with members of society who do not perform properly.

Although there is a large literature on social capital, there is a paucity of work that provides careful foundations for how social structure relates to such favor exchange and cooperative behavior. Moreover, as we show here, favor networks do not necessarily exhibit the suggested patterns predicted by some of the previous literature. These points are related to each other since some standard network measures have emerged loosely from the literature discussing the role of networks in fostering cooperation. In particular, the importance of social pressures on fostering cooperation has deep roots in the sociology literature including seminal work by Simmel (1950), Coleman (1988), and more recently by Krackhardt (1996), among others (see the literature discussion below). Standard measures of network clustering and transitivity have grown in part out of those works. Clustering measures examine the extent to which two friends of a given agent are friends of each other. In the data on favor exchange networks in rural India that we examine here, clustering is on the order of 10 to 30 percent. A puzzle emerges as to why one sees that level of clustering, and not some other higher level, and even whether clustering is really the appropriate measure for capturing social pressures. In contrast, the concept of “support” that emerges from our theoretical analysis measures the number of pairs of friends that have some other friend in common. As we shall see in the data, support is several times higher than clustering, and indeed this distinction is consistent with the theory presented here.²

To be specific, in this paper we provide a game theoretic foundation for social enforcement of informal favor exchange, and also examine network patterns of favor exchange from 75 rural villages. In particular, we consider settings where simple bilateral quid pro quo enforcement is insufficient to sustain favor exchange. Some bilateral interactions may be infrequent enough that they fail to allow natural self-enforcement of cooperation or favor exchange. When such interactions are embedded in a network of interactions whose functioning can be tied to each other, however, then individuals can find it in their interest to cooperate given (credible) threats of ostracism or loss of multiple relationships for failure to behave well in any given relationship. We provide complete characterizations of the network patterns of favor exchange that are sustainable by a form of equilibrium satisfying two robustness criteria.

The setting that we examine is such that opportunities for one agent to do a favor for another agent arrive randomly over time. Providing a favor is costly, but the benefit outweighs the cost, so that it is efficient for agents to provide favors over time. It could be, however, that the cost of providing a favor today is sufficiently high that it is not in an agent’s selfish interest to provide the favor even if that means that he or she will not receive favors from that person again. Thus, networks of relationships are needed to provide sufficient incentives for favor exchange, and it may be that an agent risks losing several relationships by failing to provide a favor. We characterize the network structures that correspond to robust equilibria of favor exchange. The criteria that we examine are twofold: first, the threats of which relationships will be terminated in response to an agent’s failure to deliver a favor must be credible.

²This does not imply that clustering might not emerge from other models of favor exchange, and clustering remains an important network statistic—but one that is conceptually distinct from support. Also, numbers of friends in common are reported in various network case studies (for an early discussion, see Barnes 1954), which is a form of support for which our theory now provides a foundation. Friends in common have also been used in modeling network formation (see, e.g., Jackson and Rogers 2007) and prediction of relationships (see, e.g., Liben-Nowell and Kleinberg 2007).

Credibility is captured by the game theoretic concept of “renegotiation-proofness.”³ After an agent has failed to deliver a favor, that relationship is lost, but which additional relationships are lost in the continuation equilibrium must be such that there is not another equilibrium continuation that all agents prefer to the given continuation. This sort of renegotiation-proofness rules out unreasonable equilibria such as the “grim trigger” sort of equilibrium where once anyone fails to provide a single favor the whole society grinds to a halt and nobody provides any favors in the future. At that point, it would be in the society’s interest to return to some equilibrium where at least some favors are provided. Renegotiation-proof equilibria can be complex, but have some nice intuitions underlying their structure, as we explain in detail. The second criterion that we impose is a robustness condition that we call “robustness against social contagion.” It is clear that to sustain favor exchange, an agent must expect to lose some relationships if the agent fails to deliver a favor. Those lost relationships can in turn cause other agents to lose some of their relationships since the incentives to provide favors change with the network structure. This can lead to some fragility of a society, as one agent’s bad behavior can ripple through the society. The robustness against social contagion requires that the ripple effects of some agent’s bad behavior be confined to that agent’s neighbors and not propagate throughout the network.

In symmetric settings, the combination of renegotiation-proofness and robustness require a unique type of network configuration of favor exchanges. We call those configurations “social quilts.” A social quilt is a union of small cliques (completely connected subnetworks), where each clique is just large enough to sustain cooperation by all of its members and where the cliques are laced together in a tree-like pattern. One of our main theoretical results shows that configurations of favor exchange that are sustained in robust equilibria are precisely the social quilts.

We then extend the model to allow heterogeneity in the cost, value, and arrival rates of favors to various individuals. In the more general setting, we prove that any robust equilibrium network must exhibit a specific trait: each of its links must be “supported.” That is, if some agent i is linked to an agent j , then there must be some agent k linked to both of them. This is related to, but quite distinct from, various clustering measures.

With the theoretical underpinnings in hand, we then examine social networks in 75 villages in southern rural India.⁴ Using these data⁵ we can examine the networks of various forms of social interaction including specific sorts of favor exchange. In line with the theoretical predictions, we find that the number of favor links that have this sort of social support is in the range of eighty percent in these villages. Moreover, the level of support is significantly higher than what would arise if links

³ Although there are several definitions in the literature for infinitely repeated games, our games have a structure such that there is a natural definition that has an inductive structure reminiscent of that of Benoit and Krishna (1993).

⁴ Although we apply some of our findings to favor relationships in Indian villages, such informal favor exchange is clearly not limited to developing countries. For example, a recent *New York Times*/CBS News poll (reported in “Poll reveals trauma of joblessness in U.S.” *New York Times*, December 15, 2009) found that 53 percent of surveyed unemployed workers in the United States had borrowed money from friends or family as a result of being unemployed.

⁵ These data are particularly well-suited for our study as they provide network structure for various favor relationships, and moreover have this information for many separate villages. We are not aware of any other dataset having these attributes. In particular, in these data we have information about who borrows rice and kerosene from whom, who borrows small sums of money from whom, who gets advice from whom, who seeks emergency medical aid from whom, and a variety of other sorts of relationships, as well as GPS data.

were formed at random (even with some geographic bias to formation), and significantly higher than levels of clustering. We analyze various aspects of the levels of support and also find that it is significantly higher for favor relationships than other sorts of relationships. Our research contributes to the understanding of informal favor exchange as well as social networks in several ways:

- We provide an analysis of repeated interactions where an individual's decisions are influenced by the network pattern of behavior in the community, and this provides new insights into repeated games on networks.
- Our model includes dynamic choices of both favor provision and relationships and provides new insights into the coevolution of networks and behavior, and in particular into the phenomenon of ostracism.⁶
- Our analysis suggests a new source of inefficiency in informal risk and favor sharing, showing why individuals may have to limit the number of relationships in which they take part.
- A byproduct of our analysis is an operational definition of social capital that is more specific and tighter than many existing definitions, and it makes tight predictions about how relationships in a society must be organized.
- We identify a necessary property of such favor exchange networks that we call "support" and show how this is distinguished from clustering measures.
- We examine data that include many sorts of interactions and cover 75 different villages, and find that the networks exhibit substantial and significant distinctions between our measure of support and standard measures of clustering.

Related Literature

As mentioned above, there is a large literature on social capital that studies the ability of a society to foster trust and cooperation among its members.⁷ Although that literature is extensive and contains important empirical studies and many intuitive ideas, it has struggled in providing firm theoretical foundations and the term "social capital" has at times been used very loosely and as a result has lost some of its bite.⁸ Part of the contribution of our paper is to provide an explicit modeling of how societies can enforce cooperative favor exchange and how this is linked to the social network structure within a society. In this way, our paper provides a concrete definition of social capital that is embedded in three components: a notion of equilibrium that embodies notions of ostracism and social expectations of individual behaviors, implications of this equilibrium for resulting social network structure, and individual payoffs from the resulting behaviors.

Coleman (1988) discusses closure in social networks, emphasizing the ability of small groups to monitor and pressure each other to behave. Here we provide a new argument for, and a very specific variety of, closure. A specific form of minimal

⁶ As we shall see, ostracism has further consequences in terms of lost relationships, beyond those directly involving the individual being punished.

⁷ For example, see Homans (1958); Loury (1977); Bourdieu (1986); Coleman (1988, 1990); Woolcock (1998); Dasgupta and Stiglitz (2000); Putnam (1993, 1995, 2000); Glaeser, Laibson, and Sacerdote (2002); Guiso, Sapienza, and Zingales (2004); and Tabellini (2010), among others.

⁸ See Sobel (2002) for an illuminating overview and critique of the literature.

clique structures emerge because of a combination of renegotiation-proofness and a local robustness condition, rather than for informational, monitoring, or pressuring reasons. Minimal-sized cliques offer credible threats of dissolving in the face of bad behavior, and in terms of minimal contagion for a society. Our analysis also formalizes this in terms of support and contrasts it with clustering.

The most closely related previous literature in terms of the theoretical analysis of a repeated game on a network is a series of papers that study prisoners' dilemmas in network settings, including Raub and Weesie (1990); Ali and Miller (2009); Lippert and Spagnolo (2011); and Mihm, Toth, Lang (2009).⁹ In particular, Raub and Weesie (1990) and Ali and Miller (2009) show how completely connected networks shorten the travel time of contagion of bad behavior, which can quicken punishment for deviations. Although cliques also play a prominent role in some of those papers, it is for very different reasons. In those settings, individuals do not have information about others' behavior except through what they observe in terms of their own interactions. Thus, punishments travel through the network only through contagious behavior (or word of mouth), and the main hurdle to enforcing individual cooperation is how long it takes for someone's bad behavior to come to reach their neighbors through chains of contagion.¹⁰ Our analysis is in a very different setting, where individuals have complete information. The quilts in our setting emerge because they *do not* lead to large contagions but instead compartmentalize the damage from an individual's defection. Moreover, the quilts consist of minimal-sized cliques because only those sorts of implicit punishments are immune to renegotiation.

Haag and Lagunoff (2006) provide another reason favoring small cliques: heterogeneity. In their analysis, large differences in preferences can preclude cooperative behavior, and so partitioning a group into more homogeneous subgroups can enable cooperative behavior that might not be feasible otherwise. Although our reasoning behind cliques comes from different sources, when we examine heterogeneous societies we do find assortativity in who exchanges favors with whom. Here, it is not because of direct reciprocity considerations, but because robustness requires balanced cliques and so agents need to have similar valuations of favors in order for their cliques to be critical. In this way, we provide new insights into homophily, where relationships of agents are biased toward others who have similar characteristics in terms of their values and arrival rates of favors.

Finally, our analysis of the data not only provides support for the support measure, but also uncovers significant differences between different sorts of relationships, as might be expected based on the different ways in which links might form across applications (see, e.g., Jackson 2008). Here we add a new angle to this understanding, finding statistically distinct patterns of support in various sorts of favor and social networks. These suggest some interesting questions for future research.

⁹Other studies of network structure and cooperative or various forms of risk-sharing behavior and the relationship to social network structures include Fafchamps and Lund (2003); De Weerd and Dercon (2006); Bramoullé and Kranton (2007); Bloch, Genicot, and Ray (2007, 2008); Karlan et al. (2009); and Balmaceda and Escobar (2011).

¹⁰That approach builds on earlier work by Greif (1989); Kandori (1992); Ellison (1994); and Okuno-Fujiwara and Postlewaite (1995), among others, who studied the ability of a society to sustain cooperation via threats of contagions of bad behavior.

I. A Model of Favor Exchange

A. Networks, Favors, and Payoffs

A finite set $N = \{1, \dots, n\}$ of agents are connected in a social network described by an undirected¹¹ graph. Given that the set of agents N is fixed throughout the analysis, we represent a network, generically denoted g , simply by the set of its links or edges. Let g^N be the set of all links (so the set of all subsets of N of size 2), and let $G = \{g \mid g \subset g^N\}$ be the set of all possible networks. For simplicity, we write ij to represent the link $\{i, j\}$, and so $ij \in g$ indicates that i and j are linked under the network g . We write $g - ij$ to denote the network obtained from g by deleting a link ij . For an integer k , $0 \leq k \leq n(n-1)/2$, let G_k be the set of all networks that have exactly k links, so that $G_k = \{g \in G : |g| = k\}$.

The neighbors of agent i are denoted $N_i(g) = \{j \mid ij \in g\}$. We follow a convention that rules out self-links, so all agents in $N_i(g)$ are distinct from i . The degree of agent i in the network g is the number of his or her neighbors denoted by $d_i(g) = |N_i(g)|$.

Time proceeds in discrete periods indexed by $t \in \{0, 1, \dots\}$ and in any given period, there is a chance that an agent will need a favor from a friend or will be called upon to grant a favor to a friend. In particular, an agent i who is connected to an agent j (so that $ij \in g$) anticipates a probability $p > 0$ that j will need a favor from i in period t and a probability p that i will need a favor from j . It is assumed that at most one favor will be needed across all agents in any given period, and so we require that $n(n-1)p \leq 1$, and we allow the sum to be less than one to admit the possibility that no favor is needed in a given period.

This is a proxy for a Poisson arrival process, where the chance that two favors are needed precisely at the same moment is 0. By letting the time between periods be small, the chance of more than one favor being called upon in the same period goes to 0. Thus, when applying the model it is important to keep in mind that periods are relatively small compared to the arrival rate of favors.

A restriction of this formulation is that p does not depend on the network structure. More generally, the chance that i needs a favor from j will depend on many things including how many other friends i has. We characterize the equilibrium networks for the more general case in Section IV. We begin with the current case since it more clearly provides the basic intuitions, but the results have very intuitive analogs for the general case that are easy to describe once we have presented the simpler case.

Doing a favor costs an agent an amount $c > 0$ and the value of the favor to an agent is an amount $v > c$. Receiving a “favor” can embody many things, including getting advice, borrowing a good, borrowing money, or receiving some service. The important aspect is that the value of a favor to the receiving agent exceeds the cost to the providing agent, so that it is ex ante Pareto efficient for agents to exchange favors over time. We examine settings where it is impossible (or too costly), however, for agents to write binding contracts to perform favors whenever called upon to do so. This applies in many developing countries, and also in developed countries where it is prohibitively

¹¹ This is not necessary for the analysis, and we comment later on possible extensions to directed networks.

costly and complex to write complete contracts covering the everyday sort of favors that one might need from friends. Thus, we examine self-enforcing favor exchange.

Agents discount payoffs over time according to a factor $0 < \delta < 1$. Thus, if there were just two agents who always performed favors for each other, then they would each expect a discounted stream of utility of $\frac{p(v-c)}{1-\delta}$. The more interesting case from a network perspective is the one that we examine, where

$$c > \frac{\delta p(v-c)}{1-\delta}.$$

In this case, favor exchange between two agents in isolation is not sustainable. When called upon to perform a favor, the agent sees a cost that exceeds the future value of potential favor exchange (in isolation) and so favor exchange cannot be sustained between two people alone, but must be embedded in a larger context in order to be sustained. Sustaining favor exchange between two individuals requires a high enough frequency of arrival coupled with a high enough marginal benefit from a favor and sufficient patience. In a marriage, there are generally sufficiently many opportunities for each spouse to help the other out with some task or need that bilateral favor exchange can be sustained. In other contexts, however, where such needs are rarer—such as a need to borrow cash due to an emergency, or a need for medical advice, etc.—one might need a multilateral setting to sustain favor exchange.

A society is described by (N, p, v, c, δ) .

B. *The Game*

The favor exchange game is described as follows:

- The game begins with some initial network in place, denoted g_0 .
- Period t begins with a network g_{t-1} in place.
- Agents (simultaneously)¹² announce the links that they are willing to retain: $L_i \subset N_i(g_{t-1})$. The resulting network is $g'_t = \{ij \mid j \in L_i \text{ and } i \in L_j\}$.
- Let k_t be the number of links in g'_t . With probability $2pk_t$ the need for a (single) favor arises and with probability $1 - 2pk_t$ there is no need for a favor in the period. If a favor is needed, then it could apply to any link in g'_t with equal likelihood and then go either direction. If a favor is needed, then let i_t denote the agent called upon to do the favor and j_t the agent who needs the favor, where $i_t, j_t \in g'_t$.
- Agent i_t chooses whether or not to perform the favor. If the favor is performed then i_t incurs the cost c and agent j_t enjoys the benefit v . Otherwise, no cost or benefit is incurred.
- The ending network, denoted g_t , is $g'_t - i_t j_t$ if the need for a favor arose and it was not performed, and is g'_t otherwise.

People make two sorts of choices: they can choose with whom they associate and they can choose to do favors or not to do favors. Opportunities for favor exchange

¹² Given the equilibrium refinements that we use, whether or not the link choices are simultaneous is effectively irrelevant.

arise randomly, as in a Poisson game, and people must choose whether to act on favors as the need arises. Choices of which relationships to maintain, however, can be made essentially at any time. In the model this is captured by subdividing the period into link choices and favor choices, so that agents have a chance to adjust the network after any favor choice, and before the next potential favor arises.

This structure embodies several things. First, favor relationships can either be sustained or not. Once a favor is denied, that relationship cannot be resuscitated. Thus, at any point in time an agent's decision is which relationships to maintain. This simplifies the analysis in that it eliminates complicated forms of punishment where various agents withhold favors from an agent over time, but then eventually revert to providing favors. It can be motivated on various behavioral (e.g., emotional) or prosocial grounds and effectively acts as a sort of refinement of the set of all possible punishments that might occur, as it requires that one of the ostracizing agents be the one who failed to get the favor. Eventually, one would like to extend the analysis to situations where after some period of time forgiveness is possible, but this simplification allows us to gain a handle on sustainable network structures as the problem is already complex, and it appears that much of the intuition carries over to the more flexible case, but that is a subject for further research.

Second, we do not consider the formation of new links, but only the dissolution of links. This embodies the idea that the formation of new relationships is a longer-term process and that decisions to provide favors and/or ostracize an agent can be taken more quickly and are shorter-term actions. It is important to note that we cover the case where society starts with the complete network, so we do not restrict the links that might be formed a priori, and so our results do make predictions about which networks can be formed/sustained in a society. The important wedge that we impose is that an agent who has lost a relationship cannot (quickly) replace it with a newly formed one.

