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Social dilemmas with manifest and latent networks

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Abstract:

This study implements an agent-based computational model to examine the impact of network structure on simple two-person coordination tasks. The conceptual contribution of the paper is the concept of relational rules, which are heuristic devices that can help harmonize expectations as a function of network ties. With relational ties as a behavioral foundation, the embedded computer experiment manipulates network density in a parametric fashion—thus examining a wide variety of network structures--to examine its impact on coordination. The results indicate that a greater frequency of ties in general does have a positive impact on group coordination. A second manipulation involves variable knowledge of network structure by participants, in particular whether participants are aware of manifest networks or not (these are latent). The impact of network awareness (or lack thereof) does not produce consistent results, and is contingent on particular informational assumptions. In particular, assuming less knowledge of underlying social structures may lead to more coordination than in the case where people make random inferences (that is, they attempt to know more) about latent network ties. Whether the distinction between manifest (known) and latent networks matters also depends on the actual density of the network.

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1. Introduction

How can societies solve social dilemmas in a decentralized fashion? How do social networks affect those potential solutions? If networks matter, how does individual knowledge (or lack thereof) of the overall network structure affect aggregate outcomes? To date the literature has addressed the first question with a particular set of assumptions whereas the second question remains largely unexplored. This paper will address these related questions under a wide variety of network structures in the context of repeated play of simple two-person coordination games.

By definition, a social dilemma occurs in situation that requires some collective action and which is characterized as a (strategic) equilibrium aggregate outcome that generates less social utility than another option that members of society also have available (Shepsle 2006), p. 31. Major examples of social dilemmas involve cooperation problems, as represented by the canonical prisoner's dilemma game, and various types of coordination failures. In general, a major reason for inferior outcomes or the inability of societies to solve social dilemmas is the pervasive conflict that exists between the public interest of society and the self-interest of individual participants (Olson 1965).

General solutions to social dilemmas involve the alignment of individual and collective incentives. The mechanism range from centralization, which either requires some entity to coerce desirable behavior or otherwise give selective incentives to participants, to decentralized options where individual participants find some autonomous way to resolve their collective action problems. In the latter case, scholars have emphasized solutions that require informal arrangements, what Shepsle (2009) denotes unstructured situations. These "informal" solutions point to the importance of social conventions, norms, and shared expectations (Schelling 1960; Young 1996). These informal solutions can also be analyzed from an institutional perspective insofar as the underlying mechanisms condition individual behavior on a regular basis, so we can consider them to be informal institutional solutions (Nee and Swedberg 2005).

One major analytical problem with the concept of informal institutions, however, is that they are hard to identify due to the lack of explicit (hard-coded) definitions (Woodruff 2006). Moreover, even if such definition exists in some form, it is also contingent on the presumed existence of formal institutions to which they can be either substitutes or complements (Levitsky and Helmke 2004). Despite the difficulties of defining informal institutions, there is a common theme in literatures that emphasize informal governance in terms of key structural aspects of informality. Applications range across disciplines, especially in economics and business literatures, but there is a widespread recognition of the importance of social

structures in defining aspects of contracting and social interactions (Hitt et al. 2002; Uhlaner et al. 2007). In fact, many such informal arrangements are recognized to have a network-like character (Williamson 1991). (Ferguson et al. 2005) also explicitly define relational governance for inter-firm exchanges in terms of networks. In political science, the study of corruption and clientelism, for instance, readily define relevant social interactions in relational terms (Kitschelt and Wilkinson 2007; McMillan and Zoido 2004). There is, in fact, an emerging notion of network institutionalism that emphasizes informal, personalistic aspects of political phenomena (Ansell 2006), a theme that has long been heralded by sociologists (Granovetter 1985).

Along the same lines of relational governance, there is a vast multidisciplinary literature on coordination and social networks. For the most part, this literature has focused on threshold models of collective action. The models involve large societies engaged in "major" coordination tasks such as riots or revolutions (Granovetter 1978). A key concept in this literature is the notion of a threshold--that individuals may choose to participate in some collective action problem provided that there is a critical mass of other willing participants. This critical mass defines the threshold level, which can vary on an individual basis. This literature provides powerful explanations for the ability of large societies to coordinate around a common task. To a large extent, these models are based on the notion that social proximity can affect otherwise isolated individual decisions through various mechanisms. Threshold models of collective action use various behavioral foundations such as imitation, coercion or other types of social influence, or simply a recognition by individuals of strategic interdependence (e.g., that a revolution may not be successful unless enough people join a revolt)(Chwe 1999; Felmlee 2003; Friedkin 2002; Gould 1993; Morris 2000; Schelling 1978).

The literature on thresholds and large-scale coordination, however, does not provide a general answer to the issue of how network structure affects collective behavior. One major reason has to do with the heterogeneity of individual threshold levels. Moreover, when spatial or network structures are introduced to the analysis, results tend to be highly sensitive to the underlying social structures. A second reason has to do with the analytical complexity of network structures, the number of which increases nonlinearly with the number of participants. In addition, network analysis can be approached from both actor-centered or group-centered perspectives (Burt 1980).

A more fundamental limitation with all strategic models of coordination, even when they incorporate relevant social structures, is that issues of multiple equilibria that arise in coordination problems need not be resolved with reliance on social networks. Even if we restrict the analysis to local rather than global interactions, strategic considerations reveal that whereas networks may sometimes facilitate collective action around a particular task, they can enable the emergence of another type of indeterminacy in social conformism (Goyal 2007, pp.

67-75). In other words, networks may sometimes enable convergence on a particular task, but depending on network structure, the initial indeterminacy about expected play may simply be replaced with indeterminacy about network effects.

The second question about the impact of network awareness on collective behavior remains a largely unexplored topic in network-analytic literatures. This is not to say that uncertainty has not been studied at all, but that its treatment has been largely restricted to uncertainty about other actors' attributes such as individual threshold levels. To be sure, there are statistical studies that address the issue of network uncertainty from an analytical perspective; that is, how researchers (or some outside observer) may be able to infer latent network structures (Hoff et al. 2002). Underlying these approaches, however, is an implicit assumption that the data generating process involves a group of participants who have common knowledge about the underlying network, which they themselves can shape. Indeed, the estimation approach relies on the idea that actor attributes may help uncover social structure insofar as behavioral postulates like homophily (which affect network formation) are operational in that particular group.

The extant literature can thus be extended to address two issues. First, can networks operate in other ways besides social proximity as in threshold collective action models? Second, how does variable individual knowledge of underlying social structures affect aggregate outcomes?

This paper contributes to the extant literature with the implementation of a computational experiment that examines varying levels of network awareness for simple coordination games. Addressing the general questions posited above from a strategic perspective is not deemed feasible at the moment for a couple of reasons. First, there are major tractability issues involved with expanding the range of uncertainty beyond player types to the conditioning network. Second, a strategic perspective, in general, runs into the problem of indeterminacy that is common to coordination games. To circumvent these limits, the main idea in this paper is the use of *relational rules*, which are deterministic non-strategic heuristic devices that guide social interactions on the basis of existing social networks. Networks thus serve to help shape common expectations thus addressing the issue of indeterminacy in coordination games. These relational rules serve as a crude, behavioral model that can serve to derive testable implications about a wider variety of network structures than those explored in the extant literature. This added analytic flexibility, however, comes at the cost of dispensing with strategic considerations. Beyond complexity issues, a rationale for this simpler approach is that social networks are indeed understood to have a powerful conditioning impact, as especially revealed in anthropological studies of collective behavior (Knox et al. 2006).

