Markets, Hierarchies, and Networks:
An Agent-Based Organizational Ecology

Abstract: Markets, hierarchies and networks are widely understood to be the three primary forms of social organization. In this article, we study the choice between these forms in a general, agent-based model (ABM) of cooperation. The organizational ecology is the product, an emergent property, of the set of choices made by agents contingent on their individual attributes and beliefs about the population of agents. This is one of the first attempts to theorize explicitly the choice between different organizational forms, especially networks and hierarchies, and certainly the first do so in an ABM. The insights of the model are applied to current research on transnational networks, social capital, and the sources of hierarchy and especially autocracy.

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Markets, hierarchies and networks are widely understood to be the three primary forms of social organization (see Powell 1990, Ronfeldt 1996). Economic transactions occur in arms-length markets between anomic buyers and sellers, hierarchically-ordered corporations (Williamson 1975, 1985), or networks of co-ethnic traders (Rauch and Trindade 2002, Grief 2006) or, in Japan, of production *keiretsu*. Insurgencies are carried out by ad hoc "groups of guys" who come together to plot and carry attacks (Sageman 2008), by militias with commanders, ranks and insignias, or by networks of loosely connected cells (Arquilla and Ronfeldt 2002). Social movements can arise in spontaneous, uncoordinated protests, as top-down, disciplined organizations, or through tightly linked policy entrepreneurs who mobilize followers. Countries cooperate with one another under anarchy, in supranational organizations, and in small groups of deeply interdependent or "networked" states (Kahler 2009a). These same organizational forms recur at all levels of social interaction, but we understand little about the conditions that give rise to one form or another. Alternatively, in the late medieval period, newly emergent sovereign territorial states, the epitome of hierarchy, decisively beat out trading networks like the Hanseatic League to become the primary units of international political life (Spruyt 1994). Similarly, legal-contracting may be displacing social networks based on personal relationships and private knowledge as the predominant form of organization in American society (Putnam 2000). At some historical junctures, one type of organization appears to win over its competitors, at least temporarily. But again, we understand little about the choice of actors between alternative organizational forms.

In this article, we study the choice between markets, hierarchies, and networks in a general, agent-based model (ABM) of cooperation. In our ABM, agents choose to cooperate or not in a market, hierarchy or network as a function of their individual attributes and their beliefs about the attributes of the other agents with whom they may interact. The set of organizations in a population -- the organizational ecology -- is an emergent property of the choices made by agents. Unlike formal, closed-form models that focus on a small number of actors in a well-defined strategic setting, our ABM shifts attention to the attributes of the *population* of interacting agents.

We theorize explicitly the choice between all three organizational forms. Markets have in the past been compared separately to hierarchies and networks, but few have compared hierarchies and networks directly to each other.[1] Past ABMs of cooperation have not included institutional or organizational features.[2] Although there are several computational models of organizations, most focus on intra-organizational attributes.[3] This is the first ABM to study the choice between organizational forms in a general model of cooperation.

The ABM reveals theoretical limitations and inconsistencies in existing theories, highlights interaction effects and population dynamics -- thereby offering new explanations for phase shifts and other phenomenon absent from purely verbal and even formal models -- and generates new theoretical insights. Networks, for instance, both provide information to agents and permit agents to select specific agents with whom to interact. We find that the informational benefits of networks are somewhat limited, valuable only to actors with contingent strategies, such as tit-for-tat within a Prisoner's Dilemma, who can learn from the knowledge of others and adjust their behavior accordingly. In a static population with no exogenous changes in the attributes of agents, the informational benefits of networks quickly decline as agents develop their own histories of play with others. When permitted to choose other agents with whom to interact within their networks, however, all types of agents may join, but this permits not only cooperation but exploitation by "bullies" as well -- offering a far less sanguine view of networks than is common. Conversely, hierarchy is preferred in relatively "nastier" populations with larger numbers of uncooperative and opportunistic agents. Paradoxically, it is the most cooperative agents who first join hierarchies to reap the benefits of centralized enforcement when the population turns nasty. In many

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[1] On markets and hierarchies, see Williamson (1975) and on markets and networks, see Rauch and Hamilton (2001). For comparisons of networks and hierarchies, see Powell (1990) and Kahler and Lake (2009).
[2] On agent-based models of cooperation and politics, see Axelrod (1984, 1997), Cederman (1997), Epstein (2007), Kollman, Miller, and Page (2003), and Miller and Page (2007).
[3] On computational models of organizations, see Prietula et al. (1998), Ilgen and Hulin (2000), and Chang and Harrington (2006).

cases, population dynamics create phase shifts in which agents flip from one organization to another as a result of small changes in their environments, captured by varying different parameters in our model.

After explaining the ABM in some detail, we apply it to the literatures on transnational networks and international governance, networks and social capital, and the sources of hierarchy. These applications are not tests of our model in any degree. Indeed, our ABM is intended to be general and is not designed to capture issues specific to these literatures. Nonetheless, we believe the model clarifies propositions central to each and raises important new questions for research.

I. Markets, Hierarchies, and Networks as Organizations

We focus on the generic problem of cooperation among self-seeking actors choosing between different organizational forms. By using simple, ideal type representations we aim to identify broad principles of organizational ecology that can be applied to an array of cooperation problems. For each organization, we distill the form to its essence as characterized in the existing literature. There are, no doubt, many hybrid forms in the real world, but to keep the analysis simple we focus only on ideal types of markets, hierarchies, and networks.

The problem of cooperation is characterized here as an iterated two-player Prisoner's Dilemma (PD) game (see Figure 1). As Axelrod (1984) and others have shown, such a model captures the essential features of a broad class of cooperation problems. To model hierarchy appropriately, however, we modify the standard PD setup slightly. Specifically, we permit agents to have individual preferences (p_i) defined by ideal points along a finite continuum.[4] Our intuition is that mutual cooperation does not mean the same thing or carry the same value for all pairs of political actors, especially under hierarchy. Cooperation with an actor that shares one's preferences is different from cooperation with an actor with preferences distant from one's own. Assuming that cooperation occurs at the median of their ideal points, two "left" actors, for instance, gain greater utility from cooperating with one another than might one "left" and one "right" actor. If cooperation means working together to promote a political cause, two left actors will pursue a

[4] Note to reviewers: We include symbols and some derived variables in the text to facilitate correspondence to the expected utility equations described in the Appendix. We will be happy to conform to the style of the AJPS.

policy closer to their preferences than would a left and right actor, for whom the median would be further from their ideal points. To anticipate a technical point below, when actors both cooperate, we subtract the weighted spatial distance between their ideal points from the payoffs from mutual cooperation ($k_{ij} = w(|p_i - p_j|/2)$). In all cases, any weight on preferences greater than zero makes cooperation less likely as it reduces the value of mutual cooperation relative to other possible outcomes. As the weight on preferences increases, agents that might otherwise choose to cooperate will now choose to defect.[5] The primary implication of this amendment to the standard PD game is that actors with more similar preferences will be more likely to cooperate than agents with more dissimilar preferences, all else considered. In hierarchy, by contrast, agents cooperate at the hierarch's ideal point (p_h) and payoffs for cooperation are adjusted by the difference not between their individual preferences but between each agent's ideal point and that assigned for the hierarchy as a whole ($k_{ih}= w|p_i - p_h|$). A key attribute of hierarchy is the ability of a third party —typically the ruler, leader, or boss— to command legitimately certain actions by the members of the organization (see below). By assuming that cooperation occurs at the hierarch's ideal point, we capture, in part, the notion of command or authority that is central to hierarchy. In the final substantive section below, we vary the hierarch's ideal point relative to the mean in society to capture variations in regime type.

Figure 1 About Here

Although a common term, the concept of market lacks a fixed analytical definition. Once referring only to a site for trading, since the early 20th century economists have tended to use market as a synonym for exchange, and to focus on variations in market structure, including the numbers of buyers and sellers, the information available to each, and so on. Sociologists focus more on production markets (of firms or factors of production), conceived as networks of linked agents.[6] As an organization,

[5] All results reported in this article, except those on hierarchy in Figures 7 and 8, have been replicated with the weight on preferences set to zero ($w = 0$), deleting preferences from the analysis (i.e., replicated the standard PD). The results on markets and networks remain nearly identical with no substantive implications. We do not focus extensively on preferences here except in the final section on hierarchy, but they are included in the parameter sweeps in the Appendix.

[6] On economic and sociological views of markets, see Swedberg 2003, Chapter 5.

according to Powell (1990, 302; italics added), markets are "the paradigm of individually self-interested, noncooperative, *unconstrained* social interaction" that engage strictly anomic agents who can form only self-enforcing agreements and know only their own past interactions with each other. This view of markets as an organization strips the concept of its focus on the exchange of goods but generalizes it to a greater range of interactions and is fully captured in a standard PD game.[7]

In the canonical definition, networks as organizations are characterized by "voluntary, reciprocal, and horizontal patterns of communication and exchange" (Keck and Sikkink 1998, 8; Podolny and Page 1998, 59).[8] Accordingly, we model networks here in two ways. First, networks are mechanisms for acquiring information on agents from other agents with whom an agent has cooperated in the past. Intuitively, networks allow one agent, say *i*, to ask a defined number of agents with whom *i* has previously cooperated if they have played agent *j*, and if so what *j* did (cooperate or defect) and what is *j*'s ideal point (p_j). With this information, agent *i* can then decide whether to cooperate or defect with *j*. Thus, networks provide information that supplements the information *i* may have acquired through its own past interactions with *j*. The primary effect of information from the network is to prevent agents from being "suckered" in the first round of play with any new agent. Information sharing can be understood as a form of indirect reciprocity (see Nowak and Sigmund 2005). Often treated as a defining attribute of networks, this first form of reciprocity is an emergent property of the agents who tend to select themselves into networks (see Powell 1990, 303, and Podolny and Page 1998, 59). Only agents that possess a contingent strategy (defined below) will ever choose to join a network to gain information about others, and having joined they will play reciprocally.

