The Network Dynamics of Social and Technological Conventions

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Abstract

When innovations compete for adoption, chance historical events can allow an inferior strategy to spread at the expense of superior alternatives. However, advantage is not always due to chance, and networks have emerged as an important determinant of organizational behavior. To understand what factors can impact the likelihood that the best alternative will be adopted, this paper asks: how does network structure shape the emergence of social and technological conventions? Prior research has found that highly influential people, or “central” nodes, can be beneficial from the perspective of a single innovation because promotion by central nodes can increase the speed of adoption. In contrast, when considering the competition of multiple strategies, the presence of central nodes may pose a risk, and the resulting “centralized” networks are not guaranteed to favor the optimal strategy. This paper uses agent-based simulation to investigate the effect of network structure on a standard model of convention formation, finding that network centralization increases the speed of convention formation but also decreases the likelihood that the best strategy will become widely adopted. Surprisingly, this finding does not indicate a speed/optimality trade-off: dense networks are both fast and optimal.

Introduction

Understanding the effect of network structure on organizational performance is a fundamental problem in social science (Borgatti & Foster, 2003; Powell, Koput, & Smith-Doerr, 1996; Salancik, 1995; Uzzi, 1997). While early research on network theory focused on the effect of a decision-maker’s position in their immediate network (Burt, 1997; Cook & Emerson, 1978; Uzzi, 1997), more recent work has begun to show that macro-level characteristics of both intra-firm and inter-firm networks can play a role in determining organizational performance (Lazer & Friedman, 2007; Schilling & Fang, 2014). Both within organizations (Berwick, 2003) and between organizations (Strang & Soule, 1998), networks play a key role in the spread and adoption of innovation, which refers not only to the spread of technologies but also to the spread of
social behaviors (Rogers, 1983) such as corporate governance practices (Davis & Greve, 1997). As a result, an organization’s behavior—and thus their performance—may be inadvertently shaped not only by their immediate peer network, but by unobservable structural features (in the geometrical sense) of the broader influence networks in which they are embedded.

One reason networks matter is that conformity dynamics play a substantial role in determining organizational behavior. These processes occur both through normative pressure, in which conformity is desirable to establish legitimacy or to avoid sanctions (Davis & Greve, 1997), and also through social learning, in which conformity is a method for reducing uncertainty (Cialdini & Goldstein, 2004; Cyert & March, 1963; Greve & Seidel, 2015) and minimizing the cost of exploration (March, 1991). Regardless of the motivation, pressures toward conformity can lead to a tradeoff between practices that are socially popular and a practices that are optimal or desirable (DiMaggio & Powell, 1983). This tradeoff is most obvious where behavior is motivated by an explicit need to coordinate, as in the adoption of communication technologies (Pfeiffer, 2012). For example, cutting edge digital protocols are useless if those peers with whom one wishes to communicate do not have compatible technology.

Decades of theoretical (Kitsak et al., 2010; Valente & Davis, 1999) and empirical (Banerjee, Chandrasekhar, Duflo, & Jackson, 2013; Katz & Lazarsfeld, 1955) research has shown that understanding technology and behavior adoption means understanding the role of “opinion leaders,” who frequently hold a central network position (Borgatti & Everett, 2006) and play a critical role in the spread of technologies and social behaviors (Rogers, 1983; Valente & Davis, 1999). This research has found that central individuals in a network play a beneficial role in the spread and adoption of social and technological behaviors, since innovations spread further and faster when they are introduced or promoted by central individuals (Banerjee et al., 2013; Rogers, 1983). Critically, however, this prior research on the adoption of innovation all shares a key organizing assumption: that there is a single thing to be spread, and that the outcome of interest is simply whether (and how fast) the innovation spreads. In contrast with this common model, conventions in practice frequently emerge from a large number of competing alternatives (Arthur, 1989; Coser, Kadushin, & Powell, 1982; DiMaggio & Powell, 1983; Pfeiffer, 2012). In such an
environment, there is no guarantee that the optimal solution will become the widely adopted solution (Arthur, 1989; Greve & Seidel, 2015; Young, 1993). As a result, the disproportionate influence of central nodes may provide some chance early advantage to one alternative, leading an inferior solution to spread at the expense of superior alternatives.

It is, of course, well established that chance advantages can allow an inferior technology or behavior spread that expense of a superior alternative. This process has been studied through formal theoretical models (Arthur, 1989), empirical case studies (Greve & Seidel, 2015), and laboratory experiments (Salganik, Dodds, & Watts, 2006), all of which show that random events early in a diffusion process can lead history to favor one solution over another. However, advantage is not always due to chance, and this paper investigates how social network structure can increase or decrease the likelihood that the best innovation will spread. In any given specific case, it is quite obvious that central nodes can provide an advantage to the adoption of some behavior or technology, as is well-demonstrated by the plethora of diffusion research described above. However, the present paper argues that the presence of central nodes introduces structural features in a network that systematically decrease the likelihood that the optimal strategy will become the widely adopted convention.