One other aspect of the model is important to mention. Agents do not exchange money for favors even though, hypothetically, favor exchange could be monetized. Of course, we do not see monetization of all favors in reality, as when a colleague asks to borrow a book we tend not to charge her or him a rental fee. But that empirical observation does not explain why we do not charge our friends and acquaintances for every favor that we perform. One explanation is a behavioral one: that monetizing favors would fundamentally change the way that people perceive the relationship, and this explanation is consistent with people no longer viewing a monetized relationship as a long-run relationship. More discussion of this point is given by Kreps (1997). The specifics of why at least some favors are not monetized is outside of our scope.

For now, we consider a complete-information version of the game, in which all agents observe all moves in the game at every node. We discuss limited information variations in Section VI.

An agent i 's expected utility from being in a network g that he or she expects to exist forever¹³ is

$$u_i(g) = \frac{d_i(g)p(v - c)}{1 - \delta}.$$

¹³This applies at any point within the period other than at the time at which the agent is called to receive or produce a favor.

If an agent i is called to do a favor to j and chooses to perform the favor and expects a network g to be played in perpetuity thereafter, then he or she expects a utility of $-c + \delta u_i(g)$. Similarly, if agent i is called to receive a favor from agent j and expects to receive the favor and then anticipates a network g to be played in perpetuity thereafter, then his or her expected discounted stream of utility is given by $v + \delta u_i(g)$.¹⁴

We note that although we work with favor exchange as the building block of our model, the analysis here extends directly to supporting cooperation more generally, and the same results apply to the play of a prisoner's dilemma between agents, or other forms of trust and cooperation games with free-rider or short-term deviation challenges.

C. Equilibrium

In this setting, any network of favor exchange g can be sustained in perpetuity as a pure strategy subgame perfect equilibrium if

$$c < d_i(g) \frac{\delta p(v - c)}{1 - \delta}$$

for every agent i . One way in which this is sustained is by a sort of “grim trigger” strategy where all relationships are sustained and favors are provided as long as no agent refuses a favor, and once any favor is denied then all agents delete all their links and never expect to receive any favors again in the future. Thus, if each agent has enough relationships that he or she might lose, then favor exchange can be sustained. So, for instance, if

$$c < (n - 1) \frac{\delta p(v - c)}{1 - \delta}$$

then the complete network with the most efficient favor exchange could be sustained.

Renegotiation-Proofness

While the above conclusion offers some optimism regarding a society's ability to sustain favor exchange efficiently, it rests upon drastic threats that are not always credible. If for some reason a favor was not performed and some link disappeared, a society might wish to reconsider its complete dissolution. Indeed, the idea that if some person in a society acts selfishly and fails to provide a favor, the whole society collapses and no favors are ever exchanged again is drastic and unrealistic. This sort of observation is not unique to this setting (see, e.g., the discussion in Bernheim, Peleg, and Whinston 1987). The issue is that if agents have some chance

¹⁴For ease of expression, we assume that the discounting parameter δ enters the agents' calculations between the announcement stage and the favor stage in any given period. This is purely for expository ease. Effectively, it ensures that whenever an agent is either making a decision of which links to announce or whether to follow through on a favor, any potential future favors that might be influenced by the decision are discounted. If discounting happens after the favor period, then when making link choices, agents would not discount one round of future favors, but when making favor decisions they would. This simply ensures that all future favors are discounted in the same way.

to communicate with each other (and perhaps even if they cannot), then when beginning some phase of equilibrium that involves low payoffs, if there is some other *equilibrium* continuation, in which all agents are better off, then they have an incentive to change to the play that gives them all better payoffs. Even though this sort of “renegotiation” problem is well known, it is rare for researchers to do more than to acknowledge it and forge ahead. The reason for this is that properly accounting for renegotiation becomes quite complicated, especially in infinite settings where it is not even clear how to define equilibrium in the face of renegotiation (e.g., Farrell and Maskin 1989; Bernheim and Ray 1989; and Abreu, Pearce, and Stacchetti 1993). Thus, there are few analyses of renegotiation-proofness outside of some of the original papers working out the definitions, although some instances of it appear in other forms (e.g., repentance strategies in Lippert and Spagnolo 2011).

Our setting has a structure that makes it relatively easy to provide a natural definition of renegotiation-proofness and to characterize such equilibria. Before moving to the formal definitions, we present an example that illustrates the ideas.

Example 1: The Logic of Renegotiation-Proofness

Let there be four agents and consider a case such that

$$2 \frac{\delta p(v - c)}{1 - \delta} > c > \frac{\delta p(v - c)}{1 - \delta}.$$

Here, no link is sustainable in isolation, since the value of providing a favor c is greater than the value of the future expected stream of giving and receiving favors: $\frac{\delta p(v - c)}{1 - \delta}$. If an agent risks losing two links by not performing a favor, however, then links could be sustainable depending on the configuration of the network, since $c < 2 \frac{\delta p(v - c)}{1 - \delta}$.

In this case, note that networks where each agent has exactly two links, for example, $g = \{12, 23, 34, 41\}$, can be sustained as a subgame perfect equilibrium. If any agent ever fails to perform a favor, then a link will be lost. For example, suppose that 1 fails to deliver a favor to 2, and so the link 12 is lost. At this point, agent 1 only has one relationship left: 14. It is now clear that agent 1 will never perform future favors for 4 and so the link 14 is effectively useless as well. The same is true of 23. Iterating on this logic, there is no subnetwork that could be sustained as a subgame perfect equilibrium. As such, an agent realizes that if he or she fails to provide a favor, then that will lead to a collapse of all favors and so the network of favor trading is sustained in equilibrium, as failing to provide one favor induces a loss of two relationships. So, starting with such a minimal network, there is no difficulty with renegotiation, as following any deviation from the prescribed favor exchange the equilibrium continuation is unique. So, favor exchange sustaining this network is renegotiation-proof as an equilibrium (to be defined shortly).

The problematic subgame perfect equilibria come with $k = 5$ or more links. Consider the network $g' = \{12, 23, 34, 41, 13\}$ as pictured in Figure 1. Agents 1 and 3 each have three links and agents 2 and 4 have two links. There is a subgame perfect equilibrium sustaining this network: if any link is ever cut, then all agents cut every link in the future. There is no renegotiation-proof equilibrium sustaining

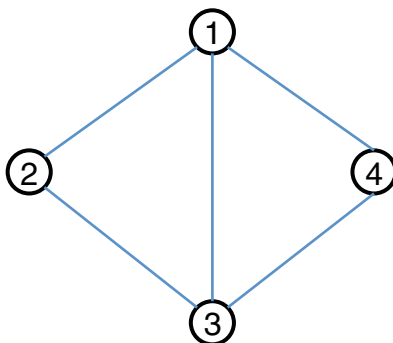


FIGURE 1. A FIVE-LINK NETWORK THAT IS NOT SUSTAINED AS A RENEGOTIATION-PROOF EQUILIBRIUM

this network, however. To see this, suppose that agent 1 is called upon to do a favor for agent 3. If agent 1 does not do the favor, then the resulting network is $g = \{12, 23, 34, 41\}$. Note that g is sustainable as a subgame perfect equilibrium as argued above (and in fact is sustainable as part of a renegotiation-proof equilibrium). The logic is now that if g is reached, then it will be sustained rather than having agents delete all links, since it is not credible for agents to destroy these links as they are all strictly better off sustaining g than going to autarchy. Thus, when reaching g , in the absence of some exogenous commitment device, the agents' previous threat to delete all links lacks credibility. As a result of this, agent 1 can cut the link 13 and still expect the network g to endure, and so this is the unique best response for agent 1 and so g' is not sustainable as an equilibrium if we require that continuations not be Pareto dominated by another (renegotiation-proof) equilibrium continuation.

We define *renegotiation-proof networks* to be networks that are sustainable via pure strategy renegotiation-proof equilibria. It is easiest to define the networks directly, in a way that simultaneously implicitly defines renegotiation-proof equilibrium and explicitly tracks the networks that are sustainable via those equilibria.

We define the set of pure strategy renegotiation-proof equilibria inductively.^{15,16} The induction operates via the number of links in the starting network. In terms of notation, it will be useful to keep track of the set of all networks that have exactly k links and can be sustained in perpetuity as part of a pure strategy renegotiation-proof equilibrium if we start at that network.

We let RPN_k denote the set of *renegotiation-proof networks* with k links.

- Let $RPN_0 = \{\emptyset\}$.

¹⁵Our analysis concentrates on pure strategy equilibria. As will become clear, considering mixed strategy equilibria would not add much to the insights regarding sustainable network structures.

¹⁶Our definition is in the spirit of Pareto perfection of Bernheim, Peleg, and Whinston (1987), but instead of induction with respect to the stages of the game, we work with induction on the size of the networks as our game is infinitely repeated.

- Let RPN_k denote the subset of G_k such that $g \in RPN_k$ if and only if beginning with $g_0 = g$ implies that there exists a pure strategy subgame perfect equilibrium¹⁷ such that
 - on the equilibrium path g is always sustained (all favors are performed and all links are maintained), and
 - in any subgame¹⁸ starting with some network $g' \in G_{k'}$ with $k' < k$, if g'' is reached with some probability¹⁹ and then played in perpetuity in the continuation, then $g'' \in RPN_{k''}$ for some k'' and there does not exist any $g''' \subset g'$ such that $g''' \in RPN_{k'''}$ and $u_i(g''') \geq u_i(g'')$ for all i with strict inequality for some i .²⁰

The concept is fairly straightforward even though the definition is inductive. It requires that any continuation equilibrium (e.g., a threat of what will happen if some agent deviates) not be Pareto dominated by some other continuation equilibrium. Thus, if society gets to some point where they are supposed to follow through with some equilibrium continuation, they should not all find it better to follow some other (feasible) continuation. The self-referential nature of the definition comes from the fact that we want society to view some continuation as a feasible option only if it is renegotiation-proof itself—as otherwise that should not be expected to be stable, either.²¹ The self-referential logic is what generally provides difficulties in identifying an unambiguously “correct” definition in an infinite setting. Here, despite our infinite horizon, we can define renegotiation-proofness cleanly since relationships can be severed but not resuscitated and so there is a natural induction on the number of links.

We say that a network g is *renegotiation-proof* or a *renegotiation-proof network* if there exists some k such that $g \in RPN_k$. As further illustration of the definition, let us return to Example 1 and characterize all of the renegotiation-proof networks.

Example 2: Renegotiation-Proof Networks

Let there be four agents and consider a case as in Example 1 such that

$$2 \frac{\delta p(v - c)}{1 - \delta} > c > \frac{\delta p(v - c)}{1 - \delta}.$$

Here, $RPN_1 = \emptyset$ since no isolated links are sustainable.

Similarly, $RPN_2 = \emptyset$ since any agent who only has one link will never perform a favor.

¹⁷ That the equilibrium is in pure strategies requires that agents (other than nature) use pure strategies at all nodes on and off the equilibrium path.

¹⁸ This includes subgames starting at any node, not just beginning-of-period nodes.

¹⁹ Even though agents use pure strategies, nature recognizes favors randomly, and so there can be some randomness in a continuation path.

²⁰ Note that this condition implies that in any subgame starting with a network $g' \in RPN_{k'}$, g' is played in the continuation.

²¹ Thus, the definition is inductive, since the logic of renegotiation-proofness requires that a network sustained in some continuation not be Pareto dominated by any other continuation that is itself renegotiation-proof.

$RPN_3 = \{g = \{ij, jh, ih\} : \text{for some distinct } h, i, j\}$. Thus, triads are sustainable, since if any agent severs a link, then that will lead to a two-link network that is not sustainable, and so becomes an empty network. Thus, not performing a favor leads to an empty network, and so it is a best response to perform a favor, anticipating favors by other agents.

$RPN_4 = \{g = \{ij, jh, h\ell, \ell i\} : \text{for distinct } h, i, j, \ell\}$. This is an obvious extension of the logic from three-link networks.

Following the argument in Example 1, it is easy to check that there are no five-link renegotiation-proof equilibria. Thus, $RPN_5 = \emptyset$.

Next, note that $RPN_6 = \emptyset$ as well. To see this, note that if some agent i deletes a link ij , then a continuation must result in a pure strategy renegotiation-proof equilibrium, which would be either a triad, four-link network (with a cycle), or the empty network. The remaining four-link network that has a cycle Pareto dominates any other continuation. Thus, if an agent i severs a link ij , then the agent is sure that he or she will still have two links in the continuation and so only loses one link.²²

Given this example, let us reemphasize an aspect of our model that simplifies the analysis. Renegotiation-proofness serves as a natural and plausible way to limit potential punishments, which tightens predictions of which networks of favor exchange are sustainable. Our model's tractability relies in part, however, on our assumption that when an agent fails to do a favor for another agent, the relationship in question is deleted. By assuming that the link in question must be part of the punishment that ensues, the analysis can move forward, as renegotiation can be anchored via an induction argument, avoiding the substantial difficulties associated with noninductive, self-referential definitions.

In terms of justifying this approach, it is important to note that clearly some punishment must occur following a failure to provide a favor if favors are to be sustained. Thus, the assumption may be viewed as focusing on equilibria where the relationship in question is necessarily involved in that punishment. Let us offer two possible justifications for this focus, without explicitly expanding the model. One justification is that there is a behavioral or emotional response that induces an agent whose favor is denied to place a sufficiently negative weight on the deviator's utility so as not to want to do any favors for the deviator in the future, even if that means losing some other relationships in the continuation. Justifications for such other-regarding preferences generally rely on psychological evidence or evolutionary-style arguments, and are well debated in the behavioral literature, so we do not discuss them here.²³ Effectively, this redirects the justification of the assumption to a well-trodden discussion in behavioral economics. Another avenue for rationalizing this behavior is that there is a relationship-specific type variable for each agent (some sort of "compatibility") that agents learn about over time by observing others' behavior. If one agent fails to deliver a favor for another agent, it

²²This conclusion depends on the way in which renegotiation is defined. Here we have defined it taking all agents into account. Another possibility is to take only the nondeviating agents into account, in which case the complete network can be sustained by having the three remaining agents sever all ties to any deviating agent. We explore this variation in the online Appendix.

²³See Camerer (2003); Fehr and Schmidt (2006); and Cooper and Kagel (forthcoming) for background discussion and evidence on other-regarding preferences.

could signal that the agent has a bad “type” for the compatibility of that relationship, and so will also fail to be able to perform favors in the future in that particular relationship, leading that relationship to no longer function. Having this be relationship-specific is important as then the subsequent deletion of other relationships need not be tied to subsequent inferences of a player’s type in further relationships (just because i and j are incompatible, it does not necessarily imply that j and k will also be incompatible). Independence of types across relationships allows further deletions to be based on the viability of the remaining network structure, and not further inference about types.²⁴

II. Characterizing Renegotiation-Proof Networks

In this section, we provide a complete characterization of renegotiation-proof networks. We begin by providing some intuitive sufficient conditions that give insight into the structure of renegotiation-proof networks.

Let m be the whole number defined by

$$(1) \quad m \frac{\delta p(v - c)}{1 - \delta} > c > (m - 1) \frac{\delta p(v - c)}{1 - \delta}.$$

It is clear that there is at most one such m and that $m \geq 1$. We work with the generic case, ignoring exact equality on either side above. The parameter m captures how many relationships, each with a future value of $\frac{\delta p(v - c)}{1 - \delta}$, an agent has to risk losing in the future in order to have incentives to perform a favor today at the cost of c . Throughout the remainder of the paper, the definitions will all be relative to m , and so we take it to be fixed and defined by equation (1) and omit explicit mention of it in some of the definitions. We begin with a formal statement of the proposition on subgame perfect equilibria that motivates our analysis of renegotiation-proof equilibria.

PROPOSITION 1: *A network is sustainable in perpetuity on the equilibrium path of a pure strategy subgame perfect equilibrium of the favor exchange game if and only if each agent has either 0 links or at least m links.*

The proof of Proposition 1 is obvious and thus omitted. Now we examine renegotiation-proof networks.

²⁴Note that expanding the model in this direction would allow for an analysis of favor exchange along our lines for some period of time. But after agents had learned sufficiently about each other’s types, then we would face an issue that agents would have an incentive to deviate and ask for forgiveness. Thus, analyzing the full long-term dynamics of such a model, and not just the short- to medium-run, would involve enriching the model to allow for some occasional deviations and potential forgiveness. That again complicates the analysis, so that the results presented here would hold for some period of time, but we do not have firm conjectures for what would happen in the very long run when types may be learned, and forgiveness is allowed.

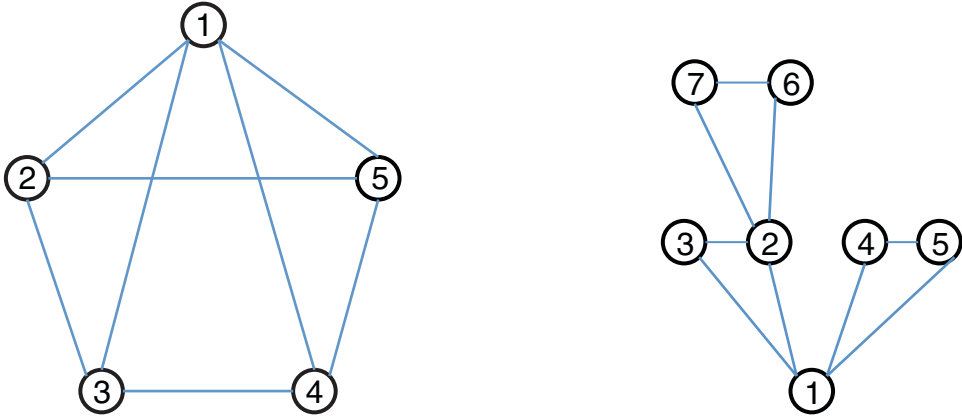


FIGURE 2

Note: Left: A critical network for $m = 3$, but where agent 1 has four links; right: a noncritical network, but still renegotiation-proof.

A. Critical Networks and Renegotiation-Proofness

Before proceeding to the complete characterization, we examine a natural class of renegotiation-proof equilibria.²⁵ These sufficient conditions provide an intuitive look at equilibrium structure and help motivate the complete characterization.

Let $G(m) = \{g \mid \forall i, d_i(g) \geq m \text{ or } d_i(g) = 0\}$ denote the set of networks in which each agent has either at least m links or zero links. So $G(m)$ is the set of networks sustainable as subgame perfect equilibria. Note that any renegotiation-proof network must be in $G(m)$ and since any network sustained in any off-equilibrium path continuation must also be a renegotiation-proof network it must also be contained in $G(m)$.

Following the argument above, one way to build a sustainable network is to offer proper incentives for sustaining favors: if an agent deletes a link in a network or fails to provide a favor, it is sufficient that the agent expect to lose at least m links in the sequel. That is captured by the following definition.