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[7] Markets might also be described as anarchy, in contradistinction to hierarchy. We defer to the larger literature, however, in the use of the term "market" in this way. We have some sympathy for critics of this thin conception of markets but, again, follow common practice. Moreover, although modern economic exchange is often embedded in larger social organizations, such as the state, this simply implies that those "markets" are actually a hybrid form of social organization. Economic exchange does occur within markets that approximate our ideal type, commonly when price accurately reflects all known information (i.e., in "competitive" markets), the costs of third party adjudication are high relative to the value of the good, contracts are incomplete, or the goods are illicit.

[8] Defined as a set of nodes (agents) and edges (interactions), almost any set of actors can be described as a network. Social network theory, in turn, has developed a host of tools and concepts for measuring and describing the structure of such networks (see Jackson 2008). We treat networks more as governance structures, but focus on the information flows and reciprocity between agents common to both approaches. On the different conceptions and uses of networks in political science, see Kahler (2009a).

Second, in some conceptions, networks permit agents to engage in a more direct form of reciprocity by intentionally selecting specific agents with whom to interact, often on a repeated basis. As explained below, in the core model agents are randomly paired in any given round of the game. Yet, in the real world, agents do not necessarily interact with a uniform probability. We implement this second type of reciprocity by a variable rate of selective affinity (η) in which "nature" permits an agent to select for play another agent it has interacted with in the past. With selective affinity, agents of all strategy types may choose to join the network.

Participating in a network is always costly, however, represented in the model as a variable fee (ϕ) subtracted from the agent's payoffs no matter the outcome of the interaction. This fee is intended to capture the transaction costs of networking, variously interpreted as the opportunity costs of providing information, engaging in activities intended to develop social capital, and sending costly signals of commitment to the group necessary to establish trust or reputation. An agent may join a network and gain information about or select its partner even if that other agent chooses a market or hierarchy during its turn of the game. In such a case, the networked agent plays with the information acquired from past cooperators, but the other agent plays using only its private knowledge.

Third party enforcement stands at the core of all definitions of hierarchy. In our model, agents within the hierarchy cooperate with one another at the hierarch's ideal point (see above) and subject to punishments for (random) defection.[9] If an agent defects, it receives the temptation (T) payoff minus the punishment, while the other receives the sucker's payoff (S).[10] We treat both the probability of cooperation within the hierarchy (q) and the magnitude of the punishment (v) as exogenous. Our intuitive analogy is to agents working in a corporation and tasked to cooperate with their fellow employees, but cooperation within the firm is contingent on factors beyond the agent's control – including the state of the macroeconomy, fickle consumer tastes, a capricious boss, and so on. Some portion of the time, the

[9] That is, agents who join a hierarchy, regardless of their strategy type (see below), play a mixed strategy in which they cooperate with other agents in the hierarchy with some exogenous but commonly known probability (q).
[10] When both agents in a hierarchy defect simultaneously they each receive the DD payoff minus the punishment. With our default settings in the ABM, mutual defection is typically rare but remains a possibility.

agent's best efforts to cooperate may nonetheless appear to be a defection for which it is punished. This intuition extends to families, clans, religious orders, and more hierarchies in which individuals are mandated to cooperate (uphold contracts) with one another and are punished by a central enforcer if they defect. It also extends to states --both democratic and autocratic, local and national -- in which law regulates the behavior of individuals in relations with one another (cooperate, observe contracts, follow established conventions, etc.) under threat of (imperfect) monitoring and sanctioning. Although random defection at an exogenously defined probability is somewhat crude, some such mechanism is necessary to prevent hierarchy from dominating all other organizational forms.[11] This representation allows us to investigate how the probability of defection and levels of punishment affect the expected utility of cooperation under hierarchy. We include a variable tax on members joining a hierarchy (τ), subtracted from the expected utility of joining the hierarchy.

Agents in the hierarchy who interact with agents outside the same hierarchy play as in the market. In a firm, for instance, some portion of any individual's daily interactions are with other employees of the same organization (e.g., as part of a team producing a new widget), but many others are with other actors outside the corporation (e.g., other firms – the local grocer, friends and families). Similarly, individuals governed by one authority, such as a state with a distinct set of laws, may interact both with one another and more or less frequently with "foreigners" in a second state with different laws. Cooperation is mandated and subject to centralized enforcement only with other members of one's own hierarchy or, in this case, state. In other words, the rule of law represented in cooperation at the hierarchy's ideal point and centralized punishment for defection does not apply "extraterritorially" or beyond the members of the same hierarchy.

[11] Ideally, one might want to endogenize defection by strategy type and levels of punishment necessary to sustain cooperation. But if so, the punishment could always be set at a level to induce cooperation by the least cooperative agent, and mutual cooperation would always occur. If agents always cooperate in hierarchy, this form will always dominate other organizational forms, which is neither true in the real world nor theoretically interesting. One might also prefer that exogenous shocks be allowed to occur in markets and networks as well. This is reasonable. In this case, we can easily interpret the exogenous probability of defection as the *difference* between exogenous shocks in markets or networks versus hierarchies.

In our model agents join only one type of organization and play only one other agent in each round of the game (although they may be selected by other agents more frequently under selective affinity). In the real world, individuals may participate in many different social organizations nearly simultaneously, sometimes with the same partners. One might, for example, gain information from a neighbor about a new job opening, a form of networking, and serve on a community organization's board with that same person. In our model, such complex relationships are simply treated as separate rounds of the game and the conditions that lead one interaction to take place within a network and another to occur within a hierarchy are studied as variables. This analytic move simplifies but does not, we believe, unduly distort more complex relationships.

Similarly, agents in the model choose freely each round to join the organization that promises the highest expected payoffs to the game, given updated beliefs. For most social organizations this is a reasonable approximation. Individuals choose whether to ask associates about the reliability and political views of potential partners and to work for one corporation or participate in one civic association rather than another. Participation in other social organizations, especially some hierarchies like the state, is less purely voluntaristic. Individuals are "born" into a state, though they may choose to immigrate at more or less cost. Young boys may be forced to join militias, and can escape only at greater or lesser personal risk. Such presumed or forced memberships are admittedly not captured well in our model. One must be careful in generalizing our results to non-voluntary organizations. Even here, however, the model helps identify conditions under which individuals and, in turn, the population (or significant portions of a population) would choose to subordinate themselves to a hierarchy and, in so doing, collectively empower the hierarch to enforce his will--including governing participation--on reluctant others.[12] Conversely, the exit of all agents from a hierarchy approximates the loss of popular support for a political regime.

Finally, as endogenous products of the choices of many independent agents, organizations are created anew each round of play. Which agents constitute the market, hierarchy, or a network are established by their choices, which may differ by round. Social scientists often treat organizations as

[12] On the collective nature of authority and hierarchy, see Lake (2009a, Chapter 1).

sticky or long-lived while individuals are variable and short-lived. As our interest is in the origins and survival of different organizational forms, the assumption of a static population of agents seems to us to be a reasonable initial simplification. To the extent that organizations change the pattern of cooperation among agents, this will inevitably feed back upon the population in some dynamic evolutionary process. We intend to study selection and evolution in the future. But understanding how individuals choose one organization over another at any moment in time is a prerequisite to modeling this possibly more complex dynamic process.

Our ideal types and the model in general cannot capture all aspects of all interactions in all real world social organizations. We emphasize generality, but this inevitably carries some cost in understanding specific organizations and individual choices. Nonetheless, given the basic character of markets, hierarchies, and networks, their ubiquitous presence in the real world, and their similar treatment across very different academic literatures, we believe the model – even or perhaps especially in its highly simplified form -- has broad applicability.

III. Modeling Organizational Ecologies in an Agent-Based Framework

We describe the ABM here in its three stages: initialization, learning, and organizational choice. The model, along with the expected utility equations for each organization and full parameter scans for each variable, are detailed in the Appendix.

Initialization

The model begins with the specification of 24 user-defined parameters. These parameters and their default values, used in all the simulations presented below unless otherwise specified, are listed in Table 1. The default values for the parameters are admittedly arbitrary but are calibrated to make all organizational forms somewhat likely in any given simulation. By setting certain parameters higher or lower than our defaults, it would be trivial to simulate worlds in which either markets, hierarchies or networks always predominate or never arise. Instead, our defaults are set relative to one another at levels such that reasonable changes in any single parameter are likely to lead at least some agents to alter their organizational choices.