This paper studies a standard model of convention formation to examine the effect of network topology on the emergence of conventions from a large set of competing behavioral strategies. As an abstract model, the formal model studied here can describe both inter-organizational networks (where firms are the decision-making agents) and intra-organizational networks (where individual people are the agents) as long as the basic premise is met: the decision-making agent’s choice is motivated not only by their own estimate about the value of alternative choices but also by the popularity of those choices, i.e. the incentive to conform or the willingness to use social information. The principle goal of this paper is to characterize the probability of optimal equilibrium selection (i.e., the probability that a population selects the best strategy) as a function of network structure. Because central individuals have emerged as a key factor in prior research on the adoption of innovation, this paper focuses on the effect of network centralization.
This model shows that centralization increases the speed of coordination but also increases probability that a population will converge on a suboptimal equilibrium. At first blush, this result seems to imply that coordination decisions face a speed-optimality tradeoff. To contextualize these results, this analysis also examines the effect of network clustering (the probability that two nodes have common peers) and network density (the average number of connections per node) which have also emerged as important factors in prior research on the spread of social and technological behaviors (Centola & Macy, 2007; Ellison, 1993, 2000; Montanari & Saberi, 2010; Morris, 2000). Surprisingly, this analysis shows that speed and optimality are not opposed: dense, decentralized networks are both fast and optimal. Based on this finding, this paper argues that speed is not inherently problematic, and the risks associated with centralized networks emerge only from the disproportionate influence of central nodes.

**Conformity, Coordination and Conventions**

Whenever decision-makers have an incentive to conform to their peers, due either to strategic advantage or to normative pressure, they face a coordination problem. Consider, for example, a company’s choice of digital communication technology prior to the establishment of widespread digital standards: firms had a large number of competing technologies to choose from, but wanted most of all to choose the same strategy as their business partners. While each firm made decisions based on their immediate network, those peers were also making decisions based on their own network, and firms faced an uphill battle when trying to ensure compatibility with their partners (Pfeiffer, 2012). Individual people face similar strategies with the emergence of new technologies, as demonstrated by the recent proliferation of digital messaging platforms (Pierce, 2015), in which there are a large number of competing options and yet the most important feature is compatibility with peers.

Even when decision-making agents make use of limited local information, responding only to the behavior of their immediate peers, this pressure toward conformity at the peer level can generate widespread conformity at the global level (Centola & Baronchelli, 2015; Young, 1993). Once global conformity is established, such that all (or most) members of a population are employing the same strategy, the behavior
is termed a convention (Bicchieri, 2005; Lewis, 1969; Young, 1993). These dynamics do not only apply to technological conventions, but apply to social behavior more broadly. At the inter-firm level, this process of conformity is demonstrated by institutional isomorphism, or the observation that firms in practice tend to become more similar over time as a result of incentives to conform (DiMaggio & Powell, 1983). Similar principles apply empirically to individual people, and induced homophily—the tendency to become more similar over time—has been observed for a wide range of social behaviors (McPherson, Smith-Lovin, & Cook, 2001). These observations show how widespread conventions can emerge from local interactions even when people are not intentionally seeking to coordinate.

Although widespread adoption can sometimes be a signal of quality (Cialdini & Goldstein, 2004), there is no guarantee that those behaviors which become conventions are superior to the abandoned alternatives (Centola, Willer, & Macy, 2005; DiMaggio & Powell, 1983). The potential for the network dynamics of conformity to generate suboptimal conventions can be illustrated intuitively through the individual decision process: when different strategies offer different payoffs, a decision-making agent may have to choose between a popular but low payoff solution—which ensures compatibility with peers—and a less popular, but more preferred solution. The tradeoff between popularity and preference is most salient when many alternative strategies emerge simultaneously. When agents learn about solutions from their immediate peers, they may have no knowledge of available alternatives circulating elsewhere in the network. As a result, people can become invested in an inferior solution before even learning about a less popular but superior alternative.

If it were the case that every agent had full knowledge of the solution space from the outset, coordination problems would be trivial: everybody would simply adopt the best solution. This example is demonstrated formally below in the analysis of fully-connected networks, where everybody observes everybody and coordination is nearly always optimal. However, when agents only become aware of strategies through peer observation, an inferior strategy can become popular and achieve “lock-in” effects. Lock-in effects occur once a behavior with positive externalities achieves sufficiently widespread adoption that alternative strategies will not be adopted even if they offer a clear advantage (Arthur, 1989). Such
lock-in effects (Arthur, 1989) have been observed historically in the case of technologies such as the QWERTY keyboard (David, 1985), alternating current (David & Bunn, 1987) and VHS tapes (Besen & Farrell, 1994). The QWERTY keyboard stands out for the numerous problems associated with its design, and the numerous failed attempts to introduce superior alternatives (David, 1985).

