# EVOLUTION OF NETWORKS

# AND THE DIFFUSION OF NEW TECHNOLOGY

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Abstract

This paper extends the theoretical framework for exploring the diffusion of new technologies through firms and industries. It is assumed that information about new and profitable technologies is not immediately available to all of the agents in the economy; this information spreads through the economy by means of a network. The pattern of diffusion will depend on the structure of this network. Ideally, firms or agents would balance the costs and benefits of information transfers to establish networks that optimally process information: a profit-maximizing outcome. The problem of determining optimal structures, however, is beyond reasonable computational limitations in many situations of interest. Furthermore, the decision to establish information links is often made by individual agents seeking to optimize their own payoffs; externalities in information processing may create differences between individual and group payoffs. The proposed alternative to the profit-maximizing outcome is that observed structures will be the result of a gradual co-evolutionary process. The focus of this paper is to identify how these evolutionary outcomes compare with optimal solutions.

The situation considered in this paper is a specific example of a more general class of problems. For this general class, the conditions necessary to guarantee that an evolutionary process will converge to an optimal outcome from any starting point are quite stringent, and are unlikely to prevail in this situation. Thus, it is useful to determine the set of initial population states that do converge to an optimal outcome. The distribution of costs and benefits among the agents within an information processing structure plays a critical role in defining this set. These distributional arrangements can be thought of as representing alternative institutional regimes. With this insight, it becomes apparent that the analysis of evolutionary outcomes hinges on the relevant institutional regime. This leads directly to the identification of institutional changes that can improve outcomes, free the flow of information, and encourage the diffusion of profitable new technologies.

## *1. Introduction*

Modern economies involve an almost boundless variety of products and services. Changes occur frequently as new items become useful and old items become obsolete. Firms operating profitably in such a fluid landscape must be prepared to update their production plans as better technologies become available. Readiness is costly, however, because processing information about new technologies requires resources that must be diverted from other productive activities. At some point diminishing returns from information processing makes it unprofitable to devote additional resources to that activity. Striking a balance between the costs and benefits of information processing is a fundamental problem in a dynamic system. The point of this paper is to explore whether that balance actually occurs in an economy, with particular attention to the question of how institutional arrangements (corresponding to specific distributions of costs and benefits of information processing) determine market outcomes.

A useful technique for studying information processing is to construct a network that models the flow of information through an economy (DeCanio & Watkins, 1998). The links of the network represent channels through which information flows between agents located at the nodes. Depending on the scope of the analysis, the nodes represent an appropriate level of abstraction for decision-making. For example, an analysis of firm decisions might have individual managers at the nodes, with the network