We say that a network g is *m-critical*, if

- $g \in G(m)$.
- For any i and $ij \in g$, $\nexists g' \subset g - ij$ such that $d_i(g') > d_i(g) - m$ and $g' \in G(m)$.

As $m \geq 2$ will generally be given in the analysis, we simply omit its reference and use the term “critical” in what follows. An easy way to build a critical network is to have each agent have exactly m links. We remark, however, that criticality does not require all agents to have exactly m links. It only requires that any possible continuation equilibrium after some agent fails to provide a favor be such that the agent lose at least m links. To see how this can allow agents to have more than m links, consider the left network in Figure 2, which pictures such a critical network for a case with $m = 3$ where agent 1 has four links.

²⁵ Additional classes of renegotiation-proof equilibria are discussed in the online Appendix.

There is no proper nonempty subnetwork in which all agents have zero or at least three links each. Thus, if agent 1 (or any other agent) severs any link, the entire network would have to collapse since any proper subnetwork that is nonempty will have some agent with fewer than three links, and thus that agent will not have incentives to provide favors. Therefore, if agent 1 fails to provide a favor on some link, then agent 1 would lose all four links.

Critical networks provide an important and nonempty class of networks that are renegotiation-proof. In the sense of Proposition 2, they are a foundational class of networks.

PROPOSITION 2: *Any nonempty network $g \in G(m)$ contains a nonempty critical network, and any critical network is renegotiation-proof.*

The last part of Proposition 2 follows from Theorem 1, but we mention the idea behind how this can be proven directly. In order to prove this, we need to show that there exists a pure strategy renegotiation-proof equilibrium such that for any i and $ij \in g$, if i is called to grant a favor to j and refuses the favor, i must lose at least m links in any continuation network g' . Renegotiation-proofness requires that the continuation g' be a subnetwork $g' \subset g - ij$ and be sustainable as a pure strategy renegotiation-proof equilibrium and so it must be in $G(m)$. By the definition of criticality, it then follows that any such $g' \in G(m)$ be such that $d_i(g') \leq d_i(g) - m$ (and there always exists at least one such g' since the empty network is in $G(m)$), and so provides the necessary incentives.

To see that criticality is not necessary for renegotiation-proofness, consider the right network in Figure 2: let $m = 2$ and $g = \{12, 23, 13, 14, 15, 45, 26, 27, 67\}$ is a tree union of three triads. This is not critical since if 1 cuts the link 12, then all agents in the subnetwork still have at least 2 links. Nonetheless, we shall see that it is renegotiation-proof below.

B. A Complete Characterization of Renegotiation-Proof Networks

We now turn to the complete characterization of renegotiation-proof networks.

Let $D(g)$ denote the profile of degrees associated with a network $g : D(g) \equiv (d_1(g), \dots, d_n(g))$ and write $D(g) > D(g')$ if $D(g) \geq D(g')$ and $D(g) \neq D(g')$.

We define *transitively critical* networks as follows. Given a whole number m satisfying equation (1), let $TC_k(m) \subset G_k$ denote the set of transitively critical networks with k links.

- Let $TC_0(m) = \{\emptyset\}$.
- Inductively on k , $TC_k(m) \subset G_k$ is such that $g \in TC_k(m)$ if and only if for any i and $ij \in g$, there exists $g' \subset g - ij$ such that $g' \in TC_{k'}(m)$ for some $k' \leq k - m$, $d_i(g') \leq d_i(g) - m$, and there is no $g'' \in TC_{k''}(m)$ such that $g'' \subset g - ij$ and $D(g'') > D(g')$.

A network g is transitively critical if when some link ij of i 's is deleted, then the next largest transitively critical network that is a subset of the remaining

network involves a loss to i of at least m links. Consider, for instance, starting with a critical network where each agent has exactly m links. Now, if we start to add links for some agent to such a network, we will have to add at least m links for that agent. This follows from renegotiation-proofness, as otherwise the agent could delete a link and expect to lose fewer than m links in landing at a critical network in the continuation. There are complicated interrelationships in the ways that links must be added, as adding links must keep the incentives for all agents in line. The definition of transitive criticality is inductive in a way that accounts for all of those incentive constraints at the same time. Basically, starting with some network that is transitively critical, the next superset of that network that will also be transitively critical, will have to add minimal numbers of links for each agent that gains links.

Even though this is also an inductive definition (not surprisingly, given that renegotiation-proof equilibria are so defined), it does not involve any incentive descriptions and is effectively an algorithm that can identify equilibria directly from m . In fact, the equivalence set forth by Theorem 1 can be used to calculate renegotiation-proof networks. In the online Appendix we present a table with the number of nonisomorphic transitively critical networks for small values of n and m , along with renderings of some of these networks.

THEOREM 1: *A network is renegotiation-proof if and only if it is transitively critical.*

Although one might expect the proof to be straightforward given that both definitions are inductive, there are some subtleties and challenges in proving Theorem 1. The main one is that there are many strategy profiles that may hypothetically sustain a collection of networks in a subgame perfect manner, in a way such that the collection satisfies the self-consistency property demanded by renegotiation-proofness. The issue then is that to show that some network is not renegotiation-proof we must be sure that none among the large number of the different strategy profiles that could sustain it actually work. Moreover, showing that some network is renegotiation-proof involves first showing that some other networks are not in the set. The way we tackle this difficulty is by arguing that we can avoid the vast set of potential equilibria that could be used to sustain networks and can focus on a nicely behaved set of strategy profiles. The details appear in the Appendix.

III. Robustness

We now turn to our criterion of robustness. The idea is that a network is robust if it relies only on local “damage” due to a failure to provide a favor, rather than more global sorts of damage. That is, failure to provide a favor will require some lost links and there is a question of how far that loss of links propagates. We begin with a simple observation.

OBSERVATION 1: *If (1) holds for $m \geq 2$, g is a renegotiation-proof network, and $ij \in g$, then $g - ij$ is not a renegotiation proof network.*

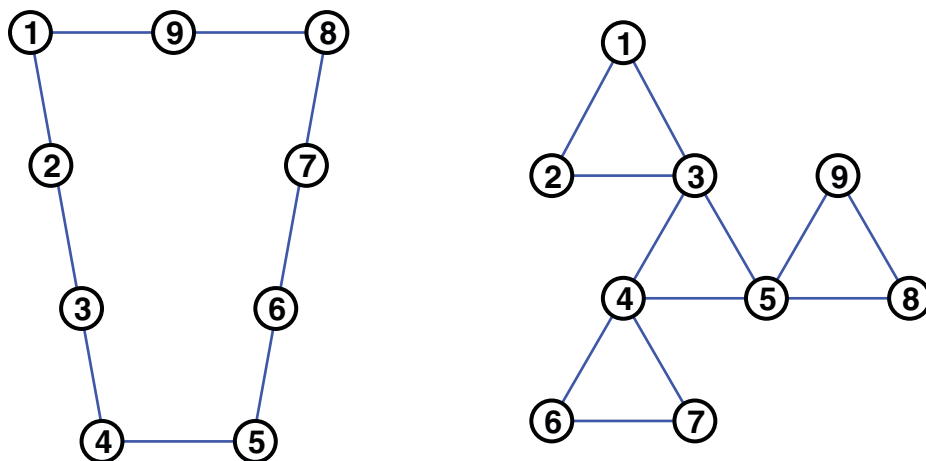


FIGURE 3. TWO RENEGOTIATION-PROOF NETWORKS WHEN $m = 2$ AND $n = 9$: A NONROBUST ONE AND A ROBUST ONE

The observation follows since otherwise the continuation from i or j failing to do each other a favor would only result in the loss of one link, and so they would not do each other favors and g would not be sustainable.

The important implication of the observation is that beginning from a network that is renegotiation-proof, if a link is deleted then the network will necessarily degrade further in terms of what is sustainable. There may be different ways in which things could degrade. Here is where the idea of robustness comes into play. Robustness against social contagion seeks to minimize the extent to which the loss of links propagates beyond the original deviator in the network.

Example 3: Robustness

Suppose that equation (1) holds for $m = 2$, and there are $n = 9$ agents. Figure 3 lists two renegotiation-proof networks: one is a single cycle containing all agents, $\{12, 23, 34, 45, \dots, 91\}$; the other is a tree union of four triads, $\{12, 23, 13, 34, 45, 35, 46, 47, 76, 58, 59, 89\}$. Note that if any link is deleted from the first network, then it collapses completely. If any link is deleted from the second network, only two other links are deleted and they are limited to a local neighborhood of the original link that is deleted.

The second network in Example 3 is more “robust” than the first one in the sense that the damage by the deletion of a link is more “local” in a sense that we now discuss.

Robustness against Social Contagion

We say that a network g is *robust against social contagion* if it is renegotiation-proof and sustained as part of a pure strategy subgame perfect equilibrium with $g_0 = g$ such that in any subgame continuation from any renegotiation proof $g' \subset g$, and for any i and $ij \in g'$, if i does not perform the favor for j when called upon and then $g'' \subset g' - ij$ is reached with positive probability and then played in perpetuity in the continuation, if $h\ell \in g'$ but $h\ell \notin g''$ then $h \in N_i(g') \cup \{i\}$ and $\ell \in N_j(g') \cup \{j\}$.

Robustness requires that a network be sustainable as part of an equilibrium such that in any continuation starting from some renegotiation-proof (sub)network, if some link is deleted then the only other links that are deleted in response must involve only the agent deleting the link and his or her neighbors. In a well-defined sense this localizes the damage to society.²⁶ We now characterize the networks that are robust against social contagion, or robust for short.

Social Quilts

The networks that are robust against social contagion have a particular structure to them that is described as follows, maintaining $m > 1$.

An *m-clique* is a complete network with $m + 1$ nodes so that every node has exactly m links; *m-cliques* are an important class of critical networks.²⁷

We can build robust renegotiation-proof networks by putting cliques together as long as we do not end up generating any cycles involving more than $m + 1$ nodes when we construct the network out of more than one clique. Thus, a social quilt is a “tree union” of networks.²⁸

We say that a network g is an *m-quilt* if g is a union of *m-cliques*²⁹ and there is no cycle in the network involving more than $m + 1$ nodes. The right network of Figure 2 shows a two-quilt. Here are some useful properties of *m-quilts*, where $m > 1$: (i) there are no bridges; and (ii) the removal of any link increases the diameter by at most one, so there are no “long-distance” links.

THEOREM 2: *A network is robust against social contagion if and only if it is a social quilt.*

Given our previous discussion of critical networks, it is a simple extension to see that social quilts are renegotiation-proof, and the critical cliques limit contagion to be local in nature. The subtle and difficult part of the proof of Theorem 2 is in showing that only social quilts are robust. For example, why is a complete network not robust? This requires an involved argument, which draws upon both the renegotiation-proofness and the local aspect of punishments. Roughly, the intuition is as follows.

²⁶ An alternative approach would be to explicitly allow nodes or links to fail with given probabilities, and then to look for networks that are still sustainable as equilibria in the face of such failures. If failure probabilities are high enough, then that will result in the definitions that we examine. For lower failure rates, however, other equilibria would also be sustainable. As the contagion effects of such probabilities become intractable quickly in a network setting, we work with the definitions as presented here, but it could be interesting to investigate other approaches.

²⁷ Note that a clique g with $m + 2$ nodes (each having $m + 1$ links) is not renegotiation-proof. To see this, suppose the contrary and have some i delete a link ij . In order for this not to be a valid deviation, it must be that i loses at least m links in the continuation, which then implies that the agent must lose all links in the continuation as having one link will not be sustainable, so that the continuation is such that there are at most $m + 1$ agents in the network and each has just m links. This is Pareto dominated by a network g' with all $m + 2$ agents such that all agents have m links except for possibly one agent. There is such a network that is a subset of $g - ij$ (which is such that all but i and j have $m + 1$ links and i and j each have m links). It also follows that g' is critical and thus renegotiation-proof. Thus, we have a contradiction.

²⁸ A union of several networks g_1, \dots, g_K is a *tree union* if the networks can be ordered in a way g_1, \dots, g_K such that successive unions

$$U_1 = g_1; \dots; U_k = U_{k-1} \cup g_k; \dots; U_K = \bigcup_{k=1 \dots K} g_k$$

are such that each additional network has at most one node in common with the preceding union: $|N(U_{k-1}) \cap N(g_k)| \leq 1$.

²⁹ That is, for any $ij \in g$ there exists a subnetwork $g' \subset g$ with $ij \in g'$ and such that g' is an *m-clique*.

First, any robust network must contain some cliques, as an agent who cheats must lose some number of links, which must all be local. In terms of continuation equilibria, any smallest sustainable subnetwork of a given network must be a clique. This follows since any deviation must lead to the loss of all its links since it is the smallest, and by locality the agents must all be neighbors. Moreover, it must be of minimal size by renegotiation-proofness as otherwise the society could renegotiate to keep a minimal-sized clique, which would contradict this being the smallest sustainable subnetwork. The proof then works by using some graph theoretic reasoning to show that any network that is not a social quilt has some subnetwork that is a critical network, and hence a smallest sustainable subnetwork, but is not a clique. Thus, if a network is not a social quilt, there is some way in which it could be broken down so that the eventual contagion in a last stage of destruction would necessarily be nonlocal.

We end this section with some results that contrast the set of subgame perfect networks with the set of robust networks. Whereas almost all networks are subgame perfect equilibria, a fraction going to zero of networks are robust. Thus, robustness is a very discriminating refinement of the set of equilibrium networks providing pointed predictions.³⁰

PROPOSITION 3: *Fix m and let n grow. Then the fraction of networks that are sustainable as pure strategy subgame perfect equilibria goes to 1 and the fraction that are social quilts (and thus robust networks) goes to 0.*

IV. Asymmetric Payoffs

Before we examine data concerning favor exchange settings, we extend the model to allow for asymmetries in payoffs. Given the heterogeneity in characteristics of agents in the societies we examine, it is clear that they may face different costs and benefits from favor exchange, and so this extension is needed to provide predictions to take to the data.

In particular, suppose that the probabilities of favors, and their values and costs, are specific to relationships and can be network dependent, so they could depend on whom else each agent is connected to, and so forth. So, doing a favor for an agent j costs an agent i an amount $c_{ji}(g)$ and the value of the favor to an agent i from an agent j is an amount $v_{ij}(g)$. Let $p_{ij}(g)$ denote the probability that i needs a favor from j . Moreover, this network dependence also allows us to encompass asymmetries in favor exchange, such as $p_{ij}(g) \neq p_{ji}(g)$, $v_{ij}(g) \neq v_{ji}(g)$, and/or $c_{ij}(g) \neq c_{ji}(g)$, including even directed or one-sided relationships.

Agents discount according to a personal factor, denoted $0 < \delta_i < 1$ for agent i . Agents' expected utilities are similar to that in the symmetric case. An agent i 's expected future utility from being in a network g where all favors are provided in perpetuity is

$$u_i(g) = \delta_i \frac{\sum_{j \in N_i(g)} p_{ij}(g) v_{ij}(g) - p_{ji}(g) c_{ji}(g)}{1 - \delta_i}.$$

³⁰ See the online Appendix for some calculations concerning the number of renegotiation-proof networks (including nonrobust ones).

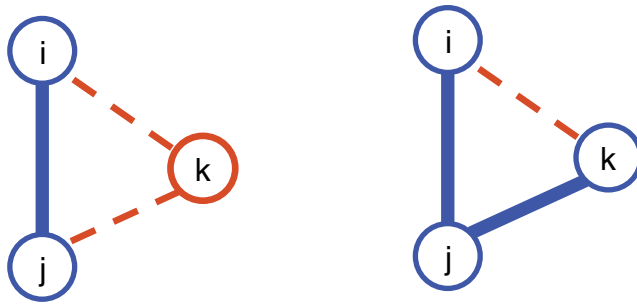


FIGURE 4. THE CONTRAST BETWEEN SUPPORT (LEFT) AND A STANDARD CLUSTERING OR TRANSITIVITY MEASURE (RIGHT)

Thus, if agent i currently provides a favor to agent j with $ij \in g$, i 's current expected discounted utility stream is $-c_{ji}(g) + u_i(g)$, whereas if agent i is called to receive a favor from agent j it is $v_{ij}(g) + u_i(g)$.

Let us consider settings such that for any link ij there is at least one of the two agents, say i , such that

$$(2) \quad c_{ji} > \delta_i \frac{p_{ij}(ij)v_{ij}(ij) - p_{ji}(ij)c_{ji}(ij)}{1 - \delta_i}.$$

Thus, no single link ij would be sustainable in complete isolation.³¹

Our definitions of renegotiation-proof networks and robustness are exactly as stated previously. A link $ij \in g$ is *supported* if there exists agent k different from i and j such that $ik \in g$ and $jk \in g$. So a link is supported if it is part of a triad. Support is a necessary condition for robustness in the general heterogeneous case where bilateral relationships are not sustainable by themselves.

THEOREM 3: *If equation (2) holds and a network g is robust against social contagion, then all links in g are supported.*

Support is distinguished from clustering measures, as illustrated in Figure 4. For example, it is possible that a standard measure of clustering³² of a network is close to zero while support is close to or even equal to one.³³ In fact, as we shall see below, the support measure in the observed networks is quite high while standard clustering measures are much lower.

³¹ $p_{ij}(ij)$ denotes the probability that i needs a favor from j in the network comprised by the solitary link ij , and similar notation for $v_{ij}(ij)$ and $c_{ji}(ij)$.

³² See Jackson (2008) for various definitions of clustering and transitivity.

³³ For example, consider an agent i who has many friends: $N_i(g) = (j_1, k_1, j_2, k_2, \dots, j_M, k_M)$ such that j_m and k_m are linked to each other for each m but such that there are no other relationships between the friends. The support measure here is one since every link is part of a triad. Yet, the clustering for i is very small: $\frac{M}{M(M-1)/2}$, which simplifies to $\frac{2}{M-1}$ and goes to 0 as M grows.

An interesting case that generalizes the homogeneous case and yet is not as fully general as the heterogeneous case examined above is one where agents may have idiosyncratic values and costs to favors v_i and c_i , and discount factors δ_i , but where these values do not depend upon who agents are linked to and also where the favor probabilities are not agent dependent. For this case, our previous results have analogs and we provide a full characterization in the online Appendix.

V. Support versus Clustering in Favor Networks in Rural India

Along with the degree distribution, and the distribution of distances between nodes, the clustering coefficient is one of the standard network statistics most often reported in network analysis. As mentioned in the introduction, it has often been thought that clustering coefficients reflect the ability of social groups to address social dilemmas.