Table 1 About Here

Payoffs for the various outcomes are set: T, R, P, and S.[13] The user defines the population of actors, specifically the distribution of strategy types, and their preferences.[14] We focus on three basic strategies: all cooperate (ALLC), all defect (ALLD), and tit-for-tat (TFT). ALLC and TFT are *nice* strategies that begin by cooperating with new agents, while ALLD is a *nasty* strategy. Below, we refer to nice and nasty populations as defined by the relative proportions of these two sets of agents. Preferences (p_i) are defined over a [0,1] space and randomly assigned from a normal distribution.[15] The weight on preferences (w) can also be varied.

The organizational parameters are also set at this stage. Networks are defined by their width (α), the number of other agents each agent can directly ask about the agent it has been randomly paired with, and their depth (l), the number of levels of agents that are polled (a 3x3 ($\alpha = 3$, $l = 3$) network is illustrated in the Appendix). Although each agent has a potentially infinite memory of its own interactions with each other agent in the population, the network is limited to a fixed memory (m_n) defined by the number of previous rounds over which it can poll. That is, if memory is set at five, any agent can poll only those agents with whom it has cooperated in the last five rounds whether they have interacted with the other agent with whom it has been randomly paired in the current round. The longer the memory (the larger is m_n) for the network, the more useful information it returns to the agent.[16] Selective affinity is defined by the probability an agent gets to select an agent (η) from its memory (m_a) with whom to

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[13] We set the default cardinal payoffs in the PD game as in Axelrod (1984) for purposes of comparability. All other default parameters were then set relative to these default payoffs.

[14] In defining the strategy space, we build off of the now accepted space defined by Axelrod (1984) and others, including Cohen et al. (2001).

[15] We have no priors about different distributions of populations. For intuitive and analytical ease, we chose a normal distribution. We anticipate that the role of preferences will be amplified in deeply divided/bimodal societies, but in an effort to make this model as generalizable as possible we feel this is an appropriate assumption.

[16] In allowing an agent's own memory of past play and the network's "memory" to differ, we are essentially assuming that an individual's memory of others lasts longer than that individual's social interactions. This seems reasonable. Those of us who hold grudges and have only fleeting friendships typically remember others who have treated us badly in the past longer than we engage in sets of social relationships. This assumption is consequential only for the transient nature of networks discussed below. If agent memory were limited to the same as the network memory, networks would remain more robust over more rounds of the game. Conversely, without this restriction on network memory, the network would return "too much" information in early rounds and become obsolete almost immediately.

interact, with one minus this probability being the rate at which that agent will be randomly paired with another agent as in the base model ($1-\eta$). The fee for joining the network (ϕ) is also set.

A hierarchy is defined by its assigned ideal point (p_h), the probability that any agent will cooperate with other agents in the hierarchy (q), the penalty that is imposed on agents for defecting on other agents in the hierarchy (ν), and the tax assessed on members (τ). These parameters are common knowledge. Since the expected utility for joining the hierarchy is contingent on the number of other agents in the hierarchy (θ), in the first round of organizational play the user sets an "advertised" number of agents in the hierarchy, which need not be the same as the actual number of agents who join. In subsequent rounds, agents know the actual number of agents who joined the hierarchy in the previous round.

Learning

Agents begin the simulation without any knowledge of the distribution of the other agents' strategies or ideal points. In the learning phase, agents are randomly paired with other agents with whom they then play a round of the game according to their fixed strategy type with payoffs as specified. Agents develop beliefs about two parameters from their interactions with other agents. First, they learn about the distribution of other strategy types. Observing their own payoffs, they then back out whether the other agent cooperated or defected, store this action in memory by agent, and update a running estimate of the proportion of cooperators and defectors in the population (β_i). From this, agents learn whether the environment is relatively nice or nasty. Importantly, agents observe only the other's actions, limited to cooperation or defection, and not their underlying types. This is equivalent to not being able to observe an individual's intent or strategy, only what he or she actually does. Thus, each agent assigns and then subsequently updates for each agent it plays a single running probability of cooperation. Second, when they cooperate with other agents, agents also learn about the distribution of preferences in the population and whether their own preferences are relatively extreme or moderate. Again, knowing only their own preference, agents who cooperate with one another examine their payoffs and back out the ideal point of the other agent, store this knowledge in memory, and then update their beliefs about the mean ideal point in the population (Þ). In this phase of the simulation, agents are restricted to the knowledge they accumulate about other agents through direct play. Each agent develops unique beliefs over the course of play, meaning that even agents with the same strategy type and similar or identical ideal points will make different organizational choices in the next stage. This introduces heterogeneity of agents even within a fixed set of strategy types. Agents who believe the population is nastier than it really is are *pessimists* and agents who believe the population is nicer than in actuality are *optimists*.

Organizational Choice and Play

Once the learning period is concluded, the main simulation of interest begins and continues for a fixed number of rounds. In this phase, a round is defined by two actions: the organizational choice of each agent for that round and the actual play in that round. Agents begin each round by calculating their expected utility for joining each type of organization and select the one they calculate will yield the highest return.

The expected utility for market interactions is the same as an agent would get in play during the learning phase described above. Agents can choose to pay the cost to join the network (ϕ) of a known selective affinity (η), affinity memory (m_a), width (α) and depth (l) of agents with whom she has a history of cooperation in the last number of rounds as defined by memory (m_n). The expected utility from the network is essentially the likelihood that the player receives information about its current partner that changes its behavior plus the likelihood it does not and the likelihood that the agent gets to select its partner from memory, less the fee imposed to join the network (ϕ). The utility for entering a hierarchy will depend on the proportion of the population in the hierarchy the player will join (θ), weighed against the likelihood of cooperation within the hierarchy (q), the punishment for defection (v), the tax (τ) and the ideal point of the hierarchy (p_h).

After agents choose the organization they will join for that round, the next stage is actual play within each organization. If a player selects the market it plays its fixed strategy. For non-contingent strategy types (ALLC and ALLD), information from the network is irrelevant, since they play the same move regardless of the type of other agent. Without selective affinity, such agents never choose to join the network even at zero cost. Since only contingent strategy types (TFT) can potentially benefit from information on other agents, only these agents will consider joining the network in the absence of selective affinity. If an agent selects the network, it will query the specified past cooperators about the agent with whom it has been randomly paired and be given a number [0,1] representing the probability of cooperation to expect from that partner. If that agent believes the other agent is likely to cooperate (the probability is ≥ 0.5), it will cooperate, otherwise the agent defects. The information returned from the network is treated as equivalent to the agent's own beliefs about the randomly paired agent acquired through direct play. That is, if agent *i* has no past play with agent *j*, and it receives a signal from the network that *j* cooperates with a probability of 0.7, it will update its belief about *j*'s type to 0.7. Similarly, if *i* believes on the basis of a single past interaction that *j* cooperates 1.0 and it receives a signal from the network that *j* has cooperated with five networked agents at a rate of 0.7, it revises its belief about *j* to 0.75—weighting its own experience equally with those received from the network. In this way, we assume that all agents are sincere in their reporting and are known to be so by all other agents.[17] If an agent joins the network and is given by nature the opportunity to select its own partner (η), it chooses the agent within memory (m_a) with whom it earned its highest payoff in previous rounds. If the agent chooses to join the hierarchy, its play depends on whether or not it is matched with another player in the hierarchy. If the two players belong to the same hierarchy, the agent will cooperate at the rate that the hierarchy enforces (q). If the agent defects ($1-q$), it will be punished at the defined level (v). If a player is matched with a player outside of its hierarchy, it will play as if it were interacting in the market.

[17] This is an important assumption. If agents lie or even communicate poorly (e.g., perform the kinds of minor distortions familiar to children from the "telephone game"), networks may actually harm rather than increase utility by causing contingent players to engage in bouts of mutual punishment. See Downs, Rocke and Siverson (1986). In this version of the model, we do not discard or discount redundant responses from the network. Intuitively, in real interactions we often do not know exactly where a friend of a friend received their information about some other actor. Given that the strategy types we examine here are pure, this assumption has no consequence for any of our results.

Following play, real payoffs are calculated as a function of the outcome of play, adjusted for the players' ideal points (*k*) if the outcome was cooperative, punishments, and fees prescribed by their organizations. Actual payoffs can differ from expected payoffs, but are on average the same.