The population-level effects of incentives toward conformity are formally analyzed with game theoretic models of coordination, which are widely used to study the spread of innovation and the emergence of convention in networks (see, among others: Centola, Becker, Brackbill, & Baronchelli, 2018; Kandori et al., 1993; Lewis, 1969; Montanari & Saberi, 2010; Young, 1993). While game theoretic coordination models make the formal assumption that alternative behaviors offer a clearly defined numeric payoff, these models are used to describe social conventions more generally, where the payoff may not be literally quantifiable (Bicchieri, 2005; Lewis, 1969).

**Centralization and Collective Decisions**

When a network has disproportionately well-connected central nodes (i.e. some nodes that are far more influential than others) that network is said to be “centralized” (Freeman, 1978). While empirical research on the emergence of conventions is limited by survivor bias—i.e., the difficulty in observing failed alternatives (Centola & Baronchelli, 2015)—previous experimental work on decision-making more generally can provide insight into the effect of network centralization. As an equilibrium selection process, the emergence of conventions is a form of distributed decision-making at the collective level, in which micro-level interactions generate macro-level solutions to a coordination problem. However, prior research on group decision-making provides conflicting conclusions on the benefits or risks of centralization.

At the intra-organizational level, some laboratory research on group dynamics has found that centralized networks can solve problems faster and with fewer errors, due to the role of central individuals and their positive effect on information exchange (Bavelas, 1950; Leavitt, 1951; Mulder, 1960). One benefit of the presence of central nodes is that they “can integrate the contributions of all individuals” (Mulder, 1960: 12) and thus act as key coordination agents, a role made possible by their greater knowledge
of the information circulating in the network. However, these studies largely focus on speed. In research focusing on other types of outcomes, centralization appears to undermine group decision-making. Soccer teams, for example, score more points when their interaction networks (who passes the ball to whom) demonstrate low centralization, such that everyone contributes equally (Grund, 2012). In one study of management decision-making, MBA students scored higher in management simulation games when their social networks (measured using both communication patterns and affectual relationships) had a decentralized structure (Rulke & Galaskiewicz, 2000).

The principle challenge in reconciling these conflicting observations is that these studies vary widely in their operationalization of group decision-making, both in terms of the task studied and the outcomes measured. The problem-solving tasks examined by Leavitt (1951), Bavelas (1950) and Mulder (1960) all rely largely on rapid information exchange, and thus may require very different structures than soccer teams (Grund, 2012) or management simulation teams (Rulke & Galaskiewicz, 2000) which may rely more heavily on coordination in the sense of aligning behaviors. Another challenge is that network structure itself is an outcome variable that is determined by group dynamics (Argote, Turner, & Fichman, 1989; Contractor, Wasserman, & Faust, 2006). Thus while the studies by Grund (2012) and Rulke and Galaskiewicz (2000) provide suggestive evidence that centralization can reduce group performance in coordination oriented tasks, these results do not provide a clear causal direction: it is unclear whether centralization causes negative performance or whether some aspect of group dynamics can cause both negative performance and centralization. For example, decentralization in a management simulation may be associated with greater team satisfaction, which could increase performance by virtue of psychological factors rather than the network dynamics of information flow.

Another limitation is that this research on small-group behavior may not generalize to the dynamics of coordination behavior in large networks such as organizations and industries. While observational data offers many examples of convention formation in such networks (Rogers, 1983) history of course offers no counterfactual—it is impossible to study what conditions could have led alternative technologies to become popular—and the laboratory offers limited means to study the spread of technologies and social behaviors
on such a large scale. For all of the reasons described above, empirical data is constrained in its ability to provide direct causal identification of the relationship between network structure and the emergence of conventions.

When causal identification in empirical data is a challenge, formal generative models (Epstein, 1999) provide a powerful way to disentangle ambiguous process definitions and provide a strong theoretical foundation for a causal theory (Abrahamson & Rosenkopf, 1997; Cohen, March, & Olsen, 1972; Kleinberg, 2000; Lazer & Friedman, 2007). In order to study the effect of central individuals on coordination dynamics, this analysis uses a computational experiment (Macy & Willer, 2002) to compare the probability of optimal equilibrium selection in centralized and decentralized networks. The limitation of this method is also its strength: this paper focuses on a single specific type of social behavior, examining pure coordination games in which agents face a trade-off between pressure toward conformity and incentives to choose the optimal strategy. Even as that formal focus limits the scope of the results, it also carries the advantage of precisely defining the behavior to be studied and making it clear how the assumptions lead to the conclusions. The parsimony of the model studied here allows for the demonstration that conformity incentives on their own are sufficient to generate a negative relationship between network centralization and organizational performance, without any additional assumptions.