Our analysis has suggested that support is a necessary condition for a society to enforce cooperation, at least in the robust manner that we have defined here. This is a distinct measure, and close scrutiny reveals that clustering and support are conceptually very different. Clustering is a property of the neighborhood of an agent while support is an edge property. While networks with very high levels of clustering will necessarily display a high fraction of supported links, the converse is not true. For example, the social quilt in Figure 3 (right) has a support measure of one (all of its links are supported) and yet has only an overall clustering of $1/2$ (as only one-half of the pairs of links ij and ik lead to a completed triad—for instance, only $1/3$ of node 3's pairs of neighbors are linked to each other). More generally, in any society in which agents tend to have multiple disjoint subneighborhoods (different cliques of friends), for instance their colleagues at work, the geographic neighbors at home, their hobby friends, etc., the fraction of supported links could be high, while the overall clustering could be low.

Given that the theory predicts support to be high, but does not predict the same for clustering, we investigate whether this is true empirically. In particular, we now analyze a large dataset of a variety of networks that include various forms of favor exchange. We find that support is quite high and significantly higher than the clustering coefficient.

Our data are particularly well-suited for our study: they document network structures for a variety of different sorts of relationships, including various sorts of favor exchange, and do so for many separate villages.

A. *Description of the Data*

The data are from 75 rural villages in Karnataka, an area of southern India within a few hours of Bangalore. The average population per village is 926.48. The survey was designed as part of a study of the deployment of a microfinance program (see the paper by Banerjee et al. 2011).

Only one-half of the households were surveyed, which could bias our support measures (most likely downward), as we discuss below. Households were selected by a stratified random sample in order to control for selection biases, with households stratified by religion (Hindu, Muslim, Christian) and also by geographic sub-locations based on a full census of the villages that was conducted just prior to

and in conjunction with the survey. Each surveyed individual was asked to name the people with whom he or she has various sorts of relationships.³⁴

There are several potential sources of measurement error in these data. First, not all people were surveyed and so there are missing nodes and links in the dataset.³⁵ Without any particular selection of which nodes are missing (given the random selection of households), the missing data would bias the measure of support downward, since support looks at observed links ij and then asks whether i and j have a common neighbor. If that neighbor is missing from the data, then support can be underestimated. Second, there are the usual measurement issues with survey data³⁶: people may forget to mention some of their connections, people get fatigued by interviews, and the survey did not allow individuals to name more than five or eight other people depending on the categories (although the cap was reached in a negligible number of cases).³⁷ We provide some analysis of measurement error in the online Appendix.

In building networks, we say that agent i borrows money from agent j if and only if either agent i reports borrowing money from j or agent j reports lending money to agent i , and we do the same with respect to lend-money, borrow-kerorice and lend-kerorice, visit-come and visit-go, and advice-come and advice-go relationships. Note that these are all directed relationships. In the case of friends, medical-help, relatives, and temple-company, we define that agent i has a relationship of the type in question with agent j if and only if at least one of them acknowledges so. One can also work with other variations on these definitions, and in the online Appendix we report on some of these variations, which do not significantly alter the conclusions.³⁸ The online Appendix contains a variety of statistical measures of these networks.

³⁴The relationships that were queried in the survey are listed as follows: (i) Friends: "Name the four nonrelatives whom you speak to the most." (ii) Visit-go: "In your free time, whose house do you visit?" (iii) Visit-come: "Who visits your house in his or her free time?" (iv) Borrow-kerorice: "If you needed to borrow kerosene or rice, to whom would you go?" (v) Lend-kerorice: "Who would come to you if he/she needed to borrow kerosene or rice?" (vi) Borrow-money: "If you suddenly needed to borrow Rs. 50 for a day, whom would you ask?" (vii) Lend-money: "Who do you trust enough that if he/she needed to borrow Rs. 50 for a day you would lend it to him/her?" (viii) Advice-come: "Who comes to you for advice?" (ix) Advice-go: "If you had to make a difficult personal decision, whom would you ask for advice?" (x) Medical-help: "If you had a medical emergency and were alone at home, whom would you ask for help in getting to a hospital?" (xi) Relatives: "Name any close relatives, aside from those in this household, who also live in this village." In defining the relatives network, we added the people in the same household. (xii) Temple-company: "Do you visit temple/mosque/church? Do you go with anyone else? What are the names of these people?" In the borrowing and lending relationships, Rs. 50 are roughly \$1 and the per capita income in the areas surveyed is currently on the order of \$3 per day or less, although a precise income census is not available.

³⁵Nodes in the networks that we construct from the surveys are individuals who were surveyed. Surveyed individuals could name nonsurveyed individuals as friends, relatives, etc., but we omit such links unless both individuals were surveyed. Thus, the networks we work with are subnetworks of the true networks.

³⁶Note that the questions were worded in ways to avoid basic perception issues that are associated with questions such as "Who are your friends?" Based on wording that is more explicit about particular interactions (borrowing rice, asking for medical advice, etc.) the relationships are more concrete.

³⁷Out of the 12 survey questions, described in footnote 34, the caps were only ever reached in those questions with codenames Visit-come, Borrow-money, Lend-money, and Relatives. The caps were 8, 5, 5, and 8, respectively, and they were reached in less than 0.6 in 10,000, 2 in 10,000, 0.5 in 10,000, and 2 in 10,000 of the total number of surveys. The online Appendix shows the cumulative distribution of the number of reported relations for each relationship type.

³⁸In particular, we reanalyze all of the data where we exclude "relative" links, among other things. Whether or not relatives are included does not significantly change the results.

B. Measuring Support and Clustering

The data include a variety of types of relationships, which are categorized as “Favor” and “Hedonic” relationships.³⁹

In our definitions of these relationships, although we call certain relationships “hedonic” (e.g., visiting), it could be that those relationships involve various sorts of interactions, including things like favor exchange or risk-sharing, and so forth, that are not reported through our data. Indeed, as we shall see, although we find more support in various “favor” relations, there is still a high level of support among the “hedonic” relationships.

In order to capture the possible combinations of various relationships, we enrich our measures of support and clustering. In particular, we can ask whether relationships of one type are supported through relationships of another type, and analogously for clustering, whether a pair of neighbors of a given node in a network of one type have a relationship of a second type.

To this end, we define the support of a network g' relative to another network g denoted $S(g', g)$ as the proportion of links in g' whose nodes have common neighbors in g . Similarly, we can define the clustering of a given network g' relative to some other network g , $Clus(g', g)$:

$$S(g', g) = \frac{\sum_{ij \in g'} 1_{\{\exists k, ik \in g, kj \in g\}}}{\sum_{ij \in g'} 1} \quad \text{and} \quad Clus(g', g) = \frac{\sum_{ij \in g', ik \in g'} 1_{\{jk \in g\}}}{\sum_{ij \in g', ik \in g'} 1}.$$

Note that $g = g'$ is allowed and this reduces these two measures to *self-support*, and to the standard clustering coefficient, respectively. We refer to g' as the *base network* and g as the *context network*.

The reason for considering variations on the support measure is that it is quite possible that exchange of one type of favor is supported via relationships involving exchange of some other sort of favor or some other valuable interaction. The corresponding variations on the standard clustering coefficients are supplied in order to have appropriate benchmarks.

C. Support in the Data

Among the relationships in the survey, we identified those that can be described accurately as favor relationships. In what follows, we focus on the average support and clustering measures setting $g' = \text{Favors}$ and $g = \text{All}$.⁴⁰ Figure 5 shows the inverse cumulative distribution function of support in the favor networks in our sample of 75 villages along with the plots of the fraction of links supported by exactly k other links in the marginal village.⁴¹

³⁹We group relationships as follows: (i) Hedonic = (Visit-go \cap Visit-come) \cup Friends; (ii) Physical Favors = (Borrow-money \cap Lend-money) \cup (Borrow-kerorice \cap Lend-kerorice); (iii) Intangible Favors = (Advice-come \cap Advice-go) \cup Medical-help; (iv) Favors = Physical Favors \cup Intangible Favors; and (v) All = Favors \cup Hedonic \cup Relatives \cup Temple-company.

⁴⁰We provide a similar analysis for all sorts of relationships in the online Appendix.

⁴¹The uppermost curve is the inverse cumulative distribution function (CDF) of the fraction of supported *favor* relationships in the *All* network. The five curves below list the breakdown of the fraction for the marginal village by

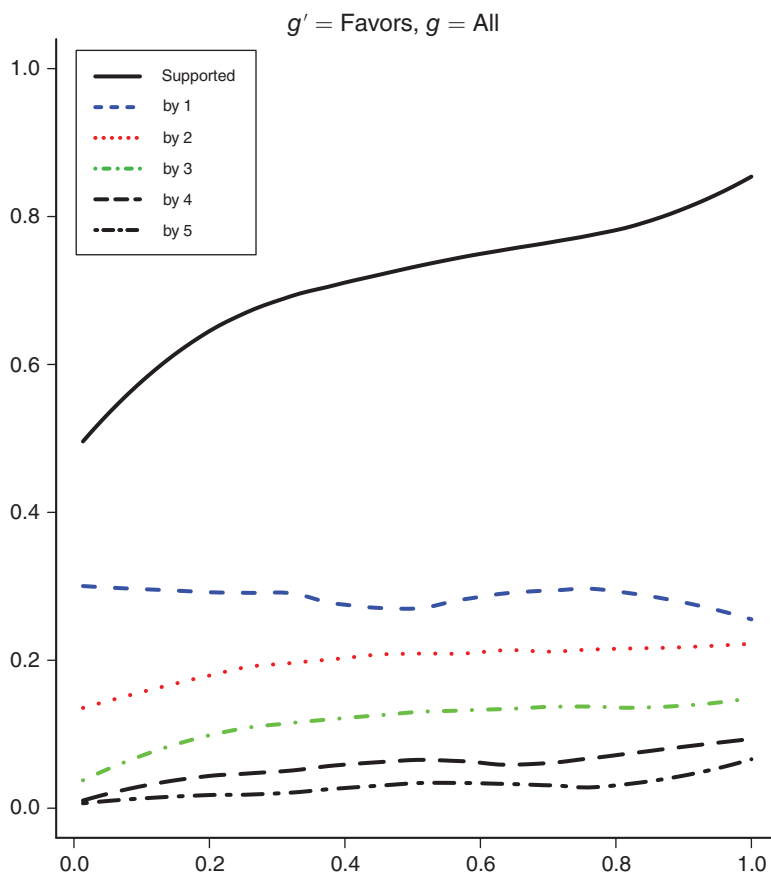


FIGURE 5. INVERSE CUMULATIVE DISTRIBUTION FUNCTION OF SUPPORT LEVELS IN THE VILLAGES

Notes: The horizontal axis is the fraction of villages having support no more than the amount listed on the vertical axis. The uppermost curve is the inverse CDF of the fraction of supported *favor* relationships in the *All* network. The five curves below list the breakdown of the fraction for the marginal village by various levels of support: “by k ” indicates the fraction of links in that village that are supported by exactly k other nodes (so that i and j have k friends in common).

The support measure is generally well above 50 percent, and ranges from more than 50 percent to over 80 percent depending on the village. We note that this measurement is likely to be biased downward by the measurement error of missing nodes, as we detail in the online Appendix. Moreover, when we look at certain kinds of favor relationships, the support measure exceeds 85 percent on average across the villages (again, see the online Appendix).

Our theory suggests that in robust favor exchange networks, any relationship that is not self-sustaining on a bilateral level requires support. In the data we see support that is less than 100 percent. Of course, this could be due to some relationships having frequent enough interaction to be self-sustaining. It could also be due to various forms of measurement error, such as missing nodes and also potentially missing

various levels of support: “by k ” indicates the fraction of links in that village that are supported by exactly k other nodes (so that i and j have k friends in common), and so the five lines below sum to the curve above.

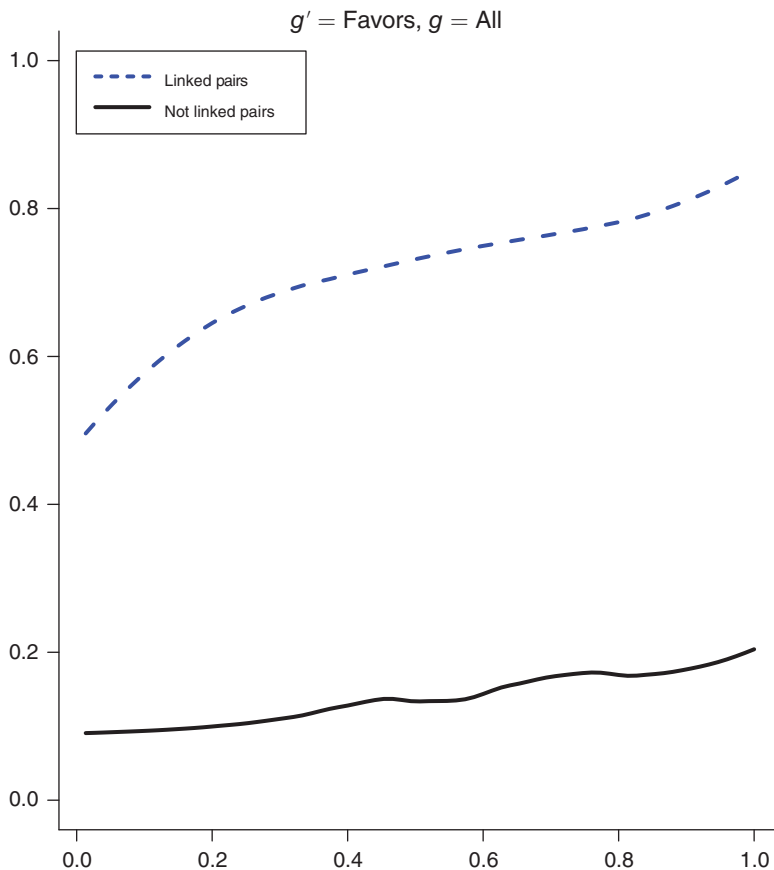


FIGURE 6. INVERSE CUMULATIVE DISTRIBUTION FUNCTION OF SUPPORT LEVELS OF LINKED PAIRS OF AGENTS AND UNLINKED PAIRS OF AGENTS IN FAVOR NETWORKS IN THE VILLAGES

links even within the observed networks. We discuss the measurement error possibility in more detail in the online Appendix.

Given that the data does not include information allowing us to determine which relationships are bilaterally self-sustaining, we need to look at other things to determine whether support is simply incidental. One way to do this is to examine pairs of nodes i and j and then examine the extent to which they have a friend in common, and to see whether this happens more frequently when i and j are exchanging favors compared to situations where they are not. Formally, we do so by extending the definition of support from linked pairs of agents to arbitrary pairs of agents.

We define the support of a collection of pairs of agents $\mathcal{P} \subset N \times N$ relative to a network g , denoted $S(\mathcal{P}, g)$, by

$$S(\mathcal{P}, g) = \frac{\sum_{\{i,j\} \in \mathcal{P}} 1_{\{\exists k, ik \in g, kj \in g\}}}{\sum_{\{i,j\} \in \mathcal{P}} 1}.$$

So, the support measures we considered previously were those where \mathcal{P} was the set of pairs of agents who exchanged favors with each other. This more general measure

allows us to also measure support for the situation where \mathcal{P} is the set of agents who do *not* exchange favors. Thus, we can see whether support is something correlated with favor exchange.

Figure 6 shows the inverse cumulative distribution function of support in the favor networks in our sample of 75 villages along with the plots of the support of the pairs of agents that do not share a link in the favors network in the marginal village. The difference is statistically significant beyond the 99.9 percent level for all villages (based on a one-sided t -test).⁴²

The figure shows the inverse cumulative distribution function of support levels of linked pairs of agents and unlinked pairs of agents in favor networks in the villages.

D. Comparing Support to Clustering

We now compare support to the clustering in the villages.

We calculate the clustering in each village and compare it to the corresponding support measure. In both cases, we work with the base of favor relationships and the context of all relationships. Similar comparisons and conclusions hold for other variations of comparisons as shown in the online Appendix.

Figure 7 shows that support levels are not only higher than clustering, but by an order of magnitude. There are various ways in which we can see that support is significantly higher than clustering in these villages. The comparison of having it be higher in 75/75 villages has a p -value that is effectively 0. Moreover, the average ratio of support over clustering across the villages is 2.94 with a standard error of 0.38, and this has a p -value of effectively 0 of being significantly higher than 1.

We can also see how the two compare for various types of relationships, as seen in Table 1, where support exceeds clustering significantly. This suggests that support should be a useful measure of social capital that is complementary to clustering, and useful in situations where social pressures may be needed to provide incentives.

Moreover, the comparison of support over clustering could also be a useful statistic in more general social network analysis. If the ratio is close to one, then effectively a typical agent would just have one group of friends, while a higher ratio would suggest that a typical agent has several disjointed groups of friends.

E. Comparing Support in Different Sorts of Relationships

The data also allow us to compare the support measures of favor networks with those of hedonic networks (HR).

We can test whether there are statistically significant differences in support among networks of different types. To do this, we compare the values of any given support measure village by village. If there were no systematic difference in support

⁴² Such a test assumes independence between the support of pairs of agents that exchange favors and pairs of agents that do not exchange favors, which is violated as some such pairs of pairs overlap, but fraction of overlapping pairs goes to 0 in n . The largest standard error for the estimated difference of support levels across the 75 villages computed under this independence assumption is 0.084. The analysis relies only on the agents who were surveyed in each of the 75 villages. The sizes of the surveyed populations range from 95 to 395. The village with the smallest number of linked pairs of agents has 115 linked pairs and 4,350 pairs that do not exchange favors. The village with the highest number of linked pairs has 843, and 76,972 pairs that are not linked. One can also test across villages, where support among linked pairs is higher than among unlinked pairs in 75 of 75 villages.