We are primarily interested here in the organizations selected overall and by specific strategy types under varying parameters and the real payoffs of the agents. Our strategy is to simulate organization choice and payoffs under varying conditions by incrementing the selected parameter values over some range (scans of all parameters with different population mixes are reported in the Appendix). Incrementing one parameter at a time is roughly equivalent to comparative static predictions in closed form models. Because several parameters are randomly assigned according to specified distributions in the initialization phase, and agents are randomly paired at each round of play in both the learning and organizational phases (unless in selective affinity), no two simulations will be identical. For the results below, unless noted otherwise, we replicate the simulation 25 times for each increment of each parameter and report the average of the results.[18]

III. Illustrations of the Model

Like others, our ABM "is a way of doing thought experiments" that, because of complex interactions, may have non-obvious conclusions (Axelrod 1997, 4). We illustrate the potential of the ABM to generalize cooperation problems by briefly summarizing simulations that capture core features of three disparate literatures in political science. Our model reveals theoretical limitations and inconsistencies in existing theories. In the case of transnational networks, for instance, we focus on the information value of networks and find that, contrary to much of the existing literature, networks rapidly decline in use. Selective affinity causes networks to be robust, on the other hand, suggesting it is not information but the opportunity to select partners which sustains networks in everyday life. By

[18] Despite the number of replications, the results reported below in graphs are not always smooth functions due to the discrete increments of the parameters. Each run of the model creates a large number of observations. We are limited by the number of increments for each variable versus the number of replications we can perform. In the Appendix, we present Figure A2 with 95 percent confidence intervals plotted around the result. As this figures demonstrates, additional replications are unlikely to produce significantly different results. Since confidence intervals make already complex graphs harder to read, we do not include them in other figures.

highlighting interaction effects and population dynamics, the ABM also offers new explanations for phenomenon absent from purely verbal and even two-player, closed-form formal models. In the case of social capital, we show the value of population models in explaining phase shifts in behavior now unexplained in the literature. Finally, the model generates new theoretical insights. Again, in the social capital literature, we demonstrate how hierarchy is a viable alternative to social networks, and may more accurately characterize modern American society than market interactions. Similarly, in a simple depiction of the emergence of political hierarchy, we not only derive the core logic of Hobbes's *Leviathan* from the model but show how hierarchy can emerge even when the ruler has preferences that are extreme or distant from the mean of society. This produces important insights into the nature of autocratic rule.

Transnational Networks and International Governance

Transgovernmental networks (TGNs) are, Anne-Marie Slaughter (2004, 8-11) claims, the solution to the governance dilemma created by a need for global institutions and a continuing fear of centralization.[19] According to Slaughter, TGNs have become prominent in coordinating central banking, corporate regulation, the international legal system, and more. Such transnational networks are, in her view, not only a building wave but also an effective solution to the absence of hierarchical, authoritative institutions in world politics. Although TGNs do many things, in Slaughter's (2004, 3) view, primary among them are creating "incentives to establish a good reputation and avoid a bad one" and exchanging "regular information about their own activities and…best practices."

Transnational economic networks (TENs) are also seen as key to economic growth and governance. In his monumental study of the Maghribi traders, entrepreneurs active in long distance exchange around the Mediterranean in the 11th-14th centuries, Avner Grief (2006, 59) finds two attributes were central to their success: the linking of each agency transaction to all future agency transactions with other merchants in the network – in a word, reciprocity – and information sharing on agents among the

[19] See also Raustiala (2002), Eilstrup-Sangiovanni (2009). For a related view emphasizing transparency, often through networks, see Florini (2003).

merchants.[20] Similarly, as Hendrick Spruyt (1994, 123) notes, one of the key tasks of the Hanseatic League, a medieval network of city states engaged in international trade, was "to facilitate the exchange of information between merchants." These same traits are key to the efficiency of Japan's corporate networks in the modern era (Lincoln and Gerlach 2004). In their emphasis on information sharing, TENs are essentially similar to TGNs.[21]

Even though our ABM is not identical to any specific network in these different literatures, it captures the essence of networks as governance structures in its focus on information sharing and reciprocity. Demonstrating much of the promise of transnational networks, our model nonetheless suggests that the conditions under which networks will be preferred to markets and hierarchies are contingent in ways not yet appreciated by the networks literature. We focus on two key limitations of networks here not because we dispute the literature's depiction of their benefits but because this is where the ABM reveals further theorizing is most necessary.

Networks as a source of information only quickly become obsolete with time (rounds of the game). In our characterization, agents acquire information about the strategy type and ideal point of another agent directly through interactions or indirectly through the network of agents with whom they have cooperated in the past. Networks are valued for the information about other agents they can provide that is not already possessed by the agent. As agents acquire knowledge of other agents through their own interactions or the network, the value of the network declines. At an extreme, after an agent has interacted with or acquired knowledge through the network about every other agent in the population, the network can return no new information of value to that agent; if there is any cost to belonging to a network, agents will then choose some other organizational form (see Figure 2a). Paradoxically, the larger the network relative to the population—making it more beneficial and attractive in early rounds of the game—the

[20] Another well known model, Milgrom, North, and Weingast's (1990) "law merchant," possesses attributes of networks, in its use of strategies of reciprocal punishment, and hierarchy, in its centralized dissemination of information. Their analysis becomes a true network only if the law merchant is depicted as a central node to which all other nodes are directly linked.

[21] Transnational advocacy networks (Keck and Sikkink 1998) are related but slightly different in that the information being shared is not about other members of the network but the states and their practices that are the targets of political change.

more quickly it becomes obsolete (not shown). Transnational networks may be initially useful in coordinating diverse actors, but all else held constant their utility declines over time as the actors become more familiar with one another.

Figure 2 about here

Similarly, the larger the population, the less likely networks are to be selected by agents (see Figure 2b). It might seem that larger populations favor networks as it takes more iterations of the game for agents to acquire direct knowledge of other agents and, therefore, networks are more valuable. Yet, for networks of a given size, larger populations also mean that the network is less likely to return information useful to the agent about the agent with whom it is randomly paired.[22] In very large populations, "small" networks are of little value and, therefore, will not be chosen by agents. This suggests that networks may develop among, say, the functional ministers of relatively small groups of countries, such as the G8, but not among broader groups like the G77 or all UN members. Likewise, networks may function effectively among small groups of traders, like the Maghribi or Hansa, but not among all traders in a region. More generally, the limited informational benefits of networks in large populations helps explain why very large numbers of individuals are governed in hierarchies, like states, rather than in more informal, less centralized networks.

In contrast to the informational benefits of networks, selective affinity produces robust networks that persist indefinitely (see Figure 3a). With a small chance of selecting a partner, agents leave the network due to the declining value of information relatively quickly (solid line), but with higher rates of selective affinity agents join and stay in the network for the dyadic cooperation it sustains (dashed lines). As might be expected, ALLC and TFT agents join the network in hopes of getting to select a partner with whom they have cooperated in the past, an effect that does not diminish as learning occurs. Selective affinity also offsets the size effect just noted (see Figure 3b). This confirms the relatively optimistic view

[22] The probability of a network returning a useful reply is $\left(\frac{m}{n-1}\right)\left(\sum_{y=1}^{l}\beta\alpha^{y}\right)$. As n increases, the probability falls. In all cases, allowing redundancy reduces the probability of a useful response. In the model, we do not adjust the expected utility of networks for redundant responses.

in much of the literature on transnational networks. As expected by their proponents, in both transgovernmental and transnational economic interactions, networks are an effective facilitator of cooperation. It also suggests that observed networks that endure for long periods are more likely founded on gains that arise from selecting one's partners than from information.

Figure 3 about here

Paradoxically, however, selective affinity also carries a "dark side." With selective affinity, nasty agents will also choose to join a network in anticipation of "suckering" or exploiting agents who cooperated with them in past plays of the game (not shown).[23] These nasty agents become essentially schoolyard bullies who identify and repeatedly then "pick on" a victim, especially ALLC types who cannot retaliate in future rounds. Examples abound in transnational terrorist and criminal networks that intimidate locals into providing resources and intelligence (see Kahler 2009b, Kenney 2009). This dark side of networks is not anticipated in the literature. Selective affinity both sustains networks and drives some nice strategy types who would otherwise remain in the network into the hierarchy. Repeatedly victimized by nasty agents, nice agents eventually update their beliefs and perceive the world as nastier than it really is and escape to the hierarchy for protection.

The optimistic expectations of proponents of transnational networks should be treated with a degree of caution. The question is not whether networks substitute for alternative forms of governance but, rather, what are the ranges of conditions under which networks will be selected. As the declining benefits of information within networks suggests, these conditions may be more restrictive than they first appear. In addition, networks may not only facilitate cooperation but create opportunities for exploitation. These findings suggest that more attention needs to be paid to the details of any specific network before assessing its overall effects on cooperation.

[23] This dark side of networks, of course, is a product of the inability of victims to decline to interact with the agent who has selected them. If agents could opt out of interactions, this effect would go away and only the cooperative effect would endure. However, all agent-based models of cooperation have this similar "involuntary" structure and, more important, much of politics is involuntary as well. When North Korea acts aggressively toward South Korea – sinking the Cheonan, for instance -- the latter has no choice whether to interact with the former as even failing to respond explicitly is a response.

Networks and Social Capital

In 2000, Robert Putnam published a path-breaking study on the decline of social capital and civic engagement in the United States. For Putnam (2000, 19), "the core idea of social capital theory is that social networks have value." As he elaborates, "social capital refers to connections among individuals – social networks and the norms of reciprocity and trustworthiness that arise from them." If social capital is at its core a social network, as Putnam indicates, our ABM may shed light on this sea-change in American society.[24] Indeed, although our model is designed to capture the general effects of organizational forms on cooperation and not specifically to represent Putnam's theory, it nonetheless has important implications for understanding the decline in social capital and alternatives to social networks.