Prior Analytical Work

This paper builds on a tradition of using game theoretic models to study equilibrium selection in the emergence of conventions. Game theoretic analyses of coordination dynamics typically seek to identify a single equilibrium solution which will become the dominant strategy in a population. A standard approach is to identify the evolutionary stable equilibrium (Kandori et al., 1993) or stochastically stable equilibrium (Young, 1993). A number of analyses using these and related approaches have supported the optimistic conclusion that the risk-dominant strategy (which in the game studied here, is the payoff-dominant solution) will always emerge as the shared convention in a population (Blume, 1993; Ellison, 2000; Kandori et al., 1993; Montanari & Saberi, 2010; Young, 1993).
A key assumption of these analyses is that a population which has already reached a shared convention can, by chance, switch to another convention, even in the absence of an exogeneous shock (Kandori et al., 1993; Young, 1993). This assumption is necessary for the statistical methods used in these analyses, and is also the root of an important conceptual limitation: while these analyses show that the optimal solution is the most likely equilibrium, they do not guarantee that the optimal solution will be the *first* equilibrium reached. As Young (1993) points out, in a population that begins with many different strategies, any potential solution may emerge as the dominant convention.

Even those models showing that the optimal equilibrium will emerge asymptotically do not guarantee that the optimal solution will be adopted in any reasonable time. Work by Ellison (1993, 2000) highlights two important properties of coordination dynamics: first, suboptimal equilibria can remain stable in networks for non-trivial periods of time; and second, network structure is a key factor shaping coordination dynamics. Ellison demonstrated that in networks characterized by high local clustering (meaning that the neighborhoods of adjacent nodes overlap) the optimal solution will spread quickly due to cascading effects, even after a suboptimal solution has been widely adopted. In contrast, it is much more difficult for the optimal solution to replace an established equilibrium in disordered networks with less clustering (random graphs) or in dense networks characterized by global ties (fully connected networks) once an inferior solution has been widely adopted (Ellison, 1993, 2000). This means that an inferior solution can remain the stable equilibrium for potentially long periods in all but the most geometrically regular networks.

Once a solution is widely adopted, it can remain stable indefinitely because of the self-reinforcing effects of adoption with coordination externalities—individuals pay a penalty if they unilaterally deviate from an established convention. Because any equilibrium may become locked-in indefinitely, it is crucial to identify not only the stochastically stable equilibrium, but also the *first* equilibrium to be reached. A Markov model of coordination with lock-in effects means that any potential solution can be an absorbing state, but may not be analytically tractable (Young, 1993)—the assumption that equilibria can be exited plays a key role in the use of statistical tools for analyzing coordination dynamics (Kandori et al., 1993;
Young, 1993). However, by studying a computational simulation of a standard model of coordination with absorbing state equilibria, this paper shows how variation in social structure can make a population more or less likely to select the optimal strategy as the first (and possibly final) equilibrium.

**Modeling Conformity Dynamics in Networks**

This paper follows a standard game theoretical model of coordination (Lewis, 1969; Morris, 2000; Young, 1993). A coordination problem can be framed in the following way: a population of decision-making agents must frequently perform some behavior, such as getting information from a business partner or sending them a message. They must choose one strategy among many, as for example a particular choice of digital communication technology. Each agent chooses a strategy by combining two piece of information: the payoff of each strategy (i.e., their preference) and the number of network neighbors using that particular strategy. Agents choose the strategy that offers the highest expected payoff (the “best response” strategy) which combines their preferences for both social conformity with the inherent quality of the strategy itself.

Formally, this paper examines an MxM pure coordination game (i.e., with $M$ possible strategies) in which a strategy $S_i$ offers payoff $V_i$ upon successful coordination, and a payoff of 0 upon miscoordination (failure to coordinate). The expected payoff for strategy $S_i$ is equal to

$$(\text{proportion of neighbors using } S_i) \times (\text{payoff of } S_i)$$

which follows the standard calculation for expected payoff. Number of neighbors can be equivalently substituted for proportion of neighbors, and this expected payoff function offers several possible interpretations in the context of coordination behavior.

In a context where agents play a series of pairwise (two player) coordination games, then the proportion of observable peers employing a given strategy represents the probability of success on a given pairwise interaction. Under one interpretation, an agent interacts only with their network neighbors. For example, a firm choosing a communication protocol must attempt to match as many possible peers in their
immediate business network. In another interpretation, agents may have some chance of interacting outside their network neighborhood, but use observations of their immediate network neighborhood as a heuristic to form beliefs about the population at large.

I follow previous work (Blume, 1995; Ellison, 2000; Kandori et al., 1993; Montanari & Saberi, 2010; Morris, 2000; Young, 1993) in using a boundedly rational model of coordination behavior with two key assumptions. First, the model assumes that an agent’s best response decision depends myopically on their immediate social environment. Second, the model assumes that agents have some chance of error, such that they do not always make a best response decision. The assumption of myopic choice is reflected in the formula for expected payoff, which is based only on the current strategies of an agent’s observable peers as determined by the social network. The second modeling assumption, the presence of statistical noise in agent decisions, is a key assumption of bounded rationality: the expected payoff function identifies an unambiguously preferred strategy (except in the case of ties) but we cannot assume that a decision-making agent will always choose the rationally preferred strategy. A detailed description of the model is provided in the Appendix.