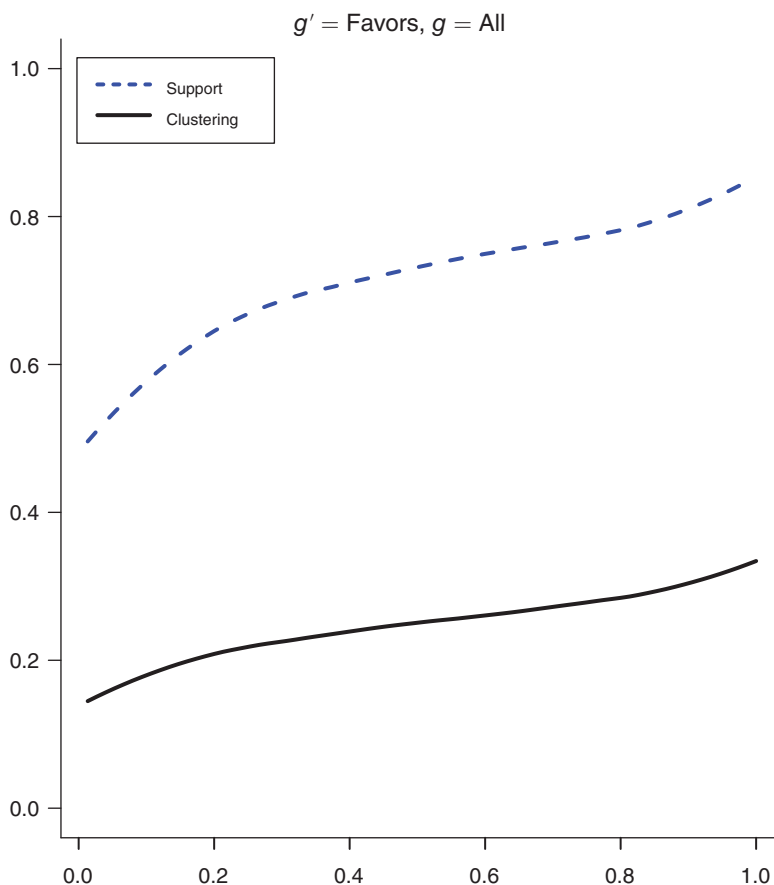


FIGURE 7. INVERSE CUMULATIVE DISTRIBUTION FUNCTION OF SUPPORT AND CLUSTERING LEVELS IN THE VILLAGES

Notes: The horizontal axis is the fraction of villages having no more support/clustering than the amount listed on the vertical axis. The uppermost curve is support and the lowermost is the clustering coefficient of the marginal village.

between relationships of the types being compared, then in any given village each one would have an equal chance to be larger than the other. Thus, under the null hypothesis that there is no difference in support, the number of villages where one has a higher support than the other should have a binomial distribution with equal probability on outcomes.

When we examine the data, we see significant differences between the support of different types of relationships. For example, in 72 out of 75 villages, the support of intangible favors $S(IFavors, All)$ is higher than that of social relationships $S(Hedonic, All)$ (both relative to the all network). Of course, the probability of a binomial random variable with equal probability on outcomes realizing a 1 in 72 out of 75 trials is effectively 0.

Table 2 shows the comparison of support measures of various relationships (based on the context of *All* relationships). The entry in the table is how many times out of 75 the support measure in the row is higher than that in the column. The Appendix has comparisons for other contexts with similar patterns.

TABLE 1—CLUSTERING AND SUPPORT MEASURES FOR VARIOUS TYPES OF RELATIONSHIPS

g	Favors	Physical favors	Intangible favors	Hedonic relationships	All
$Clus(g, All)$	0.234	0.257	0.249	0.236	0.222
$S(g, All)$	0.717	0.72	0.733	0.661	0.696

Note: In every case the *All* network serves as context.

TABLE 2—COMPARISON OF SUPPORT MEASURES

Network g'	Favors	Physical favors	Intangible favors	Hedonic	All
Favors	—	30**	24***	72***	60***
Physical favors	45**	—	38	69***	56***
Intangible favors	51***	37	—	72***	57***
Hedonic	3***	6***	3***	—	6***
All	15***	19***	18***	69***	—

Note: Entry i, j is the number of villages for which $S(g'_i, All) > S(g'_j, All)$.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

In terms of the observed differences between hedonic and explicit favor networks, a hypothesis for support in explicit favor networks emerges from our theory. With regards to hedonic relationships, there might also be some informal favor exchange as well, which would result in similar predictions. Hedonic relationships may also have some mutual gain aspects to them (engaging in activities that benefit both parties), however, which can lead them to be self-enforcing in the absence of support.⁴³

F. Comparing Observed Support to That in a Random Network

Next, we look at whether observed support is statistically significant, even when one corrects for geography.

This answers whether support patterns are something that arose simply because of geography, or whether the patterns really reflect social structure. For example, underlying social processes are likely to be influenced by geography as costs of interacting will often decrease with proximity. It is plausible that the likelihood of relationships increases with the physical proximity of the agents.⁴⁴ And, since physical proximity has some transitive features, relationships that are geographically correlated may display completed triads and therefore high support levels. To address this, we estimate exponential random graph models (ERGMs) using the observed networks. In particular, we estimate ERGMs with the likelihood of a link being present depend on (i) whether the link is supported; (ii) the observed density

⁴³For a new field experiment that includes some discussion of how behavior varies with relationship type, see D'Exelle and Riedl (2010).

⁴⁴This could be for two reasons: having links emerge because of proximity, and having people likely to be linked located close to each other.

of the network; and (iii) the physical distance of the agents involved (measured using the GPS coordinates of their respective households).⁴⁵ As should be expected, in every village the coefficient associated with physical distance was negative and significant at well less than the one percent level. Nonetheless, the coefficients on support are still large (2.4 on average) and statistically significant in every single village.⁴⁶

The online Appendix contains the full set of ERGM estimates for many other base-context pairs. The ERGM estimates suggest that the observed support levels are not merely an artifact of geographic proximity. More specifically, support of a link in the *All* network is a significant predictor (in the statistical sense) of the presence of that link in the favors network, when controlling for density and for geographic proximity of the agents involved.

G. The Relation of Support to Social Characteristics

In our analysis, whether or not a link needs to be supported as part of an equilibrium depends on whether bilateral favor exchange is enforceable in isolation (e.g., our definition of m in the symmetric case). The payoffs to different relationships depend on the value of favors, the cost of favors, interaction probabilities, discount factors, and various other characteristics of the nodes. In this section we take advantage of the richness of our dataset to relate support to various social variables of interest including population size, education level, wealth indicators, subcaste, gender, and microfinance. This is exploratory in nature, since one can think of many hypotheses of how the relative value of favors and the frequency of interaction would vary with demographics. Nonetheless, this information will still be valuable in developing models that relate demographics to patterns of favor exchange, and also provides new insights into how demographics relate to a specific measure of social capital.

Village Level Predictors of Support.—To start, we look at how the average support of a network in a village is related to the average characteristics of the village. Table 3 provides results for an ordinary least squares (OLS) regression of the fraction of links that are supported (separately for favor networks and hedonic networks) as a

⁴⁵The exponential random graph model that we estimate is

$$\log(\Pr(G = \mathbf{g})) = \beta_0 + \beta_1 \sum_{i < j} \mathbf{g}_{ij} + \beta_2 \sum_{i < j} \mathbf{g}_{ij} \mathbf{s}(\mathbf{g}, \mathbf{g}')_{ij} + \beta_3 \sum_{i < j} d(i, j) \mathbf{g}_{ij},$$

where G is a random variable taking values in the space of all possible graphs on N nodes, \mathbf{g} is a particular network, $\mathbf{s}(\mathbf{g})$ is the associated indication of whether the link ij is supported or not (which may be calculated relative to a related “all network” \mathbf{g}'), and $d(i, j)$ denotes the physical distance between i and j as measured by the GPS coordinates of their households, and normalized by the mean distance between surveyed households in the village. The standard method (and used in the program that we used for our estimation) is Markov chain Monte Carlo estimation, as outlined by Snijders (2002). More specifically, this method simulates the exponential random graph model using Gibbs or Metropolis-Hastings sampling and the Robins-Monro algorithm for approximating a solution to the likelihood function maximization problem. A problem with this methodology is that the space is too vast (the collection of graphs on n nodes is of size $2^{\binom{n}{2}}$) to search reliably, even with the most advanced algorithms. The standard errors are subject to similar noise, and should be interpreted with appropriate caution.

⁴⁶To make sense of the size of the coefficient on support being roughly two, from the ERGM specification some simple algebra shows that

$$\log[\Pr(g_{ij} = 1 | g_{-ij}) / \Pr(g_{ij} = 0 | g_{-ij})] = \beta_1 + \beta_2 \mathbf{s}(\mathbf{g}, \mathbf{g}')_{ij} + \beta_3 d(i, j),$$

so that having a link be supported roughly increases by two or more the log odds ratio that the link will be present in the network.

TABLE 3—OLS COEFFICIENTS FOR THE VILLAGE-LEVEL REGRESSIONS OF FAVOR SUPPORT AND HEDONIC SUPPORT

	Favor support	Hedonic support
Population	−0.00008**	−0.00005
Education	0.02723**	0.02669**
Rooms per person	0.1401	0.3626***
Electricity	−0.01986	−0.1025
Latrine	−0.06683	−0.09043*
Microfinance	−0.06485	−0.01758

Note: Village-level variables are averages of the values of these variables associated with surveyed individuals in the village.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

function of various village average characteristics.⁴⁷ We see that education is significantly positively related to favor support, while population size is related negatively. The patterns are similar for both favor and hedonic networks (which have nontrivial overlap).

The village-level data provides some insights, but given the relatively aggregated nature of the data, some variation is obscured. Thus, we next proceed to analyze things at the link and individual levels.

Link-Level Predictors of Support.—The next analysis examines link-level support as a function of link demographics.

We examine the likelihood that a given link is supported conditional on the two individuals involved in the link being similar/dissimilar according to various demographics: education,⁴⁸ caste, gender, and participation in microfinance.

In order to keep track of how high the support level is, we report the ratio of support for linked individuals compared to support for pairs of individuals who are unlinked.⁴⁹ So, a ratio of five indicates that the frequency of support of linked pairs of agents in a given category is five times higher than the average support level for pairs of agents that are in the same category but who are not linked. The categories here relate to whether pairs of individuals both have the same characteristic or different characteristics. For example, in Table 4 the ratio of 5.91 in the gender category of female/male means that when we look at pairs of agents with one being female and one being male, the fraction of favor-linked pairs are supported (in the All network) 5.91 times more frequently than favor-unlinked pairs that involve one female and one male.

We see that support levels are (relatively) much more distinguished when individuals fall in different castes compared to when they are in the same caste. We also see lower levels of (relative) support when individuals both participate in microfinance than when

⁴⁷ Population is in total number of people; education scale is from 0 to 15 representing years in school; wealth indicators include average number of rooms owned by each person, and whether villagers own (2), share (1), or don't have electricity (0), and similarly for latrines; microfinance is the fraction of the total eligible (women) in the village who actually participated in microfinance, and that was only in a subset of 38 villages where microfinance was offered, so the results of the regressions are for that subset of the villages.

⁴⁸ For education, we categorize individuals as either above or below the median education level, which is five.

⁴⁹ See the online Appendix for the full breakdown of all support levels.

TABLE 4

Education	Favors			Subcaste	Favors		
	Ratio	Not linked	Linked		Ratio	Not linked	Linked
Both below	5.09	26	25	Different	6.35	0	3
Above/below	5.49	3	25	Same caste	3.16	75	72
Both above	4.79	46	25				

Gender	Favors			Microfinance	Favors		
	Ratio	Not linked	Linked		Ratio	Not linked	Linked
Both male	3.48	75	16	Neither belong	6.76	7	14
Female/male	5.91	0	30	Belong/not	6.91	5	8
Both female	6.09	0	29	Both belong	3.99	26	16

Notes: Ratios: the fractions of pairs of agents that have at least one friend in common in the *All* network comparing situations where the pairs have a link in the favors network (numerator) to those where they do not have such link (denominator). Not Linked (or Linked): number of villages in which the corresponding similarity/dissimilarity class is the one with the highest fraction of pairs of agents that are supported across the three classes (or two in the case of subcaste) for pairs that are not linked (or linked) in the favor network.

they do not. Both-male links are less supported than cross-gender or both-female links. Given that support is related to incentives in our theory, this may be suggestive that some of these situations require more external incentives to enforce exchange than others. Also, Table 4 presents how support differs depending on whether the individuals have the same or different characteristics. In particular, the last two columns of the table show the number of villages in which a given categorization (row) is the one with the highest fraction of pairs of agents who are supported among all categorizations. The columns present the results for unlinked pairs and linked pairs separately.

The differences between the columns suggests that the patterns of support differ for unlinked versus linked pairs of agents not only in terms of overall likelihood (as we saw earlier in Figure 6), but also in terms of how support depends on the characteristics of the agents. The differences across columns are significant in all cases except subcaste.⁵⁰

Individual-Level Predictors of Support.—In this section we examine the relationship between an agent's characteristics and the extent to which that agent's links are supported, as well as the extent to which that agent's nonlinks are supported.

Table 5 presents the coefficients associated with two probit regressions relating the likelihood of having a friend in common in the *All* network to gender, education, age, rooms per person in the agent's household, and the household's size. In the first regression, an observation corresponds to a randomly chosen friend in the favors network of a randomly chosen agent in one of the 75 villages in our sample. In the second regression, an observation corresponds to a randomly chosen agent unrelated to a randomly chosen agent in one of the 75 villages.⁵¹

⁵⁰ Similar patterns hold for hedonic networks. More details are presented in the online Appendix.

⁵¹ We present similar probit regressions done at the household level in the online Appendix.

TABLE 5—PROBIT REGRESSIONS FOR AN INDIVIDUAL'S SUPPORT AS A FUNCTION OF THE INDIVIDUAL'S CHARACTERISTICS, FOR BOTH THE INDIVIDUAL'S LINKS AND NONLINKS

	Linked	Not linked
Gender (female)	0.075**	−0.136**
Age	0.001*	0.005**
Education	0.0016**	0.0017*
Rooms per person	−0.058**	0.031
Household size	−0.017**	0.0005*
Intercept	0.399**	−1.18**

**Significant at the 5 percent level.

*Significant at the 10 percent level.

More of an agent's links are supported if the agent is female, older, educated, and from a smaller household (both in terms of rooms and persons). Again, we see very different patterns of support as a function of characteristics for links versus nonlinks.

VI. Conclusion

Our analysis of favor exchange provides various insights. We have shown that renegotiation results in specific critical structures and that robustness involves social quilts and, more generally, supported links. Support is a local characteristic of networks that provides new insight into closure and an operationalization of a sort of social capital that emphasizes social structure's role in the enforcement of behavior.

Our empirical analysis finds high levels of support in favor networks in rural Indian villages. We also find that support levels are much higher than clustering, and that support in favor networks is higher than that of more "hedonic" networks.

In closing, we discuss some issues regarding the information observed by the agents in the society.

We have deliberately looked at a complete information setting for two reasons. First, in many applications, including the Indian villages that we examined, word-of-mouth communication travels much faster than actions and so if someone behaves badly, other people hear about it quickly. Gossip serves a strong purpose. Second, much of the previous literature has focused on the information as the driver of network structure in providing incentives and so our analysis is completely complementary. Nonetheless, there is an important observation that comes out. Our analysis ends up yielding social quilts that end up having strong informational robustness properties in addition to the properties that we have investigated. In particular, agents only need to know what the agents whom they are linked to directly are doing, and for all of those agents they also have common friends—so they are both directly and indirectly connected at a short distance through an independent channel to all of the agents whose behavior they have to be aware of in order to best respond. Thus, even with very limited communication, the robust social networks that we have uncovered can be sustained.⁵² Our analysis ends up yielding

⁵²Our social quilts satisfy a cycle completeness condition that van den Brink (2011) has shown to characterize networks that satisfy some communication and other stability conditions. Understanding the more general

networks that might otherwise be justified for their informational properties from a completely different perspective.

APPENDIX: PROOFS OF RESULTS

PROOF OF PROPOSITION 2:

Let g' be a smallest nonempty network (in the sense of set inclusion) that is a subset of g and lies in $G(m)$. Such a network exists (possibly g itself) and is thus critical by definition. The second statement is easily verified by construction, but also follows as a corollary to Theorem 1, which is proven below.

PROOF OF THEOREM 1:

We first show that if $g \in RPN_k$ then $g \in TC_k$. We work by induction in k , with the result being clear when $k = 0$. So, suppose that it holds through $k - 1$ and consider some k . Given a network $g \in RPN_k$, by the definition it follows that g is sustainable on the equilibrium path. So for any i and $ij \in g$, if i is called upon to do a favor for j and does not, then at least one possible continuation⁵³ must lead to a network $g' \subset g - ij$ such that $g' \in RPN_{k'} = TC_{k'}$, $d_i(g') \leq d_i(g) - m$, and there is no $g'' \subset g - ij$ such that $g'' \in RPN_{k''}$ and $D(g'') > D(g')$. If this were not the case, then if i did not perform the favor, he or she would save the cost c and lose at most $m - 1$ links in any continuation. Thus, i would benefit from deviating and not performing the favor since by the definition of m , equation (1) holds and so the cost of the favor outweighs the loss in future payoffs from losing no more than $m - 1$ links, which contradicts the fact that g is sustained as an equilibrium. Thus, for every i and ij , there exists $g' \subset g - ij$ such that $g' \in TC_{k'}$ for some k' , $d_i(g') \leq d_i(g) - m$, and there is no $g'' \in TC_{k''}$ such that $g'' \subset g - ij$ and $D(g'') > D(g')$. Therefore, $g \in TC_k$.

Next, we show that if $g \in TC_k$ then $g \in RPN_k$. We do this by induction on the number of links in a network. In order to establish the result, we also need to be careful about what happens starting at subgames that are off the equilibrium path. As such, we work with a stronger induction hypothesis, with the induction indexed by k .

The induction hypothesis is that starting from any node and any $g_0 \in G_k$, there exists a pure strategy subgame perfect equilibrium continuation such that (i) there is a unique network $g_1 \in RPN_{k_1}$ for some $k_1 \leq k$ that is reached and sustained in perpetuity in the continuation, with $g_1 = g_0$ if $g_0 \in TC_k$, such that (ii) on the equilibrium continuation path a favor is performed if and only if it corresponds to a link in g_1 ; and (iii) in any subgame starting with some network $g' \in G_{k'}$ with $k' \leq k$ if g'' is played in perpetuity with some probability in the continuation then $g'' \in RPN_{k''}$ for some k'' and there does not exist any $g''' \subset g'$ such that $g''' \in RPN_{k'''}$ and $u_i(g''') \geq u_i(g'')$ for all i with strict inequality for some i .

relationships between the sorts of incentive-based stability used here, and various forms of communication, as well as core- and group-based stability is an interesting issue for further research.

⁵³ Even though agents use pure strategies, nature picks which favors are asked in the future, so there are potentially many continuations from any given node.