The approach adopted here is a minimalist one inspired by previous studies of social dilemmas of coordination in the tradition of repeated, two-person prisoner-dilemma games (Axelrod 1984, 1997). Clearly, the focus on isolated two-person interactions does not cover the wide range of coordination tasks that societies may face, but for the question at hand (network awareness, which adds much complexity to the analysis) this seemed as a reasonable first step informed by a reputable tradition.[1] The paper is also informed by a recent study that analyzes the dynamics of large-scale coordination with the use of agent-based models (Siegel 2009). Unlike that latter study, however, my computer experiment examines a greater variety of network structures but without a more sophisticated behavioral model that accounts for costs and benefits of individual participation. In addition, my computer implementation is static in that repeated coordination games are not linked at all so the history of play does not affect players' behavior.

The results of this computer simulation indicate that network density matters; that is, a higher frequency of ties leads in general to more group coordination. This result holds even if we restrict the analysis to more realistic networks that may have lower density than those included in the computer experiment. In terms of network awareness, the experiment compared two basic conditions in which participants were restricted to a myopic case with knowledge limited to own ties versus a second case in which players made random guesses about the existence of other ties. Overall, the impact of latent networks was found to be variable and contingent on specific assumptions made about the knowledge of and ability to update network beliefs. A consistent result in this respect was that latent networks with random inferences led to lower levels of group coordination. In addition, the experiment examined a corollary question about whether relational strategies with a simple feedback mechanism enabled learning of latent networks, but the simulations results indicated that this was not the case.

The rest of this paper is organized as follows. Section 2 develops the concept of relational rules and the impact of network structure to derive testable implications for the computational experiment. Section 3 presents the experimental setup and a concomitant statistical analysis, including sensitivity analysis involving qualitatively different network structures. Section 4 concludes.

2. Relational rules for simple coordination problem

The scope of this paper is restricted to simple coordination tasks that require the effort of two members of society. From a strategic perspective and in the absence of prior communication,

[1] The focus on these smaller games will also make it easier to compare results across different types of social dilemmas such as repeated two-person prisoner's dilemma games.

these situations are well-known for making it difficult for players to coordinate on any of the two tasks. To illustrate this problem, the first subsection briefly reviews a coordination game to discuss one of its most important implications: namely, the inability to predict a unique (Nash) equilibrium. Beyond prediction issues for analysts, however, I focus my discussion on the substantive importance of shared expectations for players to be able to coordinate effectively.

Afterwards, I discuss the relevance of social contexts and, in particular, the idea of a relational coordination rule to "solve" coordination problems. Unlike the sophisticated best-response functions of game theory, the proposed relational rules are simple, non-strategic behavioral prescriptions that are contingent on social networks. Basically, relational rules will serve as a proxy for shared expectations, hence facilitating task coordination.

At first sight, the cognitive requirements of relational rules appear to be simpler than those of game-theoretic behavioral prescriptions insofar as players do not need to engage in strategic decision-making. However, the simplicity of relational rules is very much contingent on common knowledge of the underlying social network, a situation that I denote as *manifest* (social) networks. If players do not have complete knowledge of the social network, then they must form some beliefs about the structure of the *latent* network. In general, there is a myriad of approaches to model these beliefs. Consistent with the non-strategic definition of relational rules, I will discuss a set of simple informational assumptions about how players may deal with uncertainty about the underlying network. These assumptions will serve to derive testable implications as a foundation for the computer experiment discussed in the next section.

2.1 Two-person coordination games

Below is a typical payoff structure for a coordination game. The game has two players, 1 and 2, who make independent choices between High payoff (H) or Low payoff (L) tasks. From a utilitarian perspective where social utility equals the sum of cell payoffs, we can rank the four possible outcomes as follows: {H,H} > {L,L} > {H,L},{L,H}. The payoff structure of this game therefore indicates that coinciding on H (coordination here is more of a byproduct than a deliberate team effort) is the socially desirable outcome.[2]

[2] This is obviously a very simple coordination task, but it can be related to the literature on large-scale coordination as follows. First, we will assume that for a society of N people, there are N/2 tasks to be completed, which can be done independently. In effect, these two-person games are the building blocks of decomposable large-scale coordination problems. After tasks are completed, the social utility to the whole group is simply the sum of all resulting individual payoffs.

Figure 1 Simple coordination game

		2: H	2: L
1	H	2,2	0,0
	L	0,0	1,1

Despite the social desirability of {H,H}, strategic considerations reveal that such outcome is not guaranteed. Indeed, the Nash Equilibrium (NE) concept cannot identify a unique equilibrium and predicts that players can coordinate on either task.[3] There is, in fact, a large literature beyond the scope of this paper that addresses the general problem of multiple equilibria with the use of various equilibrium refinement concepts. The underlying reason for the multiplicity of equilibria is the inability of players to converge on a common expectation that clearly identifies an outcome as the best solution. Expectational convergence is a non-trivial task for strategic actors and hence many of the equilibrium refinements make alternative behavioral assumptions about the two players in order to point towards a particular outcome as the prescribed solution.

Especially relevant for coordination problems are the concepts of payoff dominance, risk dominance, and focal points.[4] Payoff dominance rules out {L,L} by assuming the ability of players to infer that they can harmonize their expectations around the high payoff equilibrium. Risk dominance assumes that players do their best under the belief that the other player will not choose H and, hence, rules out the pareto-optimal NE, {H,H}. A focal point—if it exists—identifies a shared understanding to focus on one outcome and rule out the other (Schelling 1960).

Ultimately, resolving the underlying strategic uncertainty requires further specification of a cognitive model that determines people's beliefs about others' expected play. For example, assuming risk-neutrality, player 1 would actually want to play H whenever it has a reason to believe that $q > 1/2$ (a similar logic applies to the second player). What all this means for an experimental setup is that as strategic uncertainty becomes more salient, there needs to be more attention to corresponding processes of belief formation.

2.2 Social context and relational rules

As presented, the two-player coordination game is devoid of social context. That is, two anonymous players play the game without the ability to communicate or to draw on contextual information that may make it easier to coordinate on mutually desirable outcomes.

[3] In addition to the two pure-strategy NE, {H,H} and {L,L}, there is also a mixed-strategy equilibrium $\{p^* = 1/3, q^* = 1/3\}$ in which players 1 and 2 choose H with probabilities p^* and q^*, respectively.

[4] See (Fudenberg and Tirole 1991, pp. 18-23) for a related discussion.

To a certain extent, equilibrium refinements focus on individual or atomistic behavioral models that may lead players to choose a particular action without a very explicit assessment of social considerations.[5] This is not to say that social considerations have been neglected in existing arguments, but that they may lack more explicit formulations. For instance, the notion of a focal point assumes the prior existence of a community and some shared mental model, or perhaps common experience, which facilitates the selection of one outcome. Likewise, the existence of conventions may facilitate decision-making by harmonizing expectations (Young 1996). Missing from such considerations, however, are more systematic questions about the nature of such mental models or common experiences.