**Model Parameters**

The primary behavior of interest here is the case in which a population must select an equilibrium from a large number of possible strategies. To study these dynamics, the main results presented here model the case in which \( M >> N \) (i.e., many more solutions \([M]\) than agents \([N]\)), so that each agent starts with a unique strategy. This paper also presents outcomes where \( M \leq N \), which produces similar results.

The payoffs for each of the \( M \) strategies are independently, identically distributed according to a fixed distribution. In the figures presented here, the payoff for a given strategy is drawn from a log-normal distribution \((\mu=0, \sigma=1)\). The log-normal distribution is chosen due to the fact that innovations often follow a long-tailed payoff distribution, with many mediocre solutions and few high quality solutions (Kauffman, 1993). Qualitatively identical results obtain when strategies follow other distributions.

Results present outcomes with \( \varepsilon=0.1 \), meaning that 1 in 10 decisions is random, and 9 in 10 decisions follow the best response strategy. However, the effect of centralization on coordination does not
depend on noise, and results are qualitatively identical when $\varepsilon=0$, such that agents follow a perfect best response strategy. For the sake of generality and consistency with previous research, this text presents results with noise.

**Network Structure**

A network is considered “centralized” when there is a large amount of inequality in the distribution of connectivity. In a highly centralized network, one or a small number of nodes have a large number of connections, while most nodes have only a few connections (Freeman, 1978). To quantify the level of centralization in a network I use the Gini coefficient, which is a widely used metric for quantifying the level of inequality in a particular resource distribution. In the case of networks, the Gini coefficient is measured for the degree distribution (Badham, 2013), where each node’s “degree” is defined as the number of connections they have to other nodes (Easley & Kleinberg, 2010). Figure 1 shows a schematic representing networks of varying centralization.

To produce centralized networks, this analysis employs two network generating algorithms. In order to generate highly centralized networks following standard methods, this analysis employs the well-known preferential attachment mechanism identified by Barabasi and Albert (1999) to explain the emergence of scaling in empirical networks. When the parameters are appropriately tuned, this algorithm can generate networks ranging from moderately centralized random networks ($\text{Gini}=0.25$) to highly centralized “hub spoke” networks ($\text{Gini}=0.5$), in which a single core group of nodes is connected to every other node, while peripheral nodes are connected only to the core nodes. However, this algorithm cannot be tuned to generate fully decentralized networks ($\text{Gini}=0$). Therefore, in order to study networks that vary continuously between fully decentralized and highly centralized networks, this analysis employs a second network algorithm, which generates networks based on an arbitrary degree distribution. Details on network generators are provided in the Appendix.
One challenge in modeling network effects is that it is difficult to change one parameter of a network while holding all other parameters constant. In particular, as networks become increasingly centralized, the average path length between two randomly selected nodes decreases. In diffusion models, this results in a more efficient spread of information (Watts & Strogatz, 1998) and therefore it is challenging to distinguish the effects of centralization (presence of more prominent nodes) from the effects of communication efficiency (which may increase the speed of coordination). In order to disentangle the effects of increasing coordination from the effects of network efficiency, this analysis also compares coordination in fully decentralized networks over a range of density, up to fully connected networks in which every agent can observe every other agent. As density increases, average path length decreases, which has been shown to increase speed of convergence in related models of coordination where every solution offers equal payoff (Dall’Asta et al, 2006).

Results: The Network Dynamics of Equilibrium Selection

In order to compare results for this absorbing state simulation to previous theoretical research on coordination, this analysis begins with a discussion of coordination in clustered lattice graphs, which nearly always select the optimal equilibrium and have been widely studied in previous research on the diffusion of innovation (Blume, 1993; Centola & Macy, 2007; Ellison, 2000; Montanari & Saberi, 2010; Morris, 2000). The analysis then examines the effect of centralization on the probability of optimal coordination, showing that centralized networks are more likely to converge on suboptimal solutions. In order to test whether the effects of centralization can be explained as a result of a speed/optimality tradeoff, this analysis also tests the effect of network efficiency by varying the density of decentralized networks. The analysis closes by discussing the robustness of the main results against variation in modeling assumptions.
Coordination in Lattice Networks

Previous theoretical work (Ellison, 1993; Blume, 1995) has shown that in lattice graphs, the overlapping structure of node neighborhoods makes it easy for the optimal solution to spread quickly, provided that it has sufficient early adoption to take hold. Conditions to ensure this cascading effect are minimal—all it requires is that a single neighborhood (one node and all their contacts) adopts the strategy, and then it is nearly guaranteed to spread through an entire population (Blume, 1995). In the model studied here, these initial conditions are almost guaranteed to occur. In the case where every node begins with a unique solution, there will of course be exactly one node employing the optimal solution. (This paper defines “optimal solution” as the best solution used by any agent in a given simulation.) The neighbors of this node will quickly adopt that superior strategy, because no other strategy yet offers a popularity advantage, and the optimal solution will spread through the network. This expectation is confirmed by simulation, in which lattice graphs converge on the optimal solution in more than 99% of trials.