As a first step in the induction, note that it follows directly from the definitions that $RPN_0 = \{\emptyset\} = TC_0$. Note also that starting from $g_0 = \emptyset$ there is a unique subgame perfect equilibrium continuation (no favors can be supplied and no links can be maintained) and so it follows directly that conditions (i)–(iii) are satisfied. So, let us presume that the induction hypothesis holds for all $k' < k$. We show that the same is true for k .

Begin with the case such that $g_0 = g \in TC_k$. On the equilibrium path, have all agents maintain all links (so $L_i(g_t) = N_i(g_t)$ whenever $g_t = g_0 = g$) and perform all favors. The off-the-equilibrium-path strategies are described as follows. If an agent i is called upon to provide a favor for an agent j such that $ij \in g$ and does not do the favor, then the continuation is as follows. Given that $g \in TC_k$, by the definition of transitive criticality, there exists $g' \subset g - ij$ such that $g' \in TC_{k'} = RPN_{k'}, d_i(g') \leq d_i(g) - m$ and there is no $g'' \in TC_{k''} = RPE_{k''}$ for any k'' such that $g'' \subset g - ij$ and $D(g'') > D(g')$. Denote this network by $g(i, j) = g'$. Following i 's failure to provide a favor to j , have the continuation be such that $L_\ell(g - ij) = N_\ell(g(i, j))$ for all ℓ . This results in the network $g(i, j) \in RPN_{k'}$ following the link announcement phase, and so from then on there is a pure strategy subgame perfect equilibrium sustaining $g(i, j)$ and satisfying (i)–(iii) by the induction step, and so have agents play the strategies corresponding to such an equilibrium in that continuation. At all other nodes off the equilibrium path for which strategies are not already specified we are necessarily at a network with fewer links, and so pick a pure strategy equilibrium continuation that satisfies (i)–(iii), which is possible by the induction hypothesis.

This satisfies (i)–(iii) by construction. To check that this is a subgame perfect equilibrium, by the specification of the strategies above, we need only check that no agent wants to deviate from the equilibrium path, and also that following some i 's failure to provide a favor to j , no agent ℓ wants to deviate from $L_\ell(g - ij) = N_\ell(g(i, j))$. We only need to check these sorts of deviations since all other continuations were specified to be pure strategy subgame perfect equilibrium continuations. By construction, an agent i who is called upon to do a favor for an agent j who deviates will end up losing at least m links, and so by equation (1) this cannot be an improving deviation. Next, consider, some agent ℓ 's incentive to deviate from $L_\ell = N_\ell(g_0)$ if g_0 is still in play, or else from $L_\ell(g - ij) = N_\ell(g(i, j))$ following some i 's failure to provide a favor to j . By not deviating, the agent gets the payoff from g_0 or $g(i, j)$ in perpetuity. By deviating, the agent ℓ will end up with a continuation starting from a network $g'' \subset g_0$ or $g'' \subset g(i, j)$, respectively, where the agent has not gained any links and may have lost some links. Since each link has a positive future expected value, this cannot be an improving deviation.

Next, let us show that from any node in the continuation from some initial $g_0 \notin TC_k$ there exists a pure strategy subgame perfect equilibrium continuation satisfying (i)–(iii). There are two types of nodes to consider. One is a node at which some agent i is called upon to provide a favor for an agent j such that $ij \in g_0$, and another is a node where agents announce the links they wish to sustain.

First, consider starting at g_0 and a node where agents announce the links that they wish to sustain. Find some g' that has the maximal $k' < k$ of links such that $g' \in RPN_{k'}$ and $g' \subset g_0$. For each ℓ set $L'_\ell = N_\ell(g')$ and then from g' play a continuation satisfying (i)–(iii) (by the induction step). If any agent deviates, to L such that

$L'_\ell \subset L$, then play the same continuation, as this will not affect the network formed. Otherwise, the continuation will lead to some g'' with strictly fewer links for ℓ and the continuation will necessarily result in a lower expected continuation payoff. This establishes the claim for this sort of node.

Next, let us consider a node at which some agent i is called upon to provide a favor for an agent j such that $ij \in g_0$. There are two cases that can follow: one where i performs the favor and so the resulting network is then g_0 . In that case, we have just shown that there is a pure strategy subgame perfect equilibrium continuation satisfying (i) to (iii). Let g' be the network sustained on the equilibrium path in one of these that has the most links for i . If i does not perform the favor, then $g - ij \in G_{k-1}$ is reached. By the induction hypothesis again there is a pure strategy subgame perfect equilibrium continuations satisfying (i)–(iii), and let g'' be a network sustained by one of these that has the most links for i . Now, based on those two continuations, have i choose a pure strategy best response. The claim follows.

PROOF OF THEOREM 2:

We first prove that m -quilts, or tree unions of m -cliques⁵⁴, are robust against social contagion. The proof proceeds by induction on the size k of the tree union.

When $k = 1$, it is a single m -clique, and so it is renegotiation-proof since it is critical. Note also that the only subnetwork of a clique that is in $G(m)$ is the empty network. Thus, it follows that any equilibrium continuation in (any) equilibrium supporting the clique is the empty network. Thus, a clique is robust against social contagion. Suppose it is true for all $k' < k$. We show that a tree union of k m -cliques is robust against social contagion. To do this, we show that tree unions of m -cliques and some nonempty strict subnetworks of m -cliques cannot be renegotiation-proof. This is enough to establish that tree unions of m -cliques are robust against social contagion, since it shows that link deletions can be punished by deleting all links in the particular m -clique that the deleted link belonged to and that will not be Pareto dominated by any continuation renegotiation-proof equilibrium. Begin with a tree union of k m -cliques, g_1, \dots, g_k . Let $g^0 = \left(\bigcup_{h=1 \dots m_0-1} g_h \right) \cup \left(\bigcup_{h=m_0 \dots k} g_h^0 \right)$, with $m_0 \leq k$, $g_h^0 \subset g_h$, $g_h^0 \neq g_h \forall h \geq m_0$ where at least one g_h^0 in the union is nonempty. So this is the tree union of m -cliques and some nonempty strict subnetworks of m -cliques. Suppose to the contrary that it is renegotiation-proof. Note that $\bigcup_{h=m_0 \dots k} g_h^0$ is a tree union of networks, and it must therefore have some leafs. Pick one such leaf and denote it $g_{h^*}^0$. Since $g_{h^*}^0$ is a strict subset of the m -clique g_{h^*} and a leaf of the subtree, there is some agent i_0 who has a positive number of links, less than m , in the subtree. Suppose this agent were to fail to provide a favor on a link $i_0 j_0$ in $g_{h^*}^0$. Since by assumption $g^0 \in RPN$, agent i_0 would have to lose at least m links if he or she failed to provide a favor on any link $i_0 j_0$ in the subtree. Since the agent does not have enough links to lose in the subtree, he or she would have to lose links in $\bigcup_{h=1 \dots m_0-1} g_h$.

⁵⁴ It is straightforward to verify that a union of m -cliques is an m -quilt (has no simple cycles of more than $m + 1$ nodes) if and only if it is a tree union of m -cliques.

Denote the continuation by g^1 which must be renegotiation-proof. Note that g^1 cannot be a strict subset of $\bigcup_{h=1 \dots m_0-1} g_h$, since by the inductive hypothesis $\bigcup_{h=1 \dots m_0-1} g_h \in RPN$. Therefore g^1 must have some links from $\bigcup_{h=m_0 \dots k} g_h^0$. In particular, $g^1 = \left(\bigcup_{h=1 \dots m_1-1} g_h \right) \cup \left(\bigcup_{h=m_1 \dots k} g_h^1 \right)$, where $g_h^1 \subset g_h$, $g_h^1 \neq g_h \forall h \geq m_1$ and $m_1 < m_0$. This last inequality results from the fact that i_0 lost links in $\bigcup_{h=1 \dots m_0-1} g_h$. Again, any agent who has fewer than m links in $\bigcup_{h=m_1 \dots k} g_h^1$ must have links in $\bigcup_{h=1 \dots m_1-1} g_h$. We then derive a subnetwork g^2 from g^1 analogously to the way we derived g^1 from g^0 . Proceeding in this fashion, we produce a finite sequence of renegotiation proof networks g^0, g^1, \dots, g^ℓ , with $m_x < m_{x-1}$ at each iteration and there is always at least one link in $\bigcup_{h=m_x \dots k} g_h^x$. Continue until $m_\ell = 0$. Using the same argument with which we found i_0 , it can be seen that we would find some node with fewer than m links in total, contradicting $g^\ell \in RPN$.

We now prove that robustness against social contagion implies that a network must be a social quilt. Suppose that g is robust against social contagion. If there is an m -clique, $g_c \subset g$, that has at most one node i connected with nodes outside of the clique, then $g - g_c$ is also robust against social contagion. This follows since if any agent $j \neq i$ who is in g_c does not perform a favor, then in order for g to have been sustainable j must expect to lose all of his or her links in the continuation (as the continuation must be in $G(m)$ to be sustainable and j will have fewer than m links). Then since all agents other than i in g_c will have fewer than m links in the continuation, they must all lose all links in order for the continuation to be sustainable. Thus, the clique must disappear in the continuation, but by robustness against social contagion no other links can be deleted. So, eliminate g_c and continue with the network $g - g_c$. If repeating this process leads to an empty network, then g must have been a social quilt. Suppose instead that this elimination process leads to some nonempty g' (and note that g' is robust by the definition of robustness) such that g' contains no m -clique where at most one agent has links outside of the clique.

By the above process, any remaining m -cliques that are subnetworks of g' must satisfy the condition that the clique has at least two agents who have links outside of the clique. So, identify some remaining m -clique that is a subnetwork of g' and delete a link between a pair of agents, say i and j , who have links outside of the clique. The remaining network is still in $G(m)$ since i and j necessarily had more than m links in g' . Note also that this removal of the link ij does not change the fact that each other clique in g' has two agents with links outside of the clique (as if either of those agents is i or j then they still maintain $m - 1$ links each in the original clique). Repeat this process once for each clique in the original network such that at least two agents have links outside of the clique until there are no m -cliques left in the resulting network, and let this nonempty resulting network be $g'' \in G(m)$.

Thus, a direct extension (literally word for word) of the proof of Proposition 2 implies that there is a subnetwork of g'' that is “minimally” critical⁵⁵ and nonempty.

⁵⁵ A critical network is called minimally critical if any deletion of a link leads to the collapse of the whole network; that is, if any subnetwork of the original network that lies in $G(m)$ is the empty network.

Let that network be g''' . It follows from our derivation of g'' that g''' cannot be a clique. Since g''' is minimally critical, however, then by robustness and the renegotiation-proofness of g , there is an equilibrium where in any subgame starting from g''' , it is sustained. Starting from g''' if any link is deleted, however, then all links must be deleted in any equilibrium continuation by the definition of minimal criticality. This contradicts the robustness of g , since g''' is not a clique and hence there is some link ij and some k who is not linked to both i and j who loses a link as a result of the deletion of the link ij .

PROOF OF PROPOSITION 3:

First, we analyze the fraction of subgame perfect equilibria. Denote by SPE_n the set of subgame perfect networks on n nodes. A network is a subgame perfect network if and only if no node in the network has at least 1 and no more than $m - 1$ links. We set a very loose upper bound on the number of networks in which at least one node has at least 1 and no more than $m - 1$ links by first picking any node and its links and then allowing the remaining $n - 1$ nodes to link among themselves however they want, and then multiplying by n to allow for any starting node. A lower bound on the cardinality of SPE_n is $2^{\frac{n(n-1)}{2}}$ minus this bound. Therefore:

$$|SPE_n| \geq 2^{\frac{n(n-1)}{2}} - n \sum_{k=1}^{m-1} \binom{n-1}{k} 2^{\frac{(n-1)(n-2)}{2}} \geq 2^{\frac{n(n-1)}{2}} - (m-1)n \binom{n-1}{m-1} 2^{\frac{(n-1)(n-2)}{2}},$$

where the inequality on the right holds for any m such that $n - 1 > 2(m - 1)$. This implies that

$$\begin{aligned} \frac{|SPE_n|}{|G_n|} &\geq 1 - \frac{(m-1)n \binom{n-1}{m-1} 2^{\frac{(n-1)(n-2)}{2}}}{2^{\frac{n(n-1)}{2}}} = 1 - \frac{(m-1)n \binom{n-1}{m-1}}{\sum_{k=0}^{n-1} \binom{n-1}{k}} \\ &= 1 - \frac{(m-1)^2 \binom{n}{m-1}}{\sum_{k=0}^{n-1} \binom{n-1}{k}} \rightarrow 1 \quad \text{as } n \text{ goes to infinity.} \end{aligned}$$

Next, we find an upper bound on the fraction of social quilts that goes to 0 as n grows. There are two possible sets of degrees that an agent can have in a network: $A = \{km < n \mid k \text{ is a nonnegative integer}\}$ and $B = \{k < n \mid k \text{ is an integer}\} - A$. In a social quilt g , every agent i has a degree $d_i(g) \in A$. We show that the number of networks such that all agents have degrees in A is a fraction of no more than $\frac{1}{2}^{n-1}$ of all possible networks.

To do this we catalog networks g by first forming a network among the agents 1 to $n - 1$, and then considering links between those agents and agent n . We show that regardless of the starting network g_0 , there is at most one configuration of links for agent n (out of 2^{n-1} possible) that will allow all agents to have degrees in A . The result then follows directly. Beginning with the network g_0 among agents 1 to $n - 1$,

if $d_i(g_0) \in A$ then it must be that there is no link between i and n in g . In contrast, if $d_i(g_0) \notin A$ then in order for $d_i(g)$ to be in A it would have to be that i and n are linked in g . Thus, if there is some configuration of links between n and the other agents that results in the correct configuration of degrees, there is at most one such configuration out of the 2^{n-1} possible configurations.

PROOF OF THEOREM 3:

Suppose to the contrary that g is robust against social contagion and some link ij is not supported. Consider $h \notin \{i, j\}$ and delete a link of h (and there is at least one such h who has a link, as the single link ij is not sustainable independently as part of a subgame perfect equilibrium by equation (2)). This leads to a continuation g' that is robust against social contagion and such that $ij \in g'$, as otherwise by robustness both i and j would have to be neighbors of h , which would contradict the fact that ij is not supported. Iterate on this argument as long as there are still links that involve any agents other than i and j in the network. Eventually, we reach a continuation that sustains the network of the solitary link ij , which is a contradiction since ij cannot be sustained on its own as a part of an equilibrium by equation (2).

REFERENCES

- Abreu, Dilip, David Pearce, and Ennio Stacchetti. 1993. "Renegotiation and Symmetry in Repeated Games." *Journal of Economic Theory* 60 (2): 217–40.
- Ali, S. Nageeb, and David A. Miller. 2009. "Cooperation and Collective Enforcement in Networked Societies." Unpublished.
- Balmaceda, Felipe, and Juan F. Escobar. 2011. "Self Governance in Networked Relationships." Unpublished.
- Banerjee, Abhijit, Arun Chandrasekhar, Esther Duflo, and Matthew O. Jackson. 2011. "The Diffusion of Microfinance." Unpublished.
- Barnes, John A. 1954. "Class and Committees in a Norwegian Island Parish." *Human Relations* 7 (1): 39–58.
- Benoit, Jean-Pierre, and Vijay Krishna. 1993. "Renegotiation in Finitely Repeated Games." *Econometrica* 61 (2): 303–23.
- Bernheim, B. Douglas, Bezalel Peleg, and Michael D. Whinston. 1987. "Coalition-Proof Nash Equilibria: Concepts." *Journal of Economic Theory* 42 (1): 1–12.
- Bernheim, B. Douglas, and Debraj Ray. 1989. "Collective Dynamic Consistency in Repeated Games." *Games and Economic Behavior* 1 (4): 295–326.
- Bloch, Francis, Garance Genicot, and Debraj Ray. 2007. "Reciprocity in Groups and the Limits to Social Capital." *American Economic Review* 97 (2): 65–69.
- Bloch, Francis, Garance Genicot, and Debraj Ray. 2008. "Informal Insurance in Social Networks." *Journal of Economic Theory* 143 (1): 36–58.
- Bourdieu, Pierre. 1986. "Forms of Capital." In *Handbook of Theory and Research for the Sociology of Education*, edited by John G. Richardson, 241–58. Westport, CT: Greenwood Press.
- Bramoullé, Yann, and Rachel Kranton. 2007. "Risk-Sharing Networks." *Journal of Economic Behavior and Organization* 64 (3–4): 275–94.
- Camerer, Colin F. 2003. *Behavioral Game Theory: Experiments in Strategic Interaction*. Princeton, NJ: Princeton University Press.
- Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." In *Organizations and Institutions: Sociological and Economic Approaches to the Analysis of Social Structure*, edited by Christopher Winship and Sherwin Rosen, 95–120. Chicago: University of Chicago Press.
- Coleman, James S. 1990. *Foundations of Social Theory*. Cambridge, MA: Harvard University Press.
- Cooper, David J., and John H. Kagel. Forthcoming. "Other Regarding Preferences: A Selective Survey of Experimental Results." *Handbook of Experimental Economics Vol. 2*, edited by John H. Kagel and Alvin E. Roth. Princeton, NJ: Princeton University Press.
- Dasgupta, Partha, and Ismail Serageldin, eds. 2000. *Social Capital: A Multifaceted Perspective*. Washington, DC: World Bank.