This section builds upon the general idea that community or some social contexts affects expectations about social behavior. To that effect, I draw heavily on Schelling (1978)'s notion of a focal point as well as the concept of relational behavioral rules (Razo 2009). I define the social context in terms of a social network $W =< N, S >$ where N is a set of $1,2, \ldots, n$ people who are connected by some social relationship S. I further assume that the relationship is undirected and serves to characterize regular interaction or common experiences that build up knowledge about expected behaviors among connected nodes. In other words, social relationships serve as a proxy for a type of shared mental model whereby players can predict the expected behavior of (socially) related players.

For the simple coordination problem, the relevance of the social network is that it highlights the salience of the high payoff task insofar as people understand that greater network connectivity means, in general terms, that there is a widely shared tacit understanding that enhances coordination, thus enabling a consistent choice of high-payoff tasks. Viewed from this perspective, the actual or expected density of the overall network structure could serve as an operational definition of shared expectations (an aggregate property of that society).

Members of society may or may not have complete knowledge of the overall network structure, however, so the operational definition cannot provide a general foundation for individual behavior, especially in the decentralized two-person coordination games studied here. A more general and simpler behavioral model is to assume that members of society make decisions on a small scale (i.e., playing two-person games) following simple rules, some of which may be contingent on aspects of the social network.

More precisely, I assume that players use basic notions of social distance in terms of individual network neighborhoods. If $W_{ij} = 1$ denotes a tie between i and j, then the

[5] Pre-play communication is a relevant issue that has been studied in this literature, but is ignored here, as it is generally predicted to not have any strategic implications (i.e., it could simply be cheap talk).

neighborhood of i can be defined as the set of connected nodes (or alters) $N_i(W) = \{j \in N \mid W_{ij} = 1\}$. More generally, one can construct neighborhoods of varying diameter d. The neighborhood defined above corresponds to $d = 1$ and is also known as a 1-neighborhood. For $d > 1$, a *d*-neighborhood can be defined recursively as $N_i^d(W) = N_i^{d-1}(W) \cup \left(\bigcup_{j \in N_i^{d-1}} N_j(W)\right)$.[6]

The concept of a neighborhood can then be used to define the simplest case of a (1-neighborhood) relational rule, which is a conditional statement of the following form:[7]

If $j \in N_i(W)$ then r_1, otherwise r_2.

Relational rules can have greater scope by using higher values of d. In general, a *d*-neighborhood relational rule is defined as followed: If $j \in N_i^d(W)$ then r_1, otherwise r_2. It is also possible to have nested conditional statements embedded in the prescribed rules r_1 and r_2, but these possibilities are not explored here. Instead, the paper will be restricted to examining 1-neighborhood and 2-neighborhood relational rules with r_1=H and r_2=L. Therefore, player i should choose H if playing a game with $j \in N_i^d(W)$.

2.3 Coordination with manifest networks

If coordination on H depends on network proximity, then the overall structure of dyads (that is, the complete network) will be important in determining the extent of successful coordination in a given society. To illustrate how this works, consider the special cases of an empty and complete network illustrated in Figure 2 for a sample society of four people.

The case of an empty graph corresponds to the anonymous nature of two-person coordination games without any social context. In this setting, we can readily predict that this society will coordinate on the low payoff task. That is, the interaction of any pair of actors will lead to the outcome {L,L} per the relational rule that distrusts unconnected players. In contrast, the case of a complete network corresponds to a situation of common expectations where everyone coordinates on the high payoff task because any potential pair of players will always be mutually connected; hence, the application of the relational rule will prescribe choosing H.[8]

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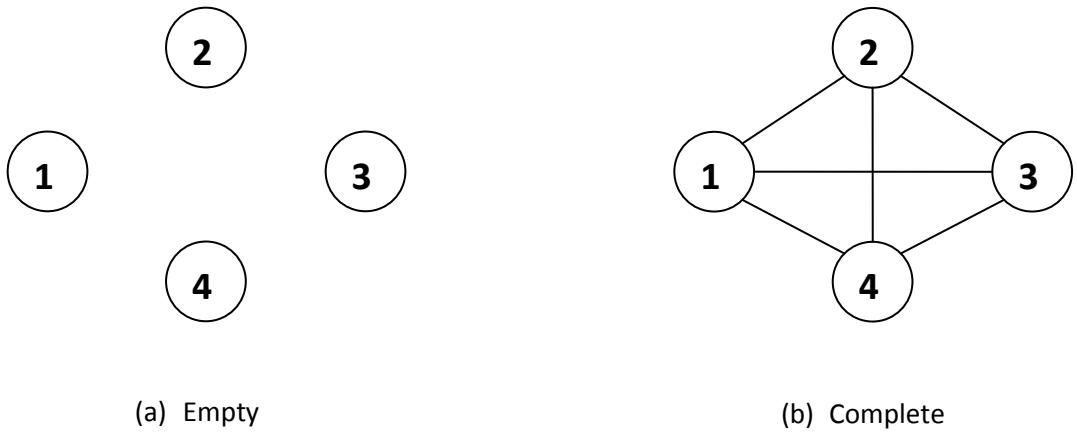
[6] (Goyal 2007), pp. 9-10.

[7] These rules were first defined in the context of repeated cooperation games in Razo (2009).

[8] The neighborhood size of relational rules is also irrelevant in these extreme cases. That is, knowledge that ties are either all nonexistent or all existent leads to observationally equivalent outcomes if players coordinated solely with their direct neighbors or if they also considered broader neighborhoods.

Figure 2 Sample empty and complete networks



(a) Empty (b) Complete

What happens when the social network is neither empty nor complete? In this more general case, we would expect more variable outcomes because the application of the relational rule depends not just on whether the two players are themselves directly connected but also whether they may be connected through a common third party. The number of potential network configurations increases greatly with group size, so it is difficult to make general predictions. However, it seems reasonable to assume that society will be better able to coordinate on H with an increasing number of ties in society or a higher network density.[9] More specifically, with more dense networks, we would expect any random pair of players to coordinate on H.[10] This conjecture about a positive relationship between network density and coordination on H will be tested in the following section.

2.4 Coordination with latent networks

Besides network structure, a relevant factor in the application of a relational coordination rule is how aware players are of the relevant network. How much players need to know about the overall network actually depends on the specific relational rule in use in terms of applicable

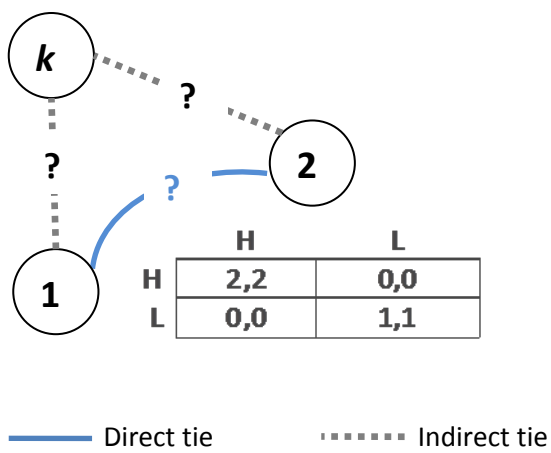
[9] Density is defined as the ratio of existing ties over the maximum number of potential ties. In the case of undirected networks, as assumed in this paper, that maximum number is equal to $n(n-1)/2$ where n is the number of nodes.