We can model the decline of social capital within our ABM in four ways, each of which captures slightly different dimensions of Putnam's analysis. First, several of the causes of the decline of social capital identified by Putnam can be represented as an increase in the costs of joining a network (see Figure 4a). Specifically, the pressures of time, money, and suburbanization, and the pull of electronic entertainment, can all be understood as increasing the opportunity costs of networking. As Americans work longer hours to earn more money while commuting longer distances and face more attractive alternatives for their shrinking leisure time, the effort spent building or maintaining social capital has a higher opportunity cost. Our cost of joining a network captures this opportunity cost directly. Although this result is straightforward and predictable, it is consistent with Putnam's description of change in American society over the last decades. As the cost of joining a social network has increased, more transactions occur in anomic markets or law-based hierarchies. Figure 4b demonstrates that as the costs of joining a network increase, agents of all types leave the network and join the market or hierarchy. Less intuitively, nicer agents leave the network first and nastier agents, who benefit from the ability to exploit

[24] Putnam's empirical claim that social capital has declined in the United States is contested. For an example, see Paxton (1999). We sidestep this debate and, for purposes of this analysis, accept Putnam's general description as correct. Our interest is more on the theoretical side in clarifying whether his conclusions about the effects of declining social capital actually follow from this theory.

others via selective affinity, leave the network last (see Figure 4b). This again shows the dark side of networks and is not predicted by Putnam or others.

Figure 4 about here

Second, the decline of social capital, or the perception of decline, can be represented by increasing the proportion of nasty strategy types in the population (see Figure 5). As social capital erodes, individuals perceive others as less trustworthy and less likely to reciprocate cooperation. In short, they perceive others as less likely to be nice strategy types and more likely to be nasty types. Although in our model the beliefs of agents will eventually converge on the true distribution of strategy types in the population, for any given agent its beliefs are the product of its "lived" experience of interacting with other agents. This is, we believe, a close analog to the perceptions of individuals about the changing social world they inhabit. As the proportion of nasty strategy types in the population increases, TFTs leave the network and join the hierarchy to protect themselves through centralized enforcement.

Figure 5 about here

Third, the increasing opportunities for interaction with others through both an increasingly integrated national market and declining transportation and communication costs, implicit in Putnam, erode the utility of social capital. While it may be possible to know everyone within a small community – or at least know someone who knows someone who knows the relevant individual – this is increasingly difficult to maintain as individuals are pulled by opportunities outside that community. We can represent this increasing opportunity structure, as above, as an increase in the population of agents (see Figure 3b). We see again the same pattern of an increasing population leading TFTs to leave the network and join the hierarchy.

Finally, a decline in social capital may also be associated with a reduced ability to select partners for interaction within the network. As with population, in a larger and more integrated society the ability to select particular agents with whom you have interacted in the past may erode as opportunities expand. As selective affinity declines, agents again leave the network more rapidly (compare the 25 and 50 percent lines in Figure 3a).

All four ways of modeling the decline of social capital point in the same direction: contingent strategy types begin in the network, and then move into the anomic market, as predicted by Putnam, or hierarchy. Agreeing with the general pattern he outlines, the model nonetheless helps to resolve a key tension in Putnam's analysis. To explain why social capital has declined in the United States, Putnam examines, as we have seen, the effects of longer working hours, suburbanization, electronic media, and other causes. Putnam is restrained in his conclusions on these possible causal variables, however, because all appear to be gradual and incremental changes but the decline in civic engagement is sharp and dramatic. All of our representations of social capital, on the other hand, have non-monotonic effects on network membership that produce a phase shift brought on by very small changes in the relevant parameters. These effects follow from population dynamics that interact with agent attributes to magnify the effect of changes on network joining. Putnam is trapped by his implicit assumption of monotonic effects. Even in our simple depiction of a social system, the interactions are sufficient to create phase shifts in network membership.

Although resolving this key empirical puzzle, our analysis also suggests that Putnam's alternatives to social networks are drawn too narrowly. Although he is correct to see markets as an alternative to networks, hierarchy is also an option, and increasingly so as network costs, the defection rate in the population, and population size increase and selective affinity decreases. Indeed, if the population is sufficiently nasty (see Figure 5), nearly all TFTs will leave the network for the benefits of centralized enforcement of cooperation. This may be what we are witnessing in the United States today. Accepting Putnam's description of the decline of social capital, we see individuals insulating themselves from opportunism by turning to the centralized, legal enforcement mechanisms of the state. Rather than relying on a personal relationship with a local business owner, for example, bankers today depend upon standardized credit reports, contracts, and legal penalties for breaches. As is frequently observed, the United States has become a significantly more litigious society. One way to interpret this is that networks are being displaced by not only the market but also various forms of hierarchy.

The consequences of Putnam's slighting of more hierarchical alternatives are brought into sharper relief in a final set of simulations in which we vary all four representations of social capital at the same time. In Figure 6, we increase simultaneously population size, the cost of joining the network, and the proportion of nasty players in the population while decreasing the rate of selective affinity. This captures the decline of social capital in all forms and along all dimensions. The effects here are quite distinct from the single dimension, comparative static results in Figures 3b, 4a, 5, and 3a. As we increase all four parameters concurrently, hierarchy becomes the dominant organizational form at lower values of each parameter and displaces markets as the likely alternative (compare especially Figures 4a and 6b). In a large, nasty population in which joining networks is costly and selective affinity is declining, virtually all TFTs join the hierarchy and remain there. The interactive effects of our four representations of the decline of social capital strongly drive agents away from markets and networks and into hierarchies. If such interactive processes are at work in the United States today, this may explain why and how "small town" America has given way so dramatically to a legalized form of enforcement over the last generation.

Figure 6 about here

What then are the welfare implications of these changing organizational ecologies? Putnam clearly expects a world of markets or hierarchy to produce less welfare for individuals and society than a world of social networks. It not just nostalgia that leads him to highlight the virtues of social capital, but a fear that markets or, by our extension, hierarchy will leave all less well off than in the past. In all of our representations of declining social capital, however, a similar pattern emerges in which payoffs in hierarchy are higher than in markets and payoffs in markets are generally higher than in networks (see Figures 6d-f; payoffs for the single-parameter simulations reported in Figures 3-5, not shown, are similar).[25] The welfare benefits of hierarchy are clearly inconsistent with Putnam's expectations about the effects of declining social capital. In Section IV of the book, Putnam describes a variety of ways in which the welfare of Americans has declined as social capital has decayed. Our analysis suggests that agents

[25] The small number of agents selecting markets in this simulation causes payoffs for these agents to be especially unstable.

may be better off under hierarchy in a world with less social capital than in networks in a world with greater social capital. Participating in a network is costly. Hours spent in a bowling league cultivating social ties and trust are hours not spent doing something else – including time with one's family or possibly acquiring greater human capital. Moreover, in worlds with very little social capital, agents are driven into the hierarchy where they are then subject to punishment for defecting on other members of the hierarchy, thereby creating a virtuous circle that leaves members better off, paradoxically, than they are in worlds with more social capital. The alternatives to social networks are not only a "Hobbesian" market of declining of cooperation, but also a civil society governed by a ruler who enforces mutually beneficial cooperation under the threat of punishment.

Hobbesian Hierarchy, or Why Don't Men Rebel?

Hierarchy is common in social life. It has been explained as an innate characteristic of individuals or societies (Michels 1966, Dumont 1980, Sidanius and Pratto 1999), a function of initial social inequalities (Diehl 2000, Godelier and Strathern 1991, Sahlins 2000), a form of socially constructed power relations (Gramsci 1971, Foucault 1977, Barnett and Duvall 2005), or an institutional solution to collective action and contracting dilemmas (Coase 1937, 1960, Williamson 1975, 1985). Our ABM suggests an approach in which hierarchy is an emergent property of the choices of many egoistic actors. As already indicated in the discussion of social capital, given a sufficiently nasty population, agents join a hierarchy and submit to its possible punishments in order to secure the benefits of cooperation it facilitates. By enforcing cooperation between agents, hierarchy improves their expected utility such that they chose to subordinate themselves to third party rule. Our ABM is, in some ways, a computational representation of Thomas Hobbes' classic argument for *Leviathan*. Nonetheless, the model has several surprising implications.

First, counter-intuitively, as a population becomes nastier, it is the nicer types of agents that join the hierarchy first, and the nastiest types who join last (see Figure 7a). A naïve expectation might posit that the ALLD agents would join the hierarchy first, as this is the only way they can escape mutual defection with one another and informed TFTs. However, there is another, countervailing process occurring simultaneously. Left to otherwise fend for themselves in the market, ALLC types are increasingly exploited by ALLDs as the latter increase as a proportion of the population. ALLCs join the hierarchy not because they are uncooperative players but precisely because they no longer have sufficient opportunities to interact with other cooperative agents. TFT types draw upon the information in the network and then their own knowledge of other agents to protect themselves from being suckered by ALLD types. Less vulnerable to exploitation, TFTs "hold out" until the population gets even nastier but eventually join the hierarchy as well. In contrast to the naïve expectation, ALLDs are the last type of agent to join the hierarchy because they benefit from exploiting others in the market. In the end, for at least the most optimistic ALLDs in our simulations, the expected benefits of defecting on the ALLCs outweigh the gains they would otherwise anticipate from cooperating under hierarchy. This pattern is magnified the higher is the rate of selective affinity. Paradoxically, in an increasingly nasty world, net payoffs increase on average for ALLC and ALLD agents and remain relatively constant for TFTs (see Figure 7b). Interestingly, even the ALLD agents achieve their highest average payoffs when the majority of them enter the hierarchy. This is, again, consistent with Hobbes's view that individuals subordinate themselves to the Leviathan to escape the state of nature and improve their welfare.