- De Weerd, Joachim, and Stefan Dercon.** 2006. "Risk-Sharing Networks and Insurance against Illness." *Journal of Development Economics* 81 (2): 337–56.
- D'Exelle, Ben, and Arno Riedl.** 2010. "Directed Generosity and Network Formation: Network Dimension Matters." Institute for the Study of Labor (IZA) Working Paper 3287.
- Ellison, Glenn.** 1994. "Cooperation in the Prisoner's Dilemma with Anonymous Random Matching." *Review of Economic Studies* 61 (3): 567–88.
- Fafchamps, Marcel, and Susan Lund.** 2003. "Risk-Sharing Networks in Rural Philippines." *Journal of Development Economics* 71 (2): 261–87.
- Farrell, Joseph, and Eric Maskin.** 1989. "Renegotiation in Repeated Games." *Games and Economic Behavior* 1 (4): 327–60.
- Fehr, Ernst, and Klaus M. Schmidt.** 2006. "The Economics of Fairness, Reciprocity and Altruism: Experimental Evidence and New Theories." In *Handbook on the Economics of Giving, Reciprocity, and Altruism, Vol. 1*, edited by Serge-Christophe Kolm and Jean Mercier Ythier, 615–91. Amsterdam: Elsevier.
- Glaeser, Edward L., David Laibson, and Bruce Sacerdote.** 2002. "An Economic Approach to Social Capital." *Economic Journal* 112 (483): F437–58.
- Greif, Avner.** 1989. "Reputation and Coalitions in Medieval Trade: Evidence on the Maghribi Traders." *Journal of Economic History* 49 (4): 857–82.
- Guiso, Luigi, Paola Sapienza, and Luigi Zingales.** 2004. "The Role of Social Capital in Financial Development." *American Economic Review* 94 (3): 526–56.
- Haag, Matthew, and Roger Lagunoff.** 2006. "Social Norms, Local Interaction, and Neighborhood Planning." *International Economic Review* 47 (1): 265–96.
- Homans, George C.** 1958. "Social Behavior as Exchange." *American Journal of Sociology* 63 (6): 597–606.
- Jackson, Matthew O.** 2008. *Social and Economic Networks*. Princeton, NJ: Princeton University Press.
- Jackson, Matthew O., Tomas Rodriguez-Barraquer, and Xu Tan.** 2012. "Social Capital and Social Quilts: Network Patterns of Favor Exchange: Dataset." *American Economic Review*. <http://dx.doi.org/10.1257/aer.102.5.1857>.
- Jackson, Matthew O., and Brian W. Rogers.** 2007. "Meeting Strangers and Friends of Friends: How Random Are Social Networks?" *American Economic Review* 97 (3): 890–915.
- Kandori, Michihiro.** 1992. "Social Norms and Community Enforcement." *Review of Economic Studies* 59 (1): 63–80.
- Karlan, Dean, Markus Mobius, Tanya Rosenblat, and Adam Szeidl.** 2009. "Trust and Social Collateral." *Quarterly Journal of Economics* 124 (3): 1307–61.
- Krackhardt, David.** 1996. "Social Networks and the Liability of Newness for Managers." In *Trends in Organizational Behavior, Vol. 3*, edited by Cary L. Cooper and Denise M. Rousseau, 159–73. New York: John Wiley and Sons.
- Kreps, David M.** 1997. "Intrinsic Motivation and Extrinsic Incentives." *American Economic Review* 87 (2): 359–64.
- Liben-Nowell, David, and Jon Kleinberg.** 2007. "The Link-Prediction Problem for Social Networks." *Journal of the American Society for Information Science and Technology* 58 (7): 1019–31.
- Lippert, Steffen, and Giancarlo Spagnolo.** 2011. "Networks of Relations and Word-of-Mouth Communication." *Games and Economic Behavior* 72 (1): 202–17.
- Loury, Glenn.** 1977. "A Dynamic Theory of Racial Income Differences." In *Women, Minorities, and Employment Discrimination*, edited by Phyllis Ann Wallace and Annette LaMond, 153–88. Lexington, MA: Lexington Books.
- Mihm, Maximilian, Russell Toth, and Corey Lang.** 2009. "What Goes Around Comes Around: A Theory of Indirect Reciprocity in Networks." Cornell University Center for Analytic Economics Working Paper 09-07.
- Okuno-Fujiwara, Masahiro, and Andrew Postlewaite.** 1995. "Social Norms and Random Matching Games." *Games and Economic Behavior* 9 (1): 79–109.
- Putnam, Robert D.** 1993. "The Prosperous Community: Social Capital and Public Life." *The American Prospect* 4 (13): 35–42.
- Putnam, Robert D.** 1995. "Bowling Alone: America's Declining Social Capital." *Journal of Democracy* 6 (1): 65–78.
- Putnam, Robert D.** 2000. *Bowling Alone: The Collapse and Revival of American Community*. New York: Simon and Schuster.
- Raub, Werner, and Jeroen Weesie.** 1990. "Reputation and Efficiency in Social Interactions: An Example of Network Effects." *American Journal of Sociology* 96 (3): 626–54.
- Simmel, Georg.** 1950. *The Sociology of Georg Simmel*. Translated by K. Wolf. Glencoe, IL: Free Press.

- Snijders, Tom A. B.** 2002. "Markov Chain Monte Carlo Estimation of Exponential Random Graph Models." *Journal of Social Structure* 3 (2): 1–40.
- Sobel, Joel.** 2002. "Can We Trust Social Capital?" *Journal of Economic Literature* 40 (1): 139–54.
- Tabellini, Guido.** 2010. "Culture and Institutions: Economic Development in the Regions of Europe." *Journal of the European Economic Association* 8 (4): 677–716.
- van den Brink, Rene.** 2011. "On Hierarchies and Communication." Tinbergen Institute Discussion Paper 2006-056/1.
- Woolcock, Michael.** 1998. "Social Capital and Economic Development: Toward a Theoretical Synthesis and Policy Framework." *Theory and Society* 27 (2): 151–208.

This article has been cited by:

1. Jaime Iranzo, Federico Pablo-Martí, Jacobo Aguirre. 2020. Emergence of complex socioeconomic networks driven by individual and collective interests. *Physical Review Research* **2**:4. . [[Crossref](#)]
2. Sumit Joshi, Ahmed Saber Mahmud. 2020. Sanctions in networks. *European Economic Review* **130**, 103606. [[Crossref](#)]
3. Heidrun Stoeger, Michael Heilemann, Tobias Debatin, Manuel D. S. Hopp, Sigrun Schirner, Albert Ziegler. 2020. Nine years of online mentoring for secondary school girls in STEM: an empirical comparison of three mentoring formats. *Annals of the New York Academy of Sciences* **20**. . [[Crossref](#)]
4. Renaud Bourlès, Yann Bramoullé, Eduardo Perez-Richet. 2020. Altruism and Risk Sharing in Networks. *Journal of the European Economic Association* **85**. . [[Crossref](#)]
5. Kaivan Munshi. 2020. Social Networks and Migration. *Annual Review of Economics* **12**:1, 503-524. [[Crossref](#)]
6. Emily Breza, Arun G. Chandrasekhar, Tyler H. McCormick, Mengjie Pan. 2020. Using Aggregated Relational Data to Feasibly Identify Network Structure without Network Data. *American Economic Review* **110**:8, 2454-2484. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
7. Lingxiao Li, Erdem Ucar, Abdullah Yavas. 2020. Social Capital and Mortgage Delinquency. *The Journal of Real Estate Finance and Economics* **105**. . [[Crossref](#)]
8. Simon Heß, Dany Jaimovich, Matthias Schündeln. 2020. Development Projects and Economic Networks: Lessons from Rural Gambia. *The Review of Economic Studies* **106**. . [[Crossref](#)]
9. Thomas Calvo, Emmanuelle Lavallée, Mireille Razafindrakoto, François Roubaud. 2020. Fear Not For Man? Armed conflict and social capital in Mali. *Journal of Comparative Economics* **48**:2, 251-276. [[Crossref](#)]
10. Mudit Kumar Singh, Jaemin Lee. 2020. Social inequality and access to social capital in microfinance interventions. *International Journal of Sociology and Social Policy* **40**:7/8, 575-588. [[Crossref](#)]
11. Francesco Drago, Friederike Mengel, Christian Traxler. 2020. Compliance Behavior in Networks: Evidence from a Field Experiment. *American Economic Journal: Applied Economics* **12**:2, 96-133. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
12. Daron Acemoglu, Alexander Wolitzky. 2020. Sustaining Cooperation: Community Enforcement versus Specialized Enforcement. *Journal of the European Economic Association* **18**:2, 1078-1122. [[Crossref](#)]
13. Vincent Boucher. 2020. Equilibrium homophily in networks. *European Economic Review* **123**, 103370. [[Crossref](#)]
14. Debraj Roy, Michael Lees. 2020. Understanding resilience in slums using an agent-based model. *Computers, Environment and Urban Systems* **80**, 101458. [[Crossref](#)]
15. Matthew O. Jackson. 2020. A typology of social capital and associated network measures. *Social Choice and Welfare* **54**:2-3, 311-336. [[Crossref](#)]
16. Michael A. Rubin. 2020. Rebel Territorial Control and Civilian Collective Action in Civil War: Evidence from the Communist Insurgency in the Philippines. *Journal of Conflict Resolution* **64**:2-3, 459-489. [[Crossref](#)]
17. Simon D. Angus, Jonathan Newton. 2020. Collaboration leads to cooperation on sparse networks. *PLOS Computational Biology* **16**:1, e1007557. [[Crossref](#)]
18. Nissim Cohen, Anna Rubinchik, Labib Shami. 2020. Towards a cashless economy: Economic and socio-political implications. *European Journal of Political Economy* **61**, 101820. [[Crossref](#)]

19. Maximilian Mihm, Russell Toth. 2020. Cooperative networks with robust private monitoring. *Journal of Economic Theory* **185**, 104974. [[Crossref](#)]
20. Tong Zhang, Huiting Liu, Pinghan Liang. 2020. Social Trust Formation and Credit Accessibility—Evidence from Rural Households in China. *Sustainability* **12**:2, 667. [[Crossref](#)]
21. Jennifer M. Larson, Janet I. Lewis. 2020. Measuring networks in the field. *Political Science Research and Methods* **8**:1, 123-135. [[Crossref](#)]
22. Wei Li, Xu Tan. 2020. Locally Bayesian learning in networks. *Theoretical Economics* **15**:1, 239-278. [[Crossref](#)]
23. Arun G. Chandrasekhar, Horacio Larreguy, Juan Pablo Xandri. 2020. Testing Models of Social Learning on Networks: Evidence From Two Experiments. *Econometrica* **88**:1, 1-32. [[Crossref](#)]
24. Bryan S. Graham, Andrin Pelican. Testing for externalities in network formation using simulation 63-82. [[Crossref](#)]
25. Talya Eden, Dana Ron, C. Seshadhri. 2020. On Approximating the Number of k -Cliques in Sublinear Time. *SIAM Journal on Computing* **49**:4, 747-771. [[Crossref](#)]
26. Matthew Elliott, Benjamin Golub, Matt V. Leduc. 2020. Supply Network Formation and Fragility. *SSRN Electronic Journal* . [[Crossref](#)]
27. Bryan S. Graham. Network data 111-218. [[Crossref](#)]
28. Emily Breza, Arun Chandrasekhar, Benjamin Golub, Aneesha Parvathaneni. 2019. Networks in economic development. *Oxford Review of Economic Policy* **35**:4, 678-721. [[Crossref](#)]
29. Andreas Dzemski. 2019. An Empirical Model of Dyadic Link Formation in a Network with Unobserved Heterogeneity. *The Review of Economics and Statistics* **101**:5, 763-776. [[Crossref](#)]
30. Toriqul Bashar, Glen Bramley. 2019. Social capital and neighbourhood cooperation: Implications for development of the urban poor in LDCs. *Urban Studies* **56**:13, 2727-2745. [[Crossref](#)]
31. Yangbo Song, Mihaela van der Schaar. 2019. Repeated Network Games with Dominant Actions and Individual Rationality. *IEEE Transactions on Network Science and Engineering* **6**:4, 812-823. [[Crossref](#)]
32. Sanjeev Goyal. 2019. Society and Economy: Frameworks and Principles: A Book Review. *Journal of Economic Literature* **57**:3, 678-689. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
33. Shijun Chai, Yang Chen, Bihong Huang, Dezhu Ye. 2019. Social networks and informal financial inclusion in China. *Asia Pacific Journal of Management* **36**:2, 529-563. [[Crossref](#)]
34. Mercy Mpinganjira. 2019. Willingness to reciprocate in virtual health communities: the role of social capital, gratitude and indebtedness. *Service Business* **13**:2, 269-287. [[Crossref](#)]
35. Yi Qi, Yuhao Yi, Zhongzhi Zhang. 2019. Topological and Spectral Properties of Small-World Hierarchical Graphs. *The Computer Journal* **62**:5, 769-784. [[Crossref](#)]
36. Sonia Di Giannatale, María José Roa. 2019. BARRIERS TO FORMAL SAVING: MICRO- AND MACROECONOMIC EFFECTS. *Journal of Economic Surveys* **33**:2, 541-566. [[Crossref](#)]
37. Ariel Mitev, András Bauer, Mirkó Gáti. 2019. A személyes értékesítők hálózatépítési tevékenysége. *Közgazdasági Szemle* **66**:01, 95-113. [[Crossref](#)]
38. Fernando Vega-Redondo. Social Networks from a Designer's Viewpoint 63-81. [[Crossref](#)]
39. Victor Lavy, Edith Sand. 2019. The Effect of Social Networks on Students' Academic and Non-cognitive Behavioural Outcomes: Evidence from Conditional Random Assignment of Friends in School. *The Economic Journal* **129**:617, 439-480. [[Crossref](#)]
40. Alastair Berg. 2019. Identity in Economics: A Review. *SSRN Electronic Journal* . [[Crossref](#)]
41. Francis Bloch, Bhaskar Dutta, Mihai Manea. 2019. Efficient partnership formation in networks. *Theoretical Economics* **14**:3, 779-811. [[Crossref](#)]

42. Raul Duarte, Frederico Finan, Horacio Larreguy Arbesu, Laura Schechter. 2019. Brokering Votes with Information Spread via Social Networks. *SSRN Electronic Journal* . [[Crossref](#)]
43. Mohamed Mostagir, Asuman E. Ozdaglar, James Siderius. 2019. When is Society Susceptible to Manipulation?. *SSRN Electronic Journal* . [[Crossref](#)]
44. Arun Advani, Bansi Malde. 2018. Methods to identify linear network models: a review. *Swiss Journal of Economics and Statistics* **154**:1. . [[Crossref](#)]
45. James P. Choy. 2018. Social Division with Endogenous Hierarchy. *The Economic Journal* **128**:615, 2711-2742. [[Crossref](#)]
46. Koen Jochmans. 2018. Semiparametric Analysis of Network Formation. *Journal of Business & Economic Statistics* **36**:4, 705-713. [[Crossref](#)]
47. Arun G. Chandrasekhar, Cynthia Kinnan, Horacio Larreguy. 2018. Social Networks as Contract Enforcement: Evidence from a Lab Experiment in the Field. *American Economic Journal: Applied Economics* **10**:4, 43-78. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
48. V. Masson, S. Choi, A. Moore, M. Oak. 2018. A model of informal favor exchange on networks. *Journal of Public Economic Theory* **20**:5, 639-656. [[Crossref](#)]
49. Arun Advani, Bansi Malde. 2018. CREDIBLY IDENTIFYING SOCIAL EFFECTS: ACCOUNTING FOR NETWORK FORMATION AND MEASUREMENT ERROR. *Journal of Economic Surveys* **32**:4, 1016-1044. [[Crossref](#)]
50. Bin Jiang, Jun Sung Kim, Chuhui Li, Ou Yang. 2018. Social Network Structure and Risk Sharing in Villages. *The B.E. Journal of Economic Analysis & Policy* **18**:3. . [[Crossref](#)]
51. Megan Konar, Xiaowen Lin, Benjamin Ruddell, Murugesu Sivapalan. 2018. Scaling properties of food flow networks. *PLOS ONE* **13**:7, e0199498. [[Crossref](#)]
52. Rebecca Bliege Bird, Elspeth Ready, Eleanor A. Power. 2018. The social significance of subtle signals. *Nature Human Behaviour* **2**:7, 452-457. [[Crossref](#)]
53. Georg Duernecker, Fernando Vega-Redondo. 2018. Social Networks and the Process of Globalization. *The Review of Economic Studies* **85**:3, 1716-1751. [[Crossref](#)]
54. Emla Fitzsimons, Bansi Malde, Marcos Vera-Hernández. 2018. Group Size and the Efficiency of Informal Risk Sharing. *The Economic Journal* **128**:612, F575-F608. [[Crossref](#)]
55. Ellen Lust, Lise Rakner. 2018. The Other Side of Taxation: Extraction and Social Institutions in the Developing World. *Annual Review of Political Science* **21**:1, 277-294. [[Crossref](#)]
56. Laura Hernández, Annick Vignes, Stéphanie Saba. 2018. Trust or robustness? An ecological approach to the study of auction and bilateral markets. *PLOS ONE* **13**:5, e0196206. [[Crossref](#)]
57. Jonathan de Quidt, Thiemo Fetzer, Maitreesh Ghatak. 2018. Market Structure and Borrower Welfare in Microfinance. *The Economic Journal* **128**:610, 1019-1046. [[Crossref](#)]
58. Tomoki Tokuda. 2018. Statistical test for detecting community structure in real-valued edge-weighted graphs. *PLOS ONE* **13**:3, e0194079. [[Crossref](#)]
59. Sarah Jane Smith, Vivien Urquhart. 2018. UK PhD assessment in accounting and finance: social capital in action. *Accounting Education* **27**:2, 160-182. [[Crossref](#)]
60. CRISTIAN E VILLANUEVA, ADRIANELA ANGELES, LUZ CECILIA REVILLA. 2018. TYING STRONG TIES IN INFORMAL ENTREPRENEURSHIP: A CONSTRAINT OR AN ENTREPRENEURIAL DRIVER?. *Journal of Developmental Entrepreneurship* **23**:01, 1850002. [[Crossref](#)]
61. Robert P. Gilles. The Principles of Economic Wealth Creation 1-82. [[Crossref](#)]
62. Itay P. Fainmesser, David A. Goldberg. 2018. Cooperation in partly observable networked markets. *Games and Economic Behavior* **107**, 220-237. [[Crossref](#)]