[10] This need not be true in general, but the expectation of a monotonic relationship between coordination on H and number of ties in the network is implied by the default rule of playing L if the other party is disconnected. With a manifest network, we can predict that the outcome of any interaction falls on the diagonal of the game matrix, either the players choose {H,H} or {L,L}. If the relational rule did not prescribe what to do in the absence of a network tie, then there would be a possibility of mismatches (one player playing H while the other plays L); that is, complete coordination failure.

neighborhood size. In general, the greater the size of such neighborhood, the greater the required knowledge of the whole network--not just immediate neighbors.[11]

To appreciate the effect of network uncertainty, consider the coordination game presented above with two players 1 and 2. Since the game is symmetric we can focus on the behavior of any player, so I will discuss player 1's decision. Whether player 1 chooses H or L depends on the belief of a direct tie between 1 and 2. This belief can be expressed in terms of the probability $\Pr(1 \leftrightarrow 2)$if the relational rule is restricted to neighbors; or, if also considering indirect ties (neighbors of neighbors), $\Pr(1 \leftrightarrow k \,\&\, k \leftrightarrow 2)$ for some other $k \in N$.[12]

Figure 3 Coordination with unknown ties



To add some plausibility to the notion that social contexts matter, I will assume henceforth that players are aware of their immediate neighbors. That is, player 1 knows that $\Pr(1 \leftrightarrow 2) = 1$ or 0. This assumption reflects a very basic social awareness, which should exist if indeed the social context is deemed relevant for analytical purposes. This assumption denoted MYOPIC also serves as a baseline case in the context of latent networks for a couple of reasons. First, it serves to identify a 1-neighborhood relational rule: in effect, whether the whole network is known is irrelevant because players only care about direct neighbors. A second interpretation, with more relevance to network inference, is that players simply assume that all other existing ties are nil. From any player i's perspective, the assumption is that $\Pr(k \leftrightarrow l) = \Pr(l \leftrightarrow m) = 0$ for any $k \in N_i(W)$ and $l, m \in N \backslash N_i(W)$.

Another plausible informational assumption is that players may suspect the existence of other ties but have no information upon which they can derive explicit forecasts. Basically, this

[11] Network density is also relevant in determining required knowledge. With more dense networks, there is also greater potential for third-parties to be affiliated with one's neighbors.
[12] Since player 2 uses the same rule, there is a separate set of probabilities corresponding to 2's beliefs.

is a situation where anything goes (in terms of the overall network structure). By the principle of indifference, all possible network structures (conditional on a node's existing neighborhood) are equally likely. In this situation, which will be denoted as a RANDOM informational assumption, the counterpart probabilities to the myopic case are as follows: $\Pr(k \leftrightarrow l) = \Pr(l \leftrightarrow m) = 0.5$ for any $k \in N_i(W)$ and $l, m \in N \backslash N_i(W)$.

Regardless of informational assumption, the case of latent networks brings to the forefront the issue of beliefs about network structure (or, equivalently, expectations about high-payoff coordination). Moreover, either assumption implies the presence of heterogeneous beliefs in non-empty networks. One purpose of this study is to examine the implications of this induced heterogeneity for the general ability of a society to coordinate on H.

Also relevant to the study of latent networks is the issue of learning. If we consider the two informational assumptions as prior probabilities, it may be possible—given some learning mechanism—to update initial beliefs. One can then ask whether resulting posterior distributions resemble the actual network.

Although learning is not the main focus of this paper, the computer experiment below will test a very simple feedback mechanism to examine the ability of societies to infer network ties solely on the basis of relational coordination. The feedback mechanism can be explained in terms of Figure 3 above. Suppose that 1 and 2 are not direct neighbors. By assumption, they both infer correctly that $\Pr(1 \leftrightarrow 2) = 0$. Hence, if they ever play this coordination game, the relational rule prescribes that, in the absence of additional information, they coordinate on the low payoff task. Future encounters can be informative in the following sense. If they get to play the game again and player 2 were to choose H, the use of a relational rule enables player 1 to infer that 2 is connected to some player k, who must be one of 1's neighbors.[13] In other words, Player 1's inference is that $\Pr(2, k) = 1$ and $\Pr(1, k) = 1$.[14]

2.5 Working Hypotheses

Here, I summarize the section by listing testable implications from the above discussion. Assuming widespread use of 2-neighborhood relational coordination rules, one should expect the following outcomes depending on various network structures and informational assumptions.

[13] If player 1 only has one neighbor, then *k* is uniquely defined. Otherwise, player 1 chooses *k* randomly from the 1-neighborhood set.

[14] Note that this inference works because players are not strategic. What this means is that player 2 who, for some reason after the first encounter, now infers that 1 and *k* are neighbors does not also consider the possibility that player 1 may not share the same belief.

- **Hypothesis 1**: More dense networks should facilitate coordination on H.

  This hypothesis examines the direct impact of network structure. Since I assume decentralized play with randomly matched members of society, this hypothesis implies that high network density should lead to more occurrences of {H,H} if members of society play coordination games repeatedly. A proxy for enhanced coordination is the average individual payoff, which equals 2 if members of society always coordinate.

- **Hypothesis 2a**: Manifest networks should enhance coordination relative to latent networks.

  This is an unconditional statement that more information about the network structure that impacts the application of relational rules should facilitate coordination. This statement does not take into account the various informational assumptions that players can have about unknown ties.

- **Hypothesis 2b**: Manifest networks should exhibit more coordination than latent networks with MYOPIC inferences.

  Manifest networks should enhance coordination relative to the case of myopic inferences for any network density simply because in the former case, players have more reliable information about additional ties.

- **Hypothesis 2c**: Low density manifest networks should exhibit less coordination on H than latent networks with RANDOM inferences.

  If network connectivity is particularly relevant to enable coordination on H, then the impact of manifest and latent networks ought to be conditional on network density. That is, if individuals have complete knowledge of a network with low density, they will certainly pick {L,L} more frequently. In contrast, RANDOM inferences enable more optimistic assessment with prior beliefs that may indicate a preponderance of connections that may or may not exist. Nonetheless, the non-strategic nature of relational rules prescribes that players choose H nonetheless.

- **Hypothesis 3**: Other things equal, a society with RANDOM inferences about network structures should exhibit a higher degree of coordination than societies with MYOPIC inference.

This hypothesis follows from the fact that myopic inferences effectively prescribe the choice of low payoff tasks when interacting with non-neighbors. The case of random inferences puts positive probability on remaining ties regardless of their actual existence. Hence, with prior beliefs about indirect ties that may or may not exist, we should see a higher predisposition to choose H.

- **Hypothesis 4a**: Relational rules facilitate learning of actual network structures.

  Because I assume relational rules throughout, this hypothesis is more limited in nature to the particular experimental setup of this paper. More precisely, this hypothesis will examine whether feedback from other players' actions enables players to guess other ties at a higher rate than if they have no feedback at all.

- **Hypothesis 4b**: Less dense networks facilitate learning of actual network structures.

  Other things equal, less dense networks imply smaller neighborhood sets for any given node. Hence, a player i can make better inferences about a common node k when observing an informative move by j (as explained above in the discussion of the basic feedback mechanism).

3. Computational Experiment

3.1 Experimental setup

I implemented an agent-based computational model to test the previous hypotheses and to better understand the impact of networks on pairwise coordination.[15] The computational model entails the creation of various artificial societies with the following general features:

- An even number *N* of people, or equivalently a large coordination task that can be decomposed into *N*/2 independent tasks.[16]
- A finite-time horizon *T* over which members of society engage in pairwise coordination games. These coordination games are presumed to be pervasive so that every member of society is always engaged in a simple coordination interaction. All people are randomly matched independently of their social connections, so at any given time, society is divided into a random partition of N/2 pairs.
- An exogenous social network W.