However, empirical networks do not display the geometric regularity of lattice graphs (Watts & Strogatz, 1998) and random graphs are more prone to lock-in effects than lattice graphs (Ellison, 2000). Even a small number of long distance ties can disrupt cascading effects (Centola & Macy, 2007) and coordination dynamics become increasingly less likely to break out of suboptimal equilibria as networks become more disordered (Montanari & Saberi, 2010). These properties indicate that in disordered networks, the first equilibrium to be reached is an important one—but previous results (Kandori et al, 1993; Young, 1993; Montaneri & Saberi, 2010) cannot guarantee that the first equilibrium will be the optimal solution. As the remainder of this analysis shows, complex networks frequently converge on a suboptimal equilibria. However, not all networks are created equal—the probability of optimal equilibrium selection varies with both network centralization and network density.

The Effect of Network Centralization

Figure 2A shows the probability of optimal coordination in random networks with increasing centralization. In decentralized networks with 20 connections per node, the population selects an optimal strategy in about
70% of simulations. As centralization is increased, however, the probability of optimal equilibrium selection decreases dramatically. In the most centralized networks, the optimal solution is selected in only about 15% of simulated trials. All the points in Figure 2 show outcomes for networks with N=1000 nodes and an average of 20 edges per node, and thus network density (0.02) is held constant as centralization increases. Black points show preferential-attachment networks, and grey points show centralized degree sequence networks. Points show average across 5,000 simulations, and 95% confidence intervals are drawn but are too small to be visible on most points.

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Insert Figure 2 about here
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One possible explanation for this reduced optimality is a speed/optimality tradeoff, since increasing centralization reduces average path length, increasing network efficiency, and Figure 2 (right) shows that speed of convergence increases with centrality. If time is needed for the best solution to surface, then centralization might simply create a scenario in which conventions are selected at random—i.e., any solution is equally likely to become convention—decreasing the probability of optimality. To test this possibility, Figure 3 (solid grey line) shows the average payoff of the equilibrium solution as a function of centralization for the data shown in Figure 2. As expected, the payoff decreases as centralization increases, which is consistent with the observation that the probability of optimality decreases as centralization increases. However, when outcomes are limited only to those cases where the optimal solution was selected, average payoff increases with centralization (dashed black line, Figure 3). This result indicates that centralization not only increases the speed of coordination, but also changes the distribution of equilibria.

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Insert Figure 3 about here
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The explanation for Figure 3 rests with central nodes, since central nodes are more influential than peripheral nodes and thus their solution is more likely to dominate regardless of payoff. Consider the case where the optimal solution is only marginally better than the second best solution. In a decentralized
network, every solution has an equal chance to spread, and the optimal solution will spread. In a centralized network, however, that optimal solution must compete against the influence of solutions introduced by central nodes. As a result, optimal solutions in centralized networks will only spread if they hold a relatively larger advantage, producing the results shown in Figure 3. This argument is supported by a direct examination of the influence of central nodes, which shows that central nodes have an easier time spreading strategies regardless of payoff.

The Influence of Central Individuals

Because every node has an equal probability of introducing the optimal solution, then the equilibrium solution should (optimally) be just as likely to come from a peripheral node as a central node, after controlling for the expected number of each type of node. However, central nodes are more likely to introduce the winning solution than would be expected by their prevalence in the population.

This effect is measured as follows. For any given simulation, let D be the degree (number of connections) for the “innovator,” i.e. the agent that introduced the equilibrium solution. If the equilibrium solution were determined only by payoff, or if equilibrium solutions were selected randomly, then the distribution of D would be equal to the degree distribution of the network itself. E.g., if only 1% of nodes have degree 10, then only 1% of the equilibrium solutions should come from nodes with degree 10. Since degree is a discrete variable (can only take integer values), the innovator degree distribution can be compared with the network degree distribution as the likelihood ratio

\[ L(D) = \frac{\text{proportion of innovators with degree } D}{\text{proportion of all nodes with degree } D} \]

where innovator refers to a node that introduced the equilibrium solution. If the likelihood ratio \( L(D) \) is greater than 1, that means that nodes with degree D are more likely than expected to introduce the equilibrium solution. If the ratio \( L(D) \) is less than 1, then nodes with degree D are less likely than expected to introduce the equilibrium solution.
Figure 4 shows $L(D)$ for 200,000 simulations on centralized networks generated with a preferential attachment algorithm and an average of 20 connections per node. The more connected an agent is, the more likely it is that the agent’s initial solution will become the equilibrium solution, regardless of payoff. This effect does not depend on the particular shape of the network degree distribution, and similar results emerge for Erdos-Renyi random graphs, which have a Poisson degree distribution.

Another way to illustrate the influence of central nodes is to compare the average payoff of equilibrium solutions introduced by central nodes with those introduced by peripheral nodes. Figure 4 as discussed above reflects the expectation that solutions introduced by central nodes are more likely to be adopted, regardless of merit. The complementary expectation is that the payoff for a solution introduced by a peripheral node—conditional upon becoming the equilibrium solution—is expected to be higher than the payoff of an equilibrium solution introduced by a central node. This relationship is shown in Figure 5 which indicates the payoff of conventions as a function of the centrality of the node who introduced the strategy. This figure indicates an “underdog” effect, such that successful strategies introduced by peripheral nodes offer a greater payoff than strategies introduced by central nodes.