Figure 7 about here

Second, the ABM also explains why hierarchies can be stable over long periods. By design in the ABM and by analogy to the real world, within a hierarchy agents do not learn anything about the strategy types or ideal points of other agents in the hierarchy. If both are in the hierarchy and agent *j* cooperates with agent *i*, *i* cannot learn whether *j* cooperated because it "wanted to" or did so only under threat of punishment. Having joined the hierarchy because it believed the population was sufficiently nasty, *i* then has fewer opportunities to revise its beliefs. Perversely, given these fewer opportunities, agent *i* will actually develop more skewed beliefs that lead it, over subsequent rounds, to believe the population is nastier than it really is, reinforcing its initial choice of hierarchy. Unable to learn from others in hierarchy, agent *i* nonetheless continues to interact with randomly paired others in the market and, as we see in Figure 7, these others are likely to be disproportionately nasty, leading *i* to update its beliefs with increasing bias. In this way, agents and, in the real world, individuals get locked into hierarchy and become complicit in the perpetuation of their own subordination.

The emergence of hierarchy may be most counter-intuitive when the hierarchy is autocratic, or when the hierarch has an ideal point that is "extreme" within the population and, by analogy, cannot stay in power simply because he reflects broadly shared preferences. It is on this point that our modification to the standard PD game (see Figure 1 and accompanying discussion above) becomes perhaps most important. Autocracy is one of the great unexplored frontiers of political science. Although there are many insightful and informative case studies, they have largely failed to cumulate into a theory that explains when autocracies are likely to arise and why they persist as often and as long as they do. General theories of autocracy, to the extent that they exist, fall into at least one of three approaches. The first treats autocracy as a default condition or almost a natural state that itself requires no real explanation. Rather, analysis focuses on the fragile nature of democracy and the determinants of successful democratic transitions (see Przeworski 1991 and Przeworski et al. 2000). A second approach, exemplified by the selectorate model of Bueno de Mesquita et al. (2003), focuses on the means by which a ruler satisfies a minimum winning coalition. How the selectorate succeeds in deterring challenges or even revolution "from below" is left implicit.[26] A third approach posits that the masses who might otherwise rebel are repressed by the coercive power of the state (see Wintrobe 1998). In this view, successful autocrats divide and conquer the subject population to thwart collective action, promote false ideological and normative appeals to persuade individuals that others support the government, and repress dissidents who might otherwise rally the masses to stand up to the regime. All these approaches agree, however, that autocrats do not rely on popular support and reflect the political preferences of a smaller group within the population. We represent different regime types in our ABM by varying the hierarch's ideal point. The more "extreme" the hierarch's preference relative to the population, the more "autocratic" the ruler is likely to be.

[26] For an effort to deal with this problem within the same model, see Bueno de Mesquita and Smith (2007). For another variant, see Acemoglu and Robinson (2006).

Our model, in turn, suggests that autocracy can emerge due to the cooperation it facilitates even when levels of distrust within the population are high. In Figure 8, agents and especially the ALLC strategy types join the hierarchy unless its ideal point is very far from the median. In this model individuals choose not to exit the hierarchy or "rebel" – and indeed, voluntarily subordinate themselves to a hierarchy even with extreme preferences -- because the coercive power of the state is believed to be the only mechanism for ensuring cooperation in a sufficiently nasty population. This implies that autocracy is most likely when many individuals believe others will exploit them or do not trust one another to cooperate in market or even networked interactions. In other words, hostile environments in which agents are sincerely nasty or believed to be nasty are likely to be organized as autocracies. This further implies that autocratic hierarchs drive wedges between individuals and groups not to suppress collective action, as traditionally understood in the notion of divide and conquer, but to exacerbate the lack of trust otherwise necessary for self-enforcing cooperation in markets or networks.

Figure 8 about here

Conclusion

Like all theories and models, ABMs are only as useful as the empirically supported, non-obvious propositions they generate. In this article, we limit our empirical applications to the established work of others. The obvious propositions generated by the model largely serve to validate our ideal types of markets, hierarchies, and networks and, equally, our implementation. The non-obvious propositions show the promise of the ABM and, especially, the value in studying population dynamics. Striking in our view, is the declining utility of networks over time and in large populations. To our minds, the biggest "surprise" of the model is that as the population becomes nastier, agents of all types are more likely to enter the hierarchy and, furthermore, nicer types will enter the hierarchy before nastier types. Possibly obvious once stated, this was certainly not a proposition that we anticipated before developing the basic architecture of the model. Indeed, it was not until we ran the model and saw this consistent pattern that we understood the exploitation that occurs in the market and explains this result.

Building off a relatively simple conceptualization of cooperation has produced new and, we think, important insights into the conditions under which networks are preferred governance structures. These insights, we believe, reveal assumptions about networks left implicit in existing literatures on networks and social capital. This same conceptualization offers a fresh if somewhat disturbing perspective on the emergence of hierarchy in sufficiently nasty populations and provides a new explanation for the persistence of autocracy.

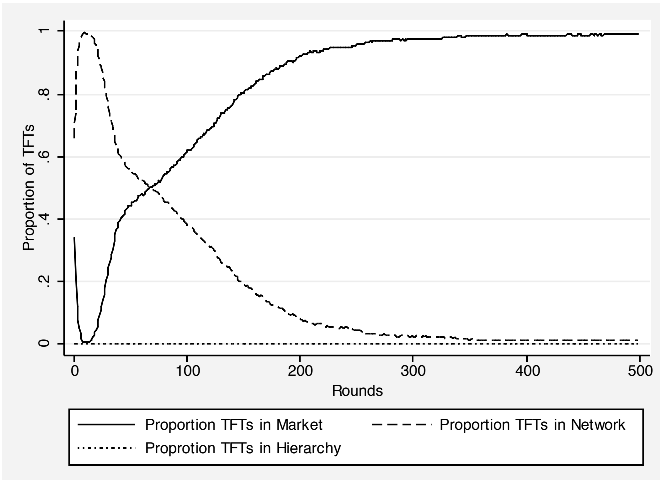
A key but also unexpected finding of the model is that different organizational forms will often co-exist across a broad range of parameter values. That is, different agents (even of the same strategy type) will join markets, hierarchies, or networks at sufficient rates to sustain multiple forms of organization at the same time. Indeed, it is only under relatively extreme values of the parameters that one organizational form will ever triumph over the others. This suggests that research ought to shift, first, from assessing the superiority of markets, hierarchies, and networks to determining superiority for whom, when, and why and, second, from organizations to organizational ecologies so as to understand how different forms complement, compete, and survive in different populations and environments.

Figure 1. The modified prisoner's dilemma game

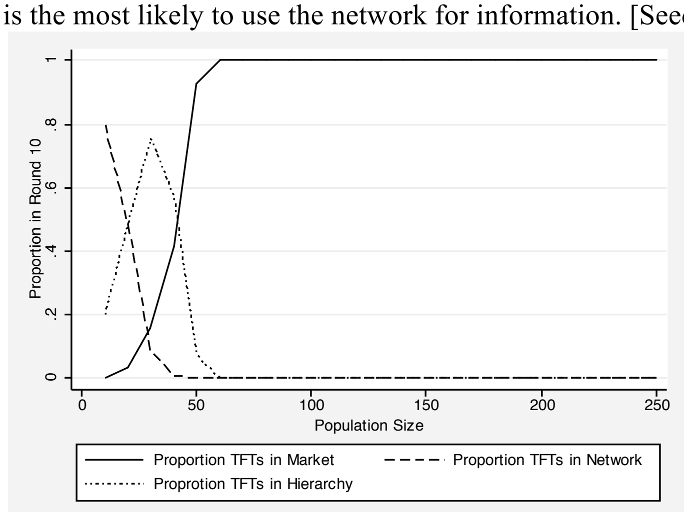
		Agent j	
		C	**D**
Agent i	**C**	**R-k, R-k**	**S, T**
	D	**T, S**	**P, P**

k = k_{ij} for markets and networks,k_{ih} for hierarchies

Figure 2. Declining network and Population Size.