[15] These simulations were implemented within the R statistical environment (R Development Core Team 2009).
[16] This restriction on the size of societies was chosen for computational convenience to enable all members to always play a coordination game in a given round.

- A relational coordination rule: for all $i \in N$, player i plays H with j if the latter is either in $N_i^2(W)$ in case the network is known or $j \in N_i(W^B)$, where W^B are player i's beliefs about W.

The computational model has two main experimental variables relevant to this study. First, I manipulated the structure of W in terms of its connectivity. More precisely, I manipulated the density of W to allow for more or less connections among members of society. This particular approach has the added value of providing a parametric approach to examine a wide range of network structures. In other words, examining the impact of network structure on coordination in this fashion is equivalent to positing a simple functional relationship between aggregate societal outcomes and the parameter d as the latter ranges from 0 to 1.

A second manipulation involved variable informational assumptions about W. In particular, I contrasted the case of manifest networks with two latent network informational assumptions, MYOPIC and RANDOM. In the case of latent networks, I also checked for the possibility of learning using the simple feedback mechanism described above.

Table 1 Experimental variables

Variable	Obs	Mean	Std. Dev.	Min	Max
N	19800	20	8.165172	10	30
T	19800	35	17.07868	10	60
density	19800	0.5	0.316236	0	1
Qualitative Informational assumptions:					
manifest					
myopic with and without feedback					
random with and without feedback					

All in all, I examined 590 different combinations derived from the variables in Table 1. Although not discussed in the previous section, the purpose of *N* and *T* in the computer experiment is to control for potential scale effects—that larger societies may have a harder time coordinating.[17] Since potential interactions are constrained by the time horizon, the experiment will use a combined measure of these two variables, *T/N*, as a proxy for meeting

[17] Given the use of relational rules, N may appear irrelevant. However, the size of society does have implications for the application of such rules in the case of latent networks. In that setting, a larger society makes it more difficult to coordinate because of the need to infer a higher number of ties.

time or interaction opportunities. This ratio ranges from 1/3 to 6. The larger the ratio the higher the probability of interacting with more distinct members of society.

As a caveat, fixing the density of a network does not uniquely identify the resulting network structure. In effect, the experiment entailed random sampling from a conditional random graph distribution with a particular density (of undirected ties). Each of these combinations, or societal configurations, was therefore repeated 20 times to avoid any randomly selected network with density d to bias the overall results. The total number of societies was therefore equal to 590*20=19,800.

3.2 Results from main experiment

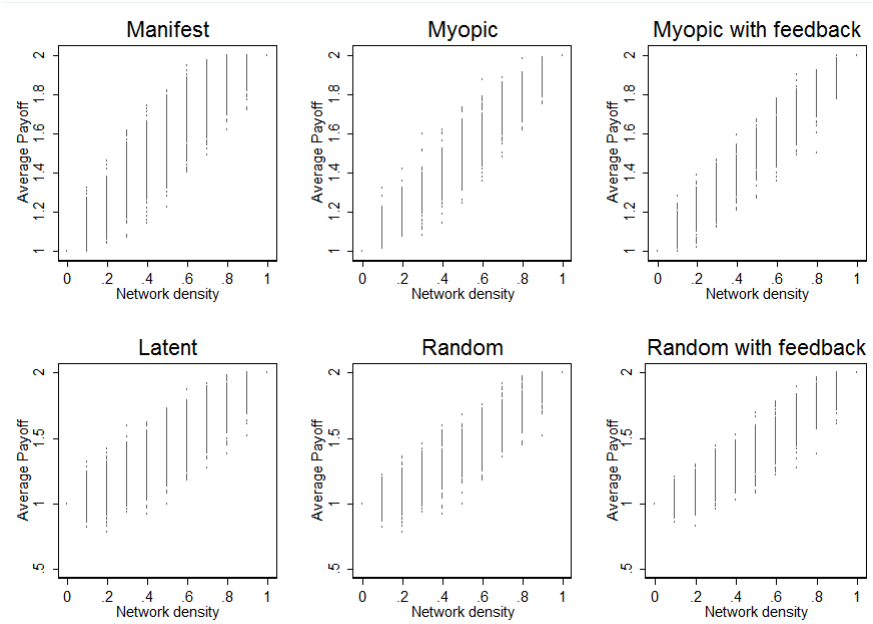
For each societal configuration, I constructed two aggregate variables to act as proxies for overall societal coordination and network belief formation. I first calculated the average payoff for society as a proxy for overall coordination. If coordination on H were attained under all circumstances, then the average payoff should be equal to 2. In the case of manifest networks, the lowest payoff was 1, corresponding to the case where players coordinated on the low payoff task, L. In the case of latent networks, it is possible for players to have mismatched strategies, thus generating zero payoffs. Therefore, this proxy measure ranges from 0 (reflecting an inability to coordinate on any task) to 2 (superior coordination on H).

To assess the ability of societies to "learn" latent networks, I first calculated the percentage of correct network beliefs that each player had at the end of the finite horizon. By assumption, direct neighbors are always known; hence, the percentage was calculated based on the number of additional ties, or $0.5n(n-1)-(n-1)$. For the case of $n=10$, for example, there are $0.5*10*9=45$ possible ties. Since player i knows 9 ties (whether or not other nodes are directly linked to i), the percentage of correct network beliefs is equal to the number of correct guesses from among the remaining 36 ties. For instance, if a player knew 18 additional ties, that percentage would be 50%. The societal version of these beliefs was defined as the mean of individual correct beliefs.

Figure 4 shows conditional scatterplots of the first aggregate variable against network density under various informational assumptions. Throughout, there is a strong pattern indicating a positive relationship between higher density and enhanced coordination as posited in the first hypothesis.[18]

[18] The grid-like nature of these plots is an artifice of the computational experiment, which used a discrete set of values for network density.

Figure 4 Network density and overall coordination



This figure also indicates that there is much variability for each particular density value. Some of the variability may be induced by the random sampling of density-conditional random graphs. Some of it may be related to other features of the social environment. In order to examine these possibilities as well as the hypotheses, I conducted a regression analysis of average payoffs as a function of the variables in Table 1. The results are shown in Table 2.

[Table 2 about here]

The statistical analysis confirms the first hypothesis regarding the positive impact of more dense networks.[19] The first specification tests an unconditional model with density as the only experimental variable (along with the control for potential interactions). [20] The corresponding 01, which is highly statistically significant, indicates that that a one-percent increase in network density increases average payoffs by 0.01. The small magnitude is solely due to the restricted range of payoffs. What is noteworthy is that the coefficient is highly statistically significant, and also that implies a strong density effect. Given the experimental setup (with density increments of 10%) and a default average payoff of one, this coefficient implies that payoffs can be incremented by .1 (or 10% of the baseline payoff).

[19] Both this and the following set of regressions account for the grouped data structure of repeated configurations. Robust standard errors were calculated using configuration # as a cluster variable.

[20] To facilitate the interpretation of estimated density coefficients, the regression analysis was done with a rescaled density measure as a percentage from 0 to 100.

Hypothesis 2a is examined with specification 2.[21] The baseline condition (or y-intercept) is a manifest network which generates an average payoff of 1.035 (corresponding to the constant coefficient). Relative to the baseline, latent networks generate 0.088 (or 8.5%) less payoffs, as indicated by the statistically significant coefficient of -0.088.