63. Ben D'Exelle, Eric Coleman, Maria Claudia Lopez. 2018. Community-Driven Reconstruction in Colombia: An Experimental Study of Collective Action beyond Program Beneficiaries. *World Development* **101**, 188-201. [[Crossref](#)]
64. Caroline Flurey, Alan White, Karen Rodham, John Kirwan, Robert Noddings, Sarah Hewlett. 2018. 'Everyone assumes a man to be quite strong': Men, masculinity and rheumatoid arthritis: A case-study approach. *Sociology of Health & Illness* **40**:1, 115-129. [[Crossref](#)]
65. Talya Eden, Dana Ron, C. Seshadhri. On approximating the number of k-cliques in sublinear time 722-734. [[Crossref](#)]
66. Seng W. Loke. Are We Ready for the Internet of Robotic Things in Public Spaces? 891-900. [[Crossref](#)]
67. Shijun Chai, Yang Chen, Bihong Huang, Dezhu Ye. 2018. Social Networks and Informal Financial Inclusion in the People's Republic of China. *SSRN Electronic Journal* . [[Crossref](#)]
68. Sidartha Gordon, Emeric Henry, Pauli Murto. 2018. Waiting for My Neighbors. *SSRN Electronic Journal* . [[Crossref](#)]
69. Dawen Meng. 2018. Sequential Nonlinear Pricing of Experience Goods with Network Effects. *SSRN Electronic Journal* . [[Crossref](#)]
70. Javier Mejia. 2018. Social Networks and Entrepreneurship: Evidence from a Historical Episode of Industrialization. *SSRN Electronic Journal* . [[Crossref](#)]
71. Javier Mejia. 2018. The Network Formation Origin of Tribal Societies. *SSRN Electronic Journal* . [[Crossref](#)]
72. Michael Rubin. 2018. Rebel Territorial Control and Civilian Collective Action in Civil War: Evidence from the Philippines. *SSRN Electronic Journal* . [[Crossref](#)]
73. Sumit Joshi, Ahmed Saber Mahmud. 2018. Unilateral and multilateral sanctions: A network approach. *Journal of Economic Behavior & Organization* **145**, 52-65. [[Crossref](#)]
74. Matthew O. Jackson, Yiqing Xing. 2018. The Interaction of Communities, Religion, Governments, and Corruption in the Enforcement of Contracts and Social Norms. *SSRN Electronic Journal* . [[Crossref](#)]
75. Goylette F. Chami, Andreas A. Kontoleon, Erwin Bulte, Alan Fenwick, Narcis B. Kabatereine, Edridah M. Tukahebwa, David W. Dunne. 2017. Diffusion of treatment in social networks and mass drug administration. *Nature Communications* **8**:1. . [[Crossref](#)]
76. Cesi Cruz, Julien Labonne, Pablo Querubín. 2017. Politician Family Networks and Electoral Outcomes: Evidence from the Philippines. *American Economic Review* **107**:10, 3006-3037. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
77. Eleonora Patacchini, Edoardo Rainone. 2017. Social Ties and the Demand for Financial Services. *Journal of Financial Services Research* **52**:1-2, 35-88. [[Crossref](#)]
78. Jennifer M. Larson. 2017. Why the West Became Wild. *World Politics* **69**:4, 713-749. [[Crossref](#)]
79. Thomas D. Jeitschko, C. Oscar Lau. 2017. Soft transactions. *Journal of Economic Behavior & Organization* **141**, 122-134. [[Crossref](#)]
80. JAMES BISBEE, JENNIFER M. LARSON. 2017. Testing Social Science Network Theories with Online Network Data: An Evaluation of External Validity. *American Political Science Review* **111**:3, 502-521. [[Crossref](#)]
81. Fabio Sabatini, Francesco Sarracino. 2017. Online Networks and Subjective Well-Being. *Kyklos* **70**:3, 456-480. [[Crossref](#)]
82. Felipe Balmaceda, Juan F. Escobar. 2017. Trust in cohesive communities. *Journal of Economic Theory* **170**, 289-318. [[Crossref](#)]

83. Thomas Davidson, Paromita Sanyal. 2017. Associational Participation and Network Expansion: Microcredit Self-Help Groups and Poor Women's Social Ties in Rural India. *Social Forces* **95**:4, 1695–1724. [[Crossref](#)]
84. René van den Brink. 2017. Games with a permission structure - A survey on generalizations and applications. *TOP* **25**:1, 1–33. [[Crossref](#)]
85. Xi Chen, Ralf Van Der Lans, Tuan Q. Phan. 2017. Uncovering the Importance of Relationship Characteristics in Social Networks: Implications for Seeding Strategies. *Journal of Marketing Research* **54**:2, 187–201. [[Crossref](#)]
86. Jennifer M. Larson, Janet I. Lewis. 2017. Ethnic Networks. *American Journal of Political Science* **61**:2, 350–364. [[Crossref](#)]
87. Matthew O. Jackson, Brian W. Rogers, Yves Zenou. 2017. The Economic Consequences of Social-Network Structure. *Journal of Economic Literature* **55**:1, 49–95. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
88. Sharon Barnhardt, Erica Field, Rohini Pande. 2017. Moving to Opportunity or Isolation? Network Effects of a Randomized Housing Lottery in Urban India. *American Economic Journal: Applied Economics* **9**:1, 1–32. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
89. Seng W. Loke. Social Links for Crowds and Things 55–63. [[Crossref](#)]
90. Holly B. Shakya, Nicholas A. Christakis, James H. Fowler. 2017. An exploratory comparison of name generator content: Data from rural India. *Social Networks* **48**, 157–168. [[Crossref](#)]
91. Shweta Jain, C. Seshadhri. A Fast and Provable Method for Estimating Clique Counts Using Turán's Theorem 441–449. [[Crossref](#)]
92. Francis Bloch, Stéphane Robin, Min Zhu. 2017. The Formation of Partnerships in Social Networks. *SSRN Electronic Journal* . [[Crossref](#)]
93. Rene van den Brink. 2017. Games with a Permission Structure: A Survey on Generalizations and Applications. *SSRN Electronic Journal* . [[Crossref](#)]
94. Jorge Marco, Renan-Ulrich Goetz. 2017. Tragedy of the Commons and Evolutionary Games in Social Networks: The Economics of Social Punishment. *SSRN Electronic Journal* . [[Crossref](#)]
95. Jean Guillaume Forand, Jan Zapal. 2017. The Demand and Supply of Favours in Dynamic Relationships. *SSRN Electronic Journal* . [[Crossref](#)]
96. Matthew O. Jackson. 2017. A Typology of Social Capital and Associated Network Measures. *SSRN Electronic Journal* . [[Crossref](#)]
97. Yangbo Song, Mihaela van der Schaar. 2017. Repeated Network Games. *SSRN Electronic Journal* . [[Crossref](#)]
98. Abhijit V. Banerjee, Emily Breza, Esther Duflo, Cynthia Kinnan. 2017. Do Credit Constraints Limit Entrepreneurship? Heterogeneity in the Returns to Microfinance. *SSRN Electronic Journal* . [[Crossref](#)]
99. Yi Wang, David Redmiles. 2016. Cheap talk, cooperation, and trust in global software engineering. *Empirical Software Engineering* **21**:6, 2233–2267. [[Crossref](#)]
100. Luke Boosey, R. Mark Isaac. 2016. Asymmetric network monitoring and punishment in public goods experiments. *Journal of Economic Behavior & Organization* **132**, 26–41. [[Crossref](#)]
101. Jaime Iranzo, Javier M. Buldú, Jacobo Aguirre. 2016. Competition among networks highlights the power of the weak. *Nature Communications* **7**:1. . [[Crossref](#)]
102. Michele Hoyman, Jamie McCall, Laurie Paarlberg, John Brennan. 2016. Considering the Role of Social Capital for Economic Development Outcomes in U.S. Counties. *Economic Development Quarterly* **30**:4, 342–357. [[Crossref](#)]

103. S. Nageeb Ali, David A. Miller. 2016. Ostracism and Forgiveness. *American Economic Review* **106**:8, 2329-2348. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
104. Vivi Alatas, Abhijit Banerjee, Arun G. Chandrasekhar, Rema Hanna, Benjamin A. Olken. 2016. Network Structure and the Aggregation of Information: Theory and Evidence from Indonesia. *American Economic Review* **106**:7, 1663-1704. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
105. Sumit Joshi, Ahmed Saber Mahmud. 2016. Sanctions in networks: "The Most Unkindest Cut of All". *Games and Economic Behavior* **97**, 44-53. [[Crossref](#)]
106. Cameron K. Murray, Paul Frijters. 2016. Clean money, dirty system: Connected landowners capture beneficial land rezoning. *Journal of Urban Economics* **93**, 99-114. [[Crossref](#)]
107. Jennifer M Larson. 2016. Interethnic conflict and the potential dangers of cross-group ties. *Journal of Peace Research* **53**:3, 459-471. [[Crossref](#)]
108. William McClain. 2016. A Pathway Forwards for the Social Capital Metaphor. *Review of Social Economy* **74**:2, 109-128. [[Crossref](#)]
109. Milan Zafirovski. 2016. Toward Economic Sociology/Socio-Economics? Sociological Components in Contemporary Economics and Implications for Sociology. *The American Sociologist* **47**:1, 56-80. [[Crossref](#)]
110. Kaivan Munshi, Mark Rosenzweig. 2016. Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap. *American Economic Review* **106**:1, 46-98. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
111. Arun G. Chandrasekhar, Matthew O. Jackson. 2016. A Network Formation Model Based on Subgraphs. *SSRN Electronic Journal* . [[Crossref](#)]
112. Jennifer Larson, Janet I. Lewis. 2016. Ethnic Networks. *SSRN Electronic Journal* . [[Crossref](#)]
113. James David Campbell. 2016. Availability of Better Data on Communication Networks Can Undermine Community Enforcement. *SSRN Electronic Journal* . [[Crossref](#)]
114. Arnold Polanski, Fernando Vega-Redondo. 2016. Homophily and Influence: The Weakness of Weak Ties. *SSRN Electronic Journal* . [[Crossref](#)]
115. Jonathan F Schulz. 2016. The Churches' Bans on Consanguineous Marriages, Kin-Networks and Democracy. *SSRN Electronic Journal* . [[Crossref](#)]
116. Jacob Dijkstra. 2015. Social exchange: relations and networks. *Social Network Analysis and Mining* **5**:1. . [[Crossref](#)]
117. Paolo Pin, Brian W. Rogers. 2015. Cooperation, punishment and immigration. *Journal of Economic Theory* **160**, 72-101. [[Crossref](#)]
118. Claudia Kasper, Monique Borgerhoff Mulder. 2015. Who Helps and Why?. *Current Anthropology* **56**:5, 701-732. [[Crossref](#)]
119. Yating Chuang, Laura Schechter. 2015. Social Networks in Developing Countries. *Annual Review of Resource Economics* **7**:1, 451-472. [[Crossref](#)]
120. Juha V. A. Ikonen. 2015. Social ties and concern for global warming. *Climatic Change* **132**:2, 173-192. [[Crossref](#)]
121. Michael P. Leung. 2015. Two-step estimation of network-formation models with incomplete information. *Journal of Econometrics* **188**:1, 182-195. [[Crossref](#)]
122. Antonio Jiménez-Martínez. 2015. A model of belief influence in large social networks. *Economic Theory* **59**:1, 21-59. [[Crossref](#)]
123. Lucas Wardil, Christoph Hauert. 2015. Origin and Structure of Dynamic Cooperative Networks. *Scientific Reports* **4**:1. . [[Crossref](#)]
124. Vincent Buskens, Rense Corten, Werner Raub. Social Networks 663-687. [[Crossref](#)]

125. Matthew O. Jackson, Yves Zenou. Games on Networks 95-163. [[Crossref](#)]
126. Holly B. Shakya, Nicholas A. Christakis, James H. Fowler. 2015. Social network predictors of latrine ownership. *Social Science & Medicine* **125**, 129-138. [[Crossref](#)]
127. Jessica M. Perkins, S.V. Subramanian, Nicholas A. Christakis. 2015. Social networks and health: A systematic review of sociocentric network studies in low- and middle-income countries. *Social Science & Medicine* **125**, 60-78. [[Crossref](#)]
128. Alexander C. Tsai, Andrew V. Papachristos. 2015. From social networks to health: Durkheim after the turn of the millennium. *Social Science & Medicine* **125**, 1-7. [[Crossref](#)]
129. Matthew O. Jackson, Brian W. Rogers, Yves Zenou. 2015. The Economic Consequences of Social Network Structure. *SSRN Electronic Journal* . [[Crossref](#)]
130. Sandra Polania-Reyes. 2015. Disentangling Social Capital: Lab-in-The-Field Evidence on Coordination, Networks and Cooperation. *SSRN Electronic Journal* . [[Crossref](#)]
131. Daron Acemoglu, Alexander Wolitzky. 2015. Sustaining Cooperation: Community Enforcement vs. Specialized Enforcement. *SSRN Electronic Journal* . [[Crossref](#)]
132. Sharon Barnhardt, Erica Field, Rohini Pande. 2015. Moving to Opportunity or Isolation? Network Effects of a Randomized Housing Lottery in Urban India. *SSRN Electronic Journal* . [[Crossref](#)]
133. Alexander Wolitzky. 2015. Communication with tokens in repeated games on networks. *Theoretical Economics* **10**:1, 67-101. [[Crossref](#)]
134. Matthew O. Jackson. 2014. Networks in the Understanding of Economic Behaviors. *Journal of Economic Perspectives* **28**:4, 3-22. [[Abstract](#)] [[View PDF article](#)] [[PDF with links](#)]
135. Yossi Feinberg, Willemien Kets. 2014. Ranking friends. *Journal of Economic Behavior & Organization* **107**, 1-9. [[Crossref](#)]
136. Alberto Antonioni, Maria Paula Cacault, Rafael Lalive, Marco Tomassini. 2014. Know Thy Neighbor: Costly Information Can Hurt Cooperation in Dynamic Networks. *PLoS ONE* **9**:10, e110788. [[Crossref](#)]
137. Adam Douglas Henry, Björn Vollen. 2014. Networks and the Challenge of Sustainable Development. *Annual Review of Environment and Resources* **39**:1, 583-610. [[Crossref](#)]
138. Arthur Campbell. 2014. Signaling in social network and social capital formation. *Economic Theory* **57**:2, 303-337. [[Crossref](#)]
139. Sarah Jacobson, Ragan Petrie. 2014. Favor trading in public good provision. *Experimental Economics* **17**:3, 439-460. [[Crossref](#)]
140. Margherita Comola, Marcel Fafchamps. 2014. Testing Unilateral and Bilateral Link Formation. *The Economic Journal* **124**:579, 954-976. [[Crossref](#)]
141. Paul D. McLean, Neha Gondal. 2014. The Circulation of Interpersonal Credit in Renaissance Florence. *European Journal of Sociology* **55**:2, 135-176. [[Crossref](#)]
142. Jie Xu, Yangbo Song, Mihaela van der Schaar. 2014. Sharing in Networks of Strategic Agents. *IEEE Journal of Selected Topics in Signal Processing* **8**:4, 717-731. [[Crossref](#)]
143. Justin H. Kirkland, R. Lucas Williams. 2014. Partisanship and Reciprocity in Cross-Chamber Legislative Interactions. *The Journal of Politics* **76**:3, 754-769. [[Crossref](#)]
144. Holly B. Shakya, Nicholas A. Christakis, James H. Fowler. 2014. Association Between Social Network Communities and Health Behavior: An Observational Sociocentric Network Study of Latrine Ownership in Rural India. *American Journal of Public Health* **104**:5, 930-937. [[Crossref](#)]
145. Daniel Enemark, Mathew D. McCubbins, Nicholas Weller. 2014. Knowledge and networks: An experimental test of how network knowledge affects coordination. *Social Networks* **36**, 122-133. [[Crossref](#)]

146. Matthew O. Jackson. 2014. Networks and the Identification of Economic Behaviors. *SSRN Electronic Journal* . [[Crossref](#)]
147. Itay Perah Fainmesser. 2014. Exclusive Intermediation. *SSRN Electronic Journal* . [[Crossref](#)]
148. Matthew O. Jackson, Stephen Nei. 2014. Networks of Military Alliances, Wars, and International Trade. *SSRN Electronic Journal* . [[Crossref](#)]
149. Daron Acemoglu, Matthew O. Jackson. 2014. Social Norms and the Enforcement of Laws. *SSRN Electronic Journal* . [[Crossref](#)]
150. Francesco Nava, Michele Piccione. 2014. Efficiency in repeated games with local interaction and uncertain local monitoring. *Theoretical Economics* **9**:1, 279-312. [[Crossref](#)]
151. Attila Ambrus, Arun Chandrasekhar, Matthew Elliott. 2014. Social Investments, Informal Risk Sharing, and Inequality. *SSRN Electronic Journal* . [[Crossref](#)]
152. Konrad B. Burchardi, Tarek A. Hassan. 2013. The Economic Impact of Social Ties: Evidence from German Reunification*. *The Quarterly Journal of Economics* **128**:3, 1219-1271. [[Crossref](#)]
153. Alexia Gaudeul, Caterina Giannetti. 2013. The role of reciprocation in social network formation, with an application to LiveJournal. *Social Networks* **35**:3, 317-330. [[Crossref](#)]
154. Matthew O. Jackson. 2013. Comment. *Journal of Business & Economic Statistics* **31**:3, 270-273. [[Crossref](#)]
155. Corrado Grappiolo, Julian Togelius, Georgios N. Yannakakis. Artificial evolution for the detection of group identities in complex artificial societies 126-133. [[Crossref](#)]
156. Michael Leung. 2013. Two-Step Estimation of Network-Formation Models with Incomplete Information. *SSRN Electronic Journal* . [[Crossref](#)]
157. Khai Xiang Chiong. 2013. Revealed Preference Tests of Network Formation Models. *SSRN Electronic Journal* . [[Crossref](#)]
158. Itay Perah Fainmesser, Andrea Galeotti. 2013. The Value of Network Information. *SSRN Electronic Journal* . [[Crossref](#)]
159. Encarnacion Algaba, Renn van den Brink, Chris Dietz. 2013. Cooperative Games on Accessible Union Stable Systems. *SSRN Electronic Journal* . [[Crossref](#)]
160. Alexia Gaudeul, Caterina Giannetti. 2012. The Role of Reciprocation in Social Network Formation, with an Application to Blogging. *SSRN Electronic Journal* . [[Crossref](#)]
161. Arun Chandrasekhar, Matthew O. Jackson. 2012. Tractable and Consistent Random Graph Models. *SSRN Electronic Journal* . [[Crossref](#)]
162. J. Mark Ramseyer. 2012. The Fable of Land Reform: Expropriation and Redistribution in Occupied Japan. *SSRN Electronic Journal* . [[Crossref](#)]
163. Holly B Shakyia, Nicholas A. Christakis, James H. Fowler. 2012. Social Network Predictors of Latrine Ownership. *SSRN Electronic Journal* . [[Crossref](#)]
164. Yossi Feinberg, Willemien Kets. 2012. Ranking Friends. *SSRN Electronic Journal* . [[Crossref](#)]
165. Itay Perah Fainmesser, David Goldberg. 2011. Bilateral and Community Enforcement in a Networked Market with Simple Strategies. *SSRN Electronic Journal* . [[Crossref](#)]
166. Itay Perah Fainmesser. 2010. Community Structure and Market Outcomes: A Repeated Games in Networks Approach. *SSRN Electronic Journal* . [[Crossref](#)]
167. Margherita Comola. 2010. The Network Structure of Mutual Support Links: Evidence from Rural Tanzania. *SSRN Electronic Journal* . [[Crossref](#)]