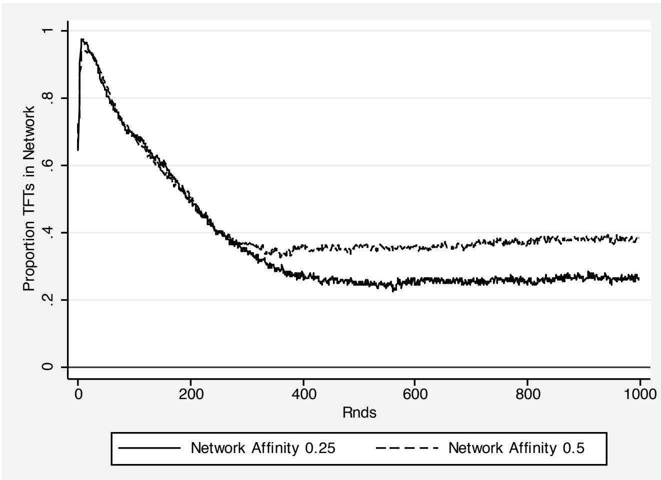


Panel a. Declining network in a nice world. TFTs quickly leave the network. The population used for this simulation—a contingent, but predominantly nice one composed of 90 TFT and 10 ALLD agents—is the most likely to use the network for information. [Seed: 703250. 10 repetitions]

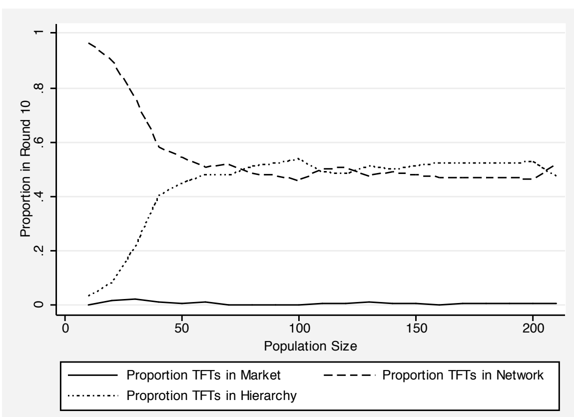


Panel b. Population size and TFT Organizational choice. As population size increases, TFTs leave the network and choose other organizational forms. This population is 40% cooperative types (30% TFTs, 10% ALLCs) and 60% ALLDs. Hierarchy is very sensitive to the number of members in small populations. At all population sizes, TFTs that go into the hierarchy believe the world is significantly nastier than those that go into the market after leaving the network (t= 95.64, df = 194998, t<0.0001). In nicer populations, TFTs generally leave the network at similar rates but interact only in the market. [Seed: 143944 10 reps, population size increases by 3 TFTs, 1 ALLC, and 6 ALLDs with each increment]

Figure 3. Declining network and Population Size in a world with Affinity.

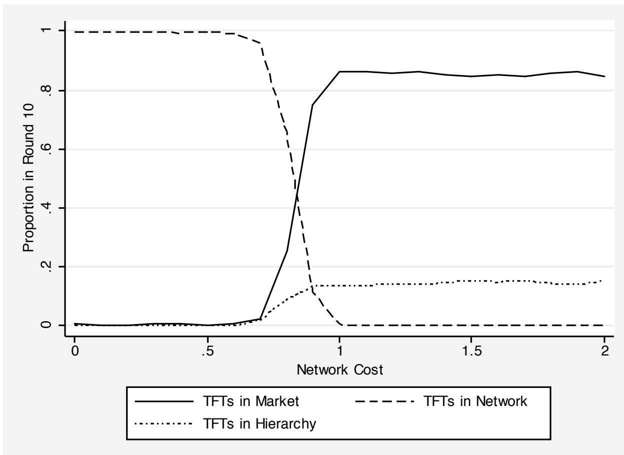


Panel a. Network decay in a world of affinity. In an identically composed population to that in panel 2a, affinity in the network is enabled, first at 25%, then at 50%. The higher the rate of selective affinity, the larger the proportion of TFT agents that remain in the network even after the information value has "worn off." [440670; 820864. Net Cost 0.75; 5 replications; 10 ALLDs, 90 TFTs]

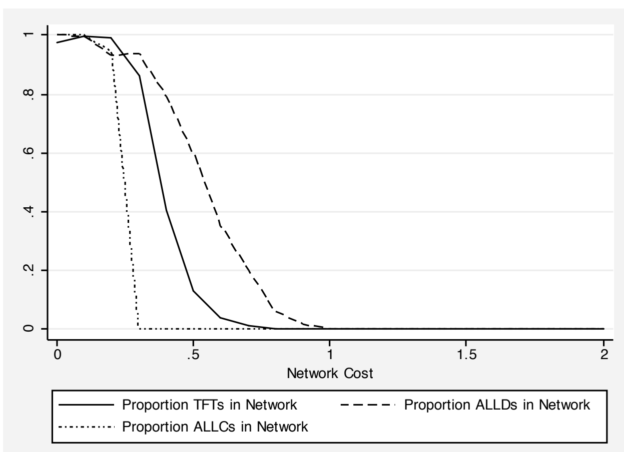


Panel b. Population size and TFT organizational choice. Proportion of TFT strategy types in each organizational form. As population size increases, TFTs leave the network and choose other organizational forms (either the market or network). Population is identical to that in Figure 2b. At all population sizes, TFTs that go into the hierarchy believe the world is significantly nastier than those that go into the market after leaving the network (t= 410.7722, df = 923998, t<0.0001). In nicer populations, TFTs generally leave the network at similar rates but interact only in the market. [Seed: 677586 40 iterations 10 reps, population size increases by 3 TFTs, 1 ALLC, and 6 ALLDs with each increment;]

Figure 4. Costs of joining a network and TFT organizational choice

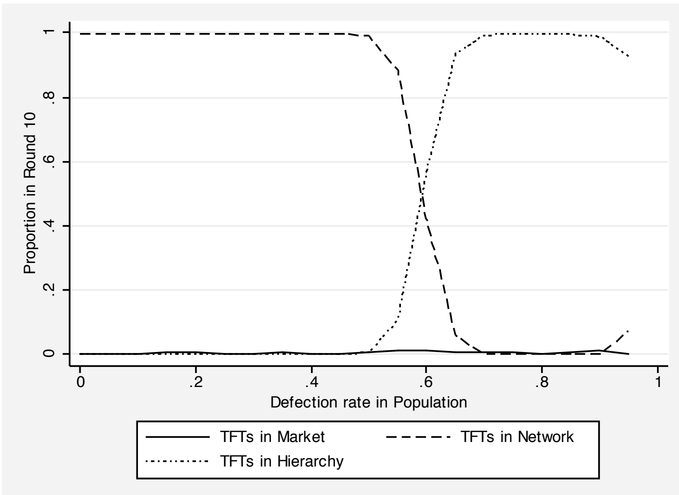


Panel a. Proportion of TFT strategy types in each organizational form. This population is composed of 15 ALLD, 15 ALLC, and 70 TFT agents, the network fee is increased from 0 by 0.1 at each of the 21 increments. Increases in network costs drive agents into the market or hierarchy. [Seed: 77092]



Panel b. All agent types choosing network. As cost of joining network increase, all strategy types leave network and join hierarchy, with nicer agents leaving first and nastier agents leaving last.

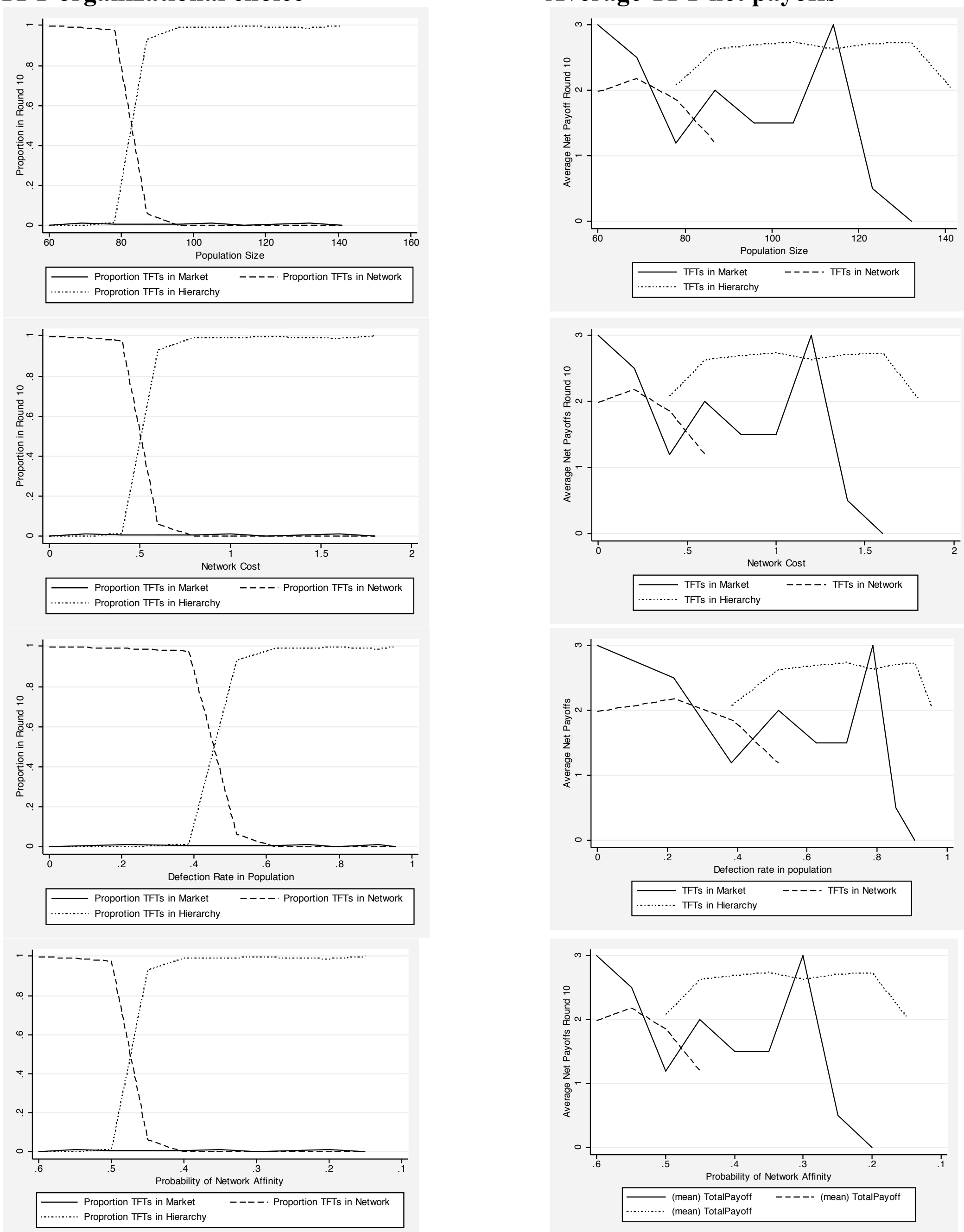
Figure 5. Proportion of nasty strategy types in population and TFT organizational choice