Hypothesis 2b posited that manifest networks should exhibit more coordination that latent networks with the MYOPIC informational assumption. To test this hypothesis, the third specification (again) uses manifest networks as the baseline condition, but allocates latent conditions to one of four possible cases, including the desired alternate conditions denoted as "myopic with feedback."[22] The coefficient for this alternate condition is -0.050 and is also highly statistically significant. Therefore, the data provides strong support that regardless of density, it is always better to know the network structure than to simply know one's neighborhood.

Hypothesis 2c recognizes that manifest networks are particularly useful when networks are dense. Conversely, in the case of low densities, knowing with certainty that there are fewer connections actually makes it easier for players to choose L, reflecting a situation of evident pessimism. In contrast, a situation of latent networks where players possess the RANDOM informational property, will probably be more optimistic. Despite not knowing whether other ties are possible, network beliefs are conducive to predicting ties that will induce coordination on H. Note that this may happen even if the density of the actual network is low.

To test this hypothesis, I created a new variable for low density manifest networks, identified as those with densities in the first quartile, or 0.25.[23] Specification 4 estimates the coefficient for this variable to be equal to -0.051.[24] If the hypothesis is correct, we should expect the corresponding coefficient for "all Random" to be less negative (thus implying higher payoffs). The results provide contrary evidence, however, so we can reject this hypothesis. Random networks provide an order of magnitude lower payoffs than low-density manifest ones.

To further assess the impact of the RANDOM informational assumption, I ran a final specification with manifest networks as the baseline condition to be compared against all

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[21] This and all subsequent specifications retain density for control purposes. The independent effect of density will be similar across all specifications suggesting that its inclusion does not bias the estimated coefficients of distinct sets of independent variables. A counterpart set of models without regression resulted in similar coefficients as the ones shown here, but the overall goodness of fit of estimated regressions was much lower without the density variable.

[22] The terms "random" and "myopic" by themselves refer to latent network conditions in configurations without updated network beliefs.

[23] Given the experimental setup, low density corresponds to three possible values of *d*: 0, 0.1, and 0.2.

[24] The baseline condition for this model are manifest networks with higher densities.

myopic and random informational configurations (each with and without belief updates). The coefficient for all RANDOM cases is again negative and of a greater magnitude than the alternative. This was an unexpected result that bears more investigation, but a plausible reason has to do with potential mismatches—that hypothesis 3 does not consider. In fact, RANDOM informational assumptions entail two countervailing effects. There is the positive one of probable optimism in that players may coordinate on H on the basis of false beliefs about nonexistent ties. However, in order to benefit from those beliefs, it must be the case that the false belief is shared by the other player. If this is not the case, and this is an equally probable outcome, then the outcome of the game will be a set of mismatched strategies ({H,L} or {L,H}) that generate zero payoffs.

[Table 3 about here]

The final set of hypotheses involves some aspects of these network beliefs, which are analyzed in Table 3. Hypothesis 4a inquires about the independent effect of belief updates, which is tested under specification 1. The baseline condition is all networks (of varying density), which may be manifest or latent. The average percentage of correct beliefs for baseline cases is 86.5%. The magnitude is high because this effect includes manifest networks, which are perfectly known. To control for this possibility, I ran a second specification that differentiates across various informational assumptions. Both specifications indicate that updates generate lower percentages, which is not surprising given the baseline condition of perfect knowledge.[25] To actually test hypothesis 4a, we need to compare the coefficients corresponding to latent networks. The estimated coefficients for cases without updates (myopic and random) are virtually identical to those with feedback. This suggests that the simple feedback mechanism proposed above does not seem to offer any advantages.

Finally, specification 2 also serves to test hypothesis 4b, which posited a negative impact of network density on network beliefs. Here, the results provide support for the notion that less dense networks enable the generation of more correct beliefs. However, although the estimated coefficient is statistical significant and has the right sign, its magnitude is much smaller than for other variables (with the exception of meeting Time, which seems to have no effect for either network beliefs or overall coordination).

[25] Given the strongly negative effect of latent networks, the estimated coefficient needs to be ignored because it exceeds 1, an impossible ratio given the calculation of network beliefs.

3.3 Discussion and a sensitivity analysis

For the most part, the statistical analysis served to confirm the stated hypotheses, with the exception of the impact of RANDOM informational assumptions (hypothesis 3). In particular, the results of the parametric experiment indicate that network density is an important determinant for the ability of societies to coordinate on high payoff tasks. Although this result makes intuitive sense—that more ties should enable relational rules to generate more coordination—there remains the question of empirical relevance to real-world rather than artificial societies. Human groups, especially if they are large, may not be able to sustain high density rates. In other words, actual human societies may operate in the low range of the density variable manipulated in this experiment.

If social networks tend to have less density, the statistical impact of density discovered here may have limited application in the real world.[26] However, there still remains the question of whether manifest or latent networks affect coordination in more realistic settings. In order to examine this question, I conducted a similar computational experiment that analyzed three types of networks that may be more accurate depictions of common social environments: (1) a star network, with one central node connected to everyone else, to analyze centralized structures; a (2) circle graph, as an example of a decentralized environment where each node has two neighbors (that is, a special type of regular network); and a small world network with low density and short average paths across nodes.[27] In this case, I could not manipulate network density, and hence this property cannot be considered to be an experimental variable but it can be calculated nonetheless.[28] Although there is some variation in estimated network densities,

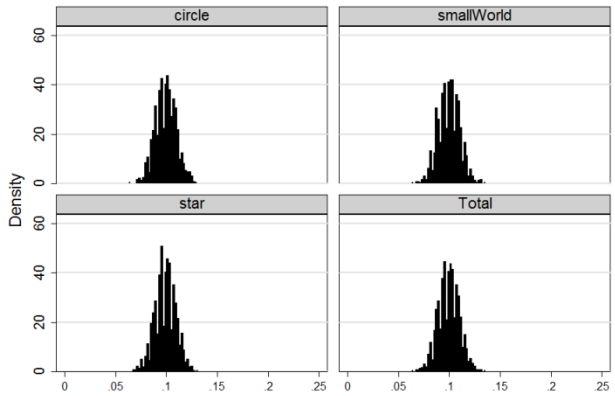
[26] Although the computational results may still apply to situations—such as laboratory experiments—where for sufficiently small groups, researchers can enable high density network conditions.

[27] The first network was created by selecting a node at random and linking it to all other nodes. The second and third networks were created using a Watts-Strogatz lattice-based model (based on the rgws command in the sna library of the statistical environment R). For the circle graph, I first used that algorithm to create a 1-dimensional lattice with 2 neighbors and a rewire probability of zero. As a second step, I linked the first and last nodes to complete the circle. For the small worlds network, I used a similar 1-dimenisional lattice with 2 neighbors, but this time with a small rewiring probability of 0.05.

[28] All other variables, and corresponding values, of the previous experiment are retained here to facilitate comparisons.

Figure 5 indicates that indeed these are network types with fewer connections, with an average density of about 0.1 .

Figure 5 Density by network type



For this second experiment I ran a comparable set of regressions to understand the impact of these social environments on overall coordination and network beliefs. First, I discuss the results for average payoffs, shown in Table 4.