Taken together, the results presented so far indicate that central nodes provide a widely observable signal guiding coordination—which increases speed, but also draws attention to the closest solution at hand, before the best solution has a chance to get noticed. One interpretation of the dual effect of centralization is that coordinating groups face an unavoidable tradeoff between speed and optimality. However, this tradeoff is not unavoidable, and in very dense networks, coordination is both fast and optimal.
Network Efficiency

Figure 6A shows the effect of network density on the probability of optimal coordination in decentralized networks, where every node has the same number of connections (10,000 simulations per point, 95% confidence intervals). Networks density counts the total number of connections as a fraction of total possible connections, and is proportional to the average number of connections per agent when the network size is held constant. The leftmost point in this figure is equivalent to the leftmost point in Figure 2A, showing networks with 20 connections per agent (density=0.02) and zero centralization. Moderate increases in density have a small but negligible effect on the probability of optimal equilibrium. As density increases beyond 50%, however, the probability of optimal coordination approaches 1. In fully connected networks, groups nearly always select an optimal equilibrium.

Increasing graph density not only increases the probability of optimal coordination, but also increases the speed of coordination. Figure 6B shows the average number of updates that each node is required to make in order for a population to reach equilibrium, and is comparable to Figure 2B. The greatest gains are shown by the sparsest networks, where only a moderate increase in density produces a large decreases in convergence time. In fully connected networks, equilibrium is reached with slightly more than 1 update per person.

The explanation for the double advantage of network density (for both speed and optimality) can be illustrated by considering the trivial case of a fully connected network, in which every agent observes every other agent. At the outset, every node has a unique solution. Because every node has full knowledge of the strategy space, and no strategy yet has any advantage of popularity, every node will simply adopt the best strategy. This argument also holds for the more general case where there are fewer strategies than people. In expectation, each strategy will be employed by the same number of people at the outset – thus, again, no strategy starts with a popularity advantage, and again the best strategy will be immediately adopted. Although the case of the fully connected network describes the trivial (and perhaps unlikely)
scenario in which every agent has full knowledge of the network and thus the solution space, it serves as an illustration for the more general advantage of network density.

**Robustness**

The results presented so far have demonstrated the properties of only one point in the parameter space with regard to statistical noise, payoff distribution, population size, and number of solutions. In particular, the simulations have assumed a large level of noise, an infinitely large strategy space (so that agents begin with individually unique solutions) and strategy payoffs drawn from a log-normal distribution. Effects are qualitatively unchanged by the absence of noise, variation in the payoff distribution for strategies, and changes in population size.

One factor that does substantially moderate the effect of centralization is the size of the solution space. As the number of solutions is reduced, the effect of centralization becomes weaker, though it still has a substantial impact on the probability of optimal coordination. Even with only 10 unique solutions, the most centralized networks still select an optimal equilibrium less than 80% of the time, as compared with near-optimality in decentralized networks. However, once the number of solutions reaches its limit (binary coordination, with 2 solutions) the effect of centralization decreases substantially. The decreased impact of centralization can be explained in terms of the initial conditions of the model. At time t=0, every begins with a randomly assigned strategy. When each strategy is unique, the strategies adopted by central nodes have a structural advantage. However, with only two strategies, the structural advantage of each strategy will, in expectation, be approximately the same: each strategy is likely to be adopted by the same number of central individuals.

Although the effect of centralization is small in binary coordination, the most centralized networks nonetheless show a slightly decreased probability of optimal coordination as compared with decentralized networks. In the most centralized preferential-attachment networks, simulations converge on the optimal
solution approximately 96% of the time, as compared with 99% optimality in the least centralized networks. The robustness of this effect shows that even in relatively straightforward two-choice decisions, the structural advantage given to solutions adopted by central nodes always has some impact, if relatively small, on collective decisions.

Discussion

Although the coordination model presented here captures a highly stylized description of human behavior, as does any model, the effects described here follow generally from the empirical observation that central nodes are influential (Banerjee et al., 2013; Katz & Lazarsfeld, 1955; Rogers, 1983). Any time centrality contributes to an idea’s popularity, there is the chance that those ideas introduced by central nodes will become popular at the expense of superior strategies introduced by peripheral nodes.

The effects described here are similar to related empirical research on collective belief formation. In experimental studies of estimation tasks, decentralized networks produce more accurate beliefs than centralized networks (Becker, Brackbill, & Centola, 2017). While estimation tasks are a fundamentally different form of social influence than coordination decisions, central nodes face a similar informational situation in both scenarios. In forming estimation judgements, a central node is in a position to integrate the information provided by group as a whole. However, the peripheral nodes are simultaneously influenced by the central node, and the network as a whole is drawn toward the belief of central nodes (Becker et al., 2017).