Proportion of TFT strategy types in each organizational form. This simulation begins with a world of 100 TFTs (reduced by 5 at each of the 21 increments), and 0 ALLDs (increased by 5 each increment). As the proportion of nasty strategy types increases in the population, TFTs exit the network and move predominantly into the hierarchy. [Seed 334396; HPC .99, incremented 21 times]

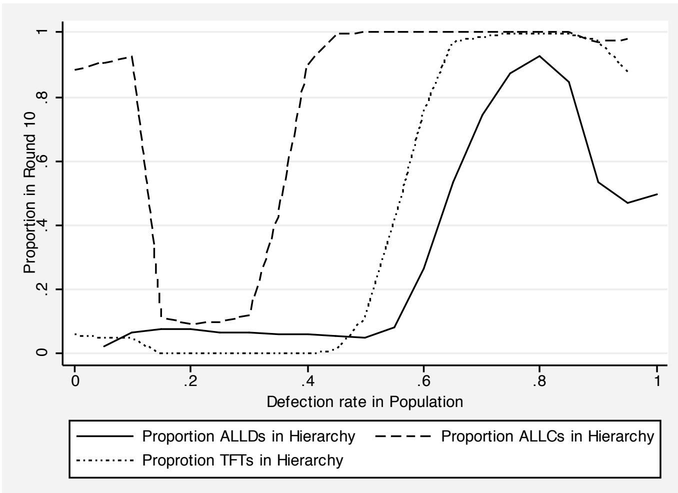
Figure 6. Multi-dimensional simulation

TFT organizational choice **Average TFT net payoffs**

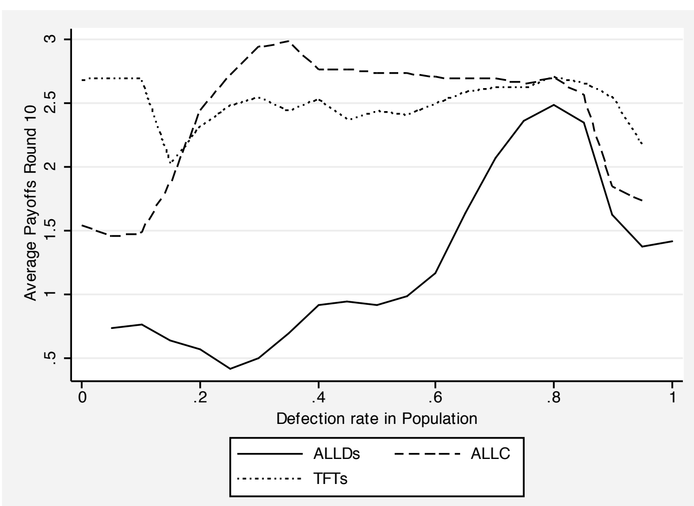


The figures on the left are similar to those from Figures 3a, 4a, 5, and 3b but increase all three dimensions simultaneously. The effect is to produce a substantially larger and nastier world with less affinity in which TFTs choose to join the hierarchy at much higher rates than when varying only a single dimension. The figures on the right are the payoffs to TFT agents in each organizational form. Note in panels on the left, agents join the market only in very small proportions scattered across the range. Payoffs are actually calculated for those segments but graphed over the complete range, and averaged across comparatively fewer players, accounting for the relative volatility of those payoffs. [Seed: 336839. Network cost incremented from 0 at a rate of 0.2, Initial population is 40 TFTs with 4 removed with each increment, 20 ALLCs with 2 removed each increment, 15 ALLDs added with each increment, Network Affinity is decremented from 0.6 by 0.05.]

Figure 7. Proportion of different strategy types joining hierarchy as the population becomes increasingly nasty

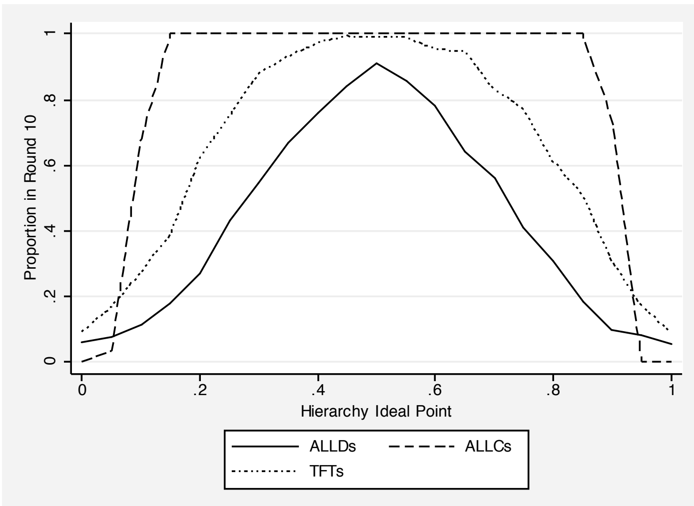


Panel a. Proportion of each strategy type choosing hierarchy. ALLCs are the first to join the hierarchy as the proportion of nasty strategy types increases in the population, followed by TFTs and then the most pessimistic ALLDs. After all of the "nice" agents are in the hierarchy, some ALLD agents return to the market to try to sucker the ALLCs and TFTs. Population begins with 40 ALLCs, 60TFTs, and 0 ALLDs. At each increment, the number of ALLDs increases by 5 and the number of ALLCs and TFTs decrease by 2 and 3 respectively. [Seed 960552; 21 iterations.]



Panel b. Net payoffs by strategy type in hierarchy. Average net payoffs for all agents increase as the proportion of agents in the hierarchy begins to rise. The decline in payoffs in the nastiest populations is due to the mutual defection of ALLDs that have moved from the hierarchy back to the market.

Figure 8. Proportion of each strategy type joining hierarchy as hierarch's ideal point varies.



This is a relatively nasty population of ALLD = 70, ALLC = 10, and TFT = 20 agents, corresponding roughly to the point where all TFT agents enter the hierarchy in Figure 7. Ideal points of agents are normally distributed with a mean of 0.5. As the hierarch's ideal point moves toward either extreme (closer to zero or closer to one), fewer agents joint the hierarchy. Importantly, however, except for very extreme values, agents still join the hierarchy for the cooperation it facilitates. As seen above, the nice agents, TFTs and ALLCs, enter the hierarchy first and at high rates; nasty agents enter later, and enter in the largest proportions when the hierarchy's ideal point is very close to the population mean. [Seed 936725, Hierarchy's ideal point incremented from 0 by 0.05 over 11 iterations.]

Table 1. User defined parameters and default values.

Parameter	Symbol	Description	Default Value
General			
Increments		Number of times the simulation is run incrementing a parameter	25
Repetitions		Number of times the identical simulation is repeated with different random seeds	25
Rounds		Number of rounds of play	20
Mean for ideal point		Distribution of actors' policy preferences in population	0.5
Weight on ideal	w	Weight on policy preferences	1.0
Learning rounds		Set as either number of rounds or population convergence to within a proportion of the true population mean	5 rounds
Agents (Total)			100
All Cooperate		Number of actors of type always cooperate	
All Defect		Number of actors of type always defect	
TFT		Number of actors playing tit-for tat strategy	
Payoffs			
R	R	Payoff for CC outcome	3
S	S	Payoff for CD outcome	0
T	T	Payoff for DC outcome	5
P	P	Payoff for DD outcome	1
Hierarchy			
Initial size	θ	Proportion of the population in hierarchy. In first round of play, this variable is set exogenously; after the first round, this variable is endogenous and defined as the number of players in the previous round.	10
Penalty	V	Penalty for defection within the hierarchy	0.5
Probability of Cooperation	Q	Rate at which the agents cooperate with other agents in the hierarchy	0.95
Tax	τ	Tax assessed on members of the hierarchy	0.3
Ideal point	p_h	Ideal point of the hierarchy	0.5
Network			
Cost	ϕ	Fee for joining the network	0.3
Width	α	Number of past cooperative partners each agent *i* can ask for information about agent *j*	3
Depth	L	Number of levels agent *i* can survey	3
Memory	m_n	How many past moves each agent remembers within the network	5
Selective Affinity			
Network Affinity	η	Probability of network players being able to pick their partner	0.1
Affinity Memory	m_a	How far back affinity players can look into their memory	5

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