[Table 4 about here]

Before discussing estimates, it is important to note two important features of this set of regression models. First, relative to a baseline of circle graphs, the star network and small world do not appear to have a distinctive advantage, and in fact, their estimated coefficients are both small and insignificant. A second feature is the impact of network density. Although simply an observed control variable, the estimated coefficient for density mirrors the results of the previous experiment, but with an even stronger impact due to the large magnitude of this coefficient across all specifications.

Hypothesis 2b is rejected for these types of networks, however. The baseline condition is a manifest circle network. The positive coefficient of 0.479, which is statistically significant, indicates that latent networks produced higher payoffs on average. Hypothesis 3, which posits that RANDOM informational settings are better than MYOPIC ones, finds support here as shown in specification 2. Here, the coefficient for random is positive whereas that of myopic is negative, thus accentuating the difference between these two latent network informational assumptions.

[Table 5 about here]

The question of network beliefs is analyzed with the use of Table 5. In this case, changes in observed density do not have a systematic effect. As in the previous regression, the impact of star and small world network structures is also negligible as shown in the first, basic, specification, and throughout the others. The relevant variable to assess hypothesis 4a is "updates" in Table 5. This variable applies to all network types and indicates that allowing players to make simple inferences actually decreases the correctness of their beliefs about actual network structures. A potential reason for this result is that these types of networks are already characterized by low density (an overall property that is not itself known to participants). Hence, players probably overestimate the presence of non-existent ties, which greatly lowers their percentage of correct beliefs.

In sum, it appears that greater connectivity is invariably useful to enhance coordination regardless of the range of possible values—whether they extend from 0 to 1 or they operate in the lower range of the spectrum. This is the most robust result that emerges from comparing both experiments. Density is also important for the formation of network beliefs, but here the results are mixed. The first computer experiment supported the view that lower-density networks lead to more correct network beliefs, but in the second experiment the effect was null.[29] Another consistent result is that the possibility of belief updates did not improve any of the aggregate outcomes, so learning—at least in the crude way modeled here—does not have a positive impact.

4. Conclusion

This paper addressed two major questions. First, whether network structure affected the ability of people to coordinate in simple tasks (as modeled in simple two-person coordination games). Second, whether knowledge of actual network structures had any impact on this simple collective action problems. The main quantity of interest was the degree of attained coordination at the societal level as proxied by average payoffs.

Answering those questions requires a behavioral model to derive predictions about the expected interaction of players. Since standard game-theoretic treatments do not generate unique predictions, I posited a basic non-strategic model in which players condition their behavior on social network with the use of simple relational rules. With manifest networks, one can readily infer coordination on either high-payoff or low-payoff coordinated tasks depending on whether the underlying network is complete or empty, respectively. The main conjecture that emerges from the theoretical section is the possible existence of a monotonic relationship between overall success of high-payoff coordination and the density of a network,

[29] But the second result is not completely inconsistent with the hypothesis insofar as density is not shown to have the opposite effect.

a simple parametric specification that enables analysis of a wide range of network structures. As a corollary question, I also examined whether societies with latent networks were able to learn the structure of the actual network on the basis of simple relational play rules and simple feedback mechanisms to infer unknown ties.

To investigate those questions, I developed a computational model that incorporated relevant social features, in particular an exogenous network structure upon which actors could condition their behavior. The two main manipulations involved altering the density of the network as well as the knowledge that people had about the network. In cases where that knowledge was incomplete, I examined a couple of informational assumptions about how members of society could make inferences about latent network structures.

In terms of network structure, statistical analysis of the data generated by the computational model provided strong and robust support for the claim that more connected networks enhance coordination. That claim was made on the basis of a simple non-strategic model of rule-driven behavior and the results apply to both manifest and latent networks. However, the impact of latent networks was contingent on specific informational assumptions. The most surprising result was that the RANDOM informational conditions, which reflects a situation of extreme uncertainty—but also optimistic beliefs about potential ties—performed worse than a situation where players possessed myopic knowledge of the underlying network.

Clearly, there is much room to improve and expand this study. First, the same experiment could be replicated under a larger number of configurations, including larger societies and longer time horizons for social interactions. Second, a more refined analysis of density is in order in two respects: (a) decreasing the grid interval to accommodate more density values; and, most importantly, (b) have a larger number of repetitions to have a more representative sample of density-conditioned random networks.

A couple of extensions that retain the same framework involve the use of variable neighborhood sizes and additional informational assumptions. Regarding the former, the experiment was restricted to 2-neighborhood relational rules, but especially if future experiments incorporate much larger societies, it would be interesting to examine the implications of broader neighborhoods. If the relevant neighborhood size is changed, then it may also be relevant to incorporate other informational assumptions that capture more possibilities about the formulation of latent networks. For instance, players could be assumed to have partial knowledge of an actual network up to a certain neighborhood of size greater than 1.

Beyond the scope of this paper, the analysis could be extended to incorporate individual level data as well. Although not practical for the computer experiments, given the large

number of artificial societies, there remain important questions about how players' place within the network, such as their centrality, may affect their ability to successfully engage in various social interactions.

Finally, future extensions can address a major limitation of this study, which is its focus on very simple coordination tasks in a context of decentralized social interactions. The literature on collective action analyzes a wider array of situations such as public goods and threshold coordination tasks that involve more than two people at once. These situations may also possess additional features, such as leadership or some organizational hierarchy, that structure how groups may interact in various complex ways.

References

Ansell, Christopher. 2006. "Network institutionalism." In *The Oxford handbook of political institutions*, ed. R. A. W. Rhodes, S. A. Binder and B. A. Rockman. Oxford ; New York: Oxford University Press.

Axelrod, Robert M. 1984. *The evolution of cooperation*. New York: Basic Books.

———. 1997. *The complexity of cooperation: agent-based models of competition and collaboration*. Princeton, N.J.: Princeton University Press.

Burt, Ronald. 1980. "Models of Network Structure." *Annual Review of Sociology* 6:79-141.

Chwe, Michael S. 1999. "Structure and strategy in collective action." *American Journal of Sociology* 105 (1):128-56.

Felmlee, Diane H. 2003. "Interaction in social networks." In *Handbook of Social Psychology*, ed. J. D. DeLamater. New York: Kluwer Academic.

Ferguson, R. J., M. Paulin, and J. Bergeron. 2005. "Contractual governance, relational governance, and the performance of interfirm service exchanges: The influence of boundary-spanner closeness." *Journal of the Academy of Marketing Science* 33 (2):217-34.

Friedkin, N. E. 2002. "Social Influence Network Theory: Toward a Science of Strategic Modification of Interpersonal Influence Systems."

Fudenberg, Drew, and Jean Tirole. 1991. *Game theory*. Cambridge, Mass.: MIT Press.

Gould, RV. 1993. "Collective action and network structure." *American Sociological Review* 58 (2):182-96.

Goyal, Sanjeev. 2007. *Connections: an introduction to the economics of networks*. Princeton, NJ: Princeton University Press.

Granovetter, M. 1978. "Threshold models of collective behavior." *American Journal of Sociology* 83 (6):1420.

Granovetter, Mark. 1985. "Economic Action and Social Structure: the Problem of Embeddedness." *American Journal of Sociology* 91:481-93.

Hitt, M. A., H. U. Lee, and E. Yucel. 2002. "The importance of social capital to the management of multinational enterprises: Relational networks among Asian and Western firms." *Asia Pacific Journal of Management* 19 (2):353-72.