When a central node is aware of their influence, they could conceivably take steps to aggregate information from their peers before making a decision. This strategy is reflected in a management practice wherein leaders intentionally avoid influencing others, in order to take advantage of social learning (Sunstein & Hastie, 2014). However, the challenge with the structural effects of network dynamics is that a central individual can be influential without even realizing it, since the influence of a central node extends far beyond their immediate, observable network.
The random networks used here generate a very tight correlation between a node’s count of connections—their immediately observable centrality, or degree centrality—and their influence in the network. However, empirical social networks allow for the possibility that influence in the broader network can be decoupled from immediate degree centrality. This possibility is reflected in the importance of eigenvector centrality in measuring influence (Banerjee et al., 2013; Kitsak et al., 2010), which counts not only a person’s direct contacts, but also iteratively counts the connectedness of those contacts, and those contacts’ contacts, and so forth. As a result, a decision-maker may have a small number of immediate contacts and yet be highly influential, if their immediate contacts are well connected. Thus, a person or organization may be influential without knowing it.

Ultimately, central nodes—be they well-connected organizations, or well-connected individuals—are a bit of a paradox. On the one hand, their centrality enables them to obtain a wide view of the social world. The results presented here are consistent with previous research arguing that central nodes can effectively coordinate group dynamics actively integrating the information of more peripheral nodes (Mulder, 1960). The challenge facing central nodes is that their social information is ultimately mirror-like: these central nodes observe individuals who, simultaneously, observe them. Thus whereas social information in general provides a rational way to reduce uncertainty (Cialdini & Goldstein, 2004), this effect can backfire in centralized networks.

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Figure 1. Schematic showing increasingly centralized networks.

Figure 2. The effect of network centralization on the probability of optimal coordination.
Figure 3. The effect of network centralization on the payoff of equilibrium solutions.

Figure 4. The influence of central nodes
Figure 5. The payoff as a function of the originating node.

Figure 6. The effect of network density on the probability of optimal coordination.
Figure 7. The detrimental effect of centralization is robust to the size of the strategy space.
Appendix

Model Definition

Each run of the simulation is generated as follows:

- N agents are embedded in an undirected, binary network
- Initially, each agent is randomly assigned a strategy from a set of M possible strategies.
- At each time step, an agent is randomly selected from the set of agents whose strategy is not already the best response to their social environment.
- The focal agent adopts the best response strategy with probability \((1-\varepsilon)\). With probability \(\varepsilon\), the agent randomly selects a peer and adopts their strategy.
- The model is run until all agents are employing a best-response strategy

Overall, the model employed here is nearly identical to the several models used in previous coordination research, and varies in the specification of the error term. In previous implementations of this model (Blume, 1993; Ellison, 2000; Kandori et al., 1993; Montanari & Saberi, 2010; Young, 1993) agents who “err” (via the noise term \(\varepsilon\)) randomly select a strategy from all possible strategies. This assumption means that even once a convention is established, there is a non-zero probability that the population will spontaneously adopt a different convention, which is necessary for the conclusion in previous work that the optimal solution will emerge in the long run. However, a principle goal of the present work is to model the emergence of lock-in effects. By modeling agents that select only from strategies currently in use throughout the population, this model allows for unused strategies to “die out” as they are no longer used by any agent. By implementing noise in this way, the model reaches an absorbing state, and the first equilibrium to be reached is the long term convention.

It is worth noting that a system can reach an equilibrium where multiple strategies are in use throughout a population (Blume, 1995). However, such outcomes are rare, and the networks presented here reach a global convention in more than 99% of simulations. It may occur in empirical settings that
conformity dynamics do not lead to full convergence, but the cases where conventions are widely established are the ones in which conformity pressures are of greatest concern, and are the primary interest of the current investigation.

Network Generators

In the study here, two primary network generators are used. Preferential attachment networks are generated according to the algorithm developed by Barabasi and Albert (1999). To vary the range of centralization produced by this generator, I vary the strength of preferential attachment. As new nodes are connected, they are connected to existing nodes with probability

\[ P \sim ck^a \]  

where \( k \) is a node’s degree, \( a \) controls the strength of preferential attachment and \( c \) is a normalizing constant. This model reduces to the original Barabasi-Albert algorithm when \( a=1 \).

The preferential attachment generator produces networks with a Gini coefficient in the range of 0.25 to 0.5. To increase the range available for study, and to allow for the study of a continuous variation from decentralized (Gini=0) to centralized networks, I also generate networks using arbitrary degree distributions. To accomplish this, I first produce arbitrarily centralized degree sequences (random number distributions) drawing from an approximately power-law distribution with a range of parameters, producing degree distributions with Gini coefficients ranging from Gini=0 to Gini=0.5. I then use these sequences to produce networks with the Viger and Latapy (2005) method. When Gini=0, every node has the same number of neighbors. The parameters are selected through a trial-and-error method to ensure a constant average degree (i.e., to vary centralization while holding graph density constant).