Hoff, PD, AE Raftery, and MS Handcock. 2002. "Latent space approaches to social network analysis." *Journal of the American Statistical Association* 97 (460):1090-8.

Kitschelt, Herbert, and Steven Wilkinson. 2007. "Citizen-politician linkages: an introduction." In *Patrons, clients, and policies: patterns of democratic accountability and political competition*, ed. H. Kitschelt and S. Wilkinson. Cambridge, UK; New York: Cambridge University Press.

Knox, Hannah, Mike Savage, and Penny Harvey. 2006. "Social networks and the study of relations: networks as method, metaphor and form." *Economy and Society* 35 (1):113-40.

Levitsky, Steven, and Gretchen Helmke. 2004. "Informal Institutions and Comparative Politics: A Research Agenda." *Perspectives on Politics* 2 (4):725-40.

McMillan, John, and Pablo Zoido. 2004. "How to Subvert Democracy: Montesinos in Peru." In *Stanford Graduate Business School Research Papers*. Stanford, CA.

Morris, S. 2000. "Contagion." *Review of Economic Studies* 67 (1):57-78.

Nee, Victor, and Richard Swedberg. 2005. "Economic Sociology and New Institutional Economics." In *Handbook of New Institutional Economics*, ed. C. Menard and M. M. Shirley. Dordrecht, Netherlands: Springer.

Olson, Mancur. 1965. *The logic of collective action; public goods and the theory of groups*. Cambridge, Mass.,: Harvard University Press.

R Development Core Team, ed. 2009. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

Razo, Armando. 2009. "Rules and Relations in Comparative Politics: Connecting the dots between formal and informal institutions." Bloomington, IN: Indiana University.

Schelling, TC. 1960. *The strategy of conflict*: Cambridge, MA: Harvard University Press.

Schelling, Thomas C. 1978. *Micromotives and macrobehavior*. 1st ed. New York: Norton.

Shepsle, Kenneth. 2006. "Rational choice institutionalism." In *The Oxford handbook of political institutions*, ed. R. A. W. Rhodes, S. A. Binder and B. A. Rockman. Oxford ; New York: Oxford University Press.

Siegel, DA. 2009. "Social networks and collective action." *American Journal of Political Science* 53 (1):122-38.

Uhlaner, L. M., R. H. Floren, and J. R. Geerlings. 2007. "Owner Commitment and Relational Governance in the Privately-Held Firm: An Empirical Study." *Small Business Economics* 29 (3):275-93.

Williamson, Oliver E. 1991. "Comparative economic organization: The analysis of discrete structural alternatives." *Administrative science quarterly* 36 (2).

Woodruff, Christopher. 2006. "Measuring Institutions." In *International handbook on the economics of corruption*, ed. S. Rose-Ackerman. Cheltenham, UK; Northampton, MA: Edward Elgar.

Young, HP. 1996. "The economics of convention." *The Journal of Economic Perspectives* 10 (2):105-22.

Appendix A: Computational Implementation

Social Environment setup

(1) Associate with each configuration, the following variables:
Network density: d
Knowledge: Manifest or Latent Network
If Latent, whether players should update beliefs
# of rounds for repeated play: *T*

(2) Create a society of size *N* (represented by a vector {1,2,…,N}

(3) Create a random social network *actualNet* with density *d*

(4) Set up *netBeliefs* (a counterpart adjacency matrix to *actualNet*)
for each k in N,
   a. If manifest, *netBeliefs* = *actualNet*
   b. If myopic, copy k^{th} row and columns from *actualNet*
      set all other entries of *netBeliefs* to zero
   c. If random, copy k^{th} row and columns from *actualNet*
      set all other entries of *netBeliefs* to the outcome of a Bernoulli random variable with probability 0.5

(5) Society plays T rounds of pairwise coordination games
   a. Calculate average payoffs of N players
   b. Calculate % of correct Network beliefs=(Correct guesses/Total possible ties)
      Total # possible ties: $0.5 * n(n-1) - (n-1)$, since players know their own ties
      A correct belief occurs when *netBeliefs*$[j,k]$=*actualNet*$[j,k]$ for j and k not in player I's neighborhood

Repeated games within one session

For each round in in 1,2,…,*T*:

(1) Randomly match players into *N*/2 pairs

(2) For each pair, play the coordination game depicted in Figure 1as follows:
   a. Player i plays H if $j \in N_i^2(netBeliefs)$; otherwise, play L
   b. If beliefs are to be updated:
      Player i checks whether $\{i,j\}$ have played before
       If yes, check if j's strategy has changed from L to H
         If so, update *netBeliefs*$[k,j]$=*netBeliefs*$[k,j]$=1 for a random k in $N_i^1(actualNet)$.

Table 2: Regression Analysis of Average Payoffs

Dependent Variable: Avg. Coordination Payoff	(1)	(2)	(3)	(4)	(5)
density	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
latent		-0.088***			
		(0.003)			
random			-0.128***		
			(0.005)		
random with feedback			-0.125***		
			(0.005)		
myopic			-0.050***	-0.064***	
			(0.003)	(0.003)	
myopic with feedback			-0.049***	-0.063***	
			(0.003)	(0.003)	
low density manifest				-0.051***	
				(0.004)	
all random				-0.140***	-0.126***
				(0.004)	(0.004)
all myopic					-0.050***
					(0.003)
meeting Time (Rounds/N)	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
constant	0.965***	1.035***	1.035***	1.055***	1.035***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	19,800	19,800	19,800	19,800	19,800
R-squared	0.936	0.947	0.958	0.959	0.958

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Regression Analysis of Network Beliefs

Dependent Variable: % of Correct Network Beliefs	(1)	(2)
density	-0.004***	-0.004***
	(0.000)	(0.000)
random		-0.500***
		(0.013)
random with feedback		-0.500***
		(0.013)
myopic		-0.499***
		(0.016)
myopic with feedback		-0.499***
		(0.016)
feedback	-0.166***	
	(0.014)	
meeting Time (rounds/N)	0.000	0.000
	(0.005)	(0.003)
constant	0.865***	1.198***
	(0.018)	(0.015)
Observations	19,800	19,800
R-squared	0.279	0.692

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression Analysis of Coordination by Network Type

Dependent Variable: Avg. Coordination Payoff	(1)	(2)
density	3.938***	4.346***
	(0.486)	(0.502)
latent	0.479***	
	(0.018)	
star network	-0.000	0.000
	(0.033)	(0.039)
small world	0.007	0.007
	(0.033)	(0.040)
meeting Time (T/N)	0.004	0.004
	(0.009)	(0.011)
all random		0.290***
		(0.032)
all myopic		-0.168***
		(0.032)
constant	0.262***	0.550***
	(0.057)	(0.053)
Observations	4,320	4,320
R-squared	0.441	0.283

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regression Analysis of Network Beliefs by Network Type

Dependent Variable: % of Correct Network Beliefs	(1)	(2)
density	0.178	0.258
	(0.316)	(0.255)
star network	0.000	0.000325
	(0.038)	(0.0313)
small world	-0.000	-0.000
	(0.038)	(0.0312)
updates		-0.305***
		(0.0170)
random		
myopic		
meeting Time (T/N)	-0.000	-0.000
	(0.010)	(0.00839)
Constant	0.706***	0.774***
	(0.047)	(0.0416)
Observations	4,320	4,320
R-squared	0.000	0.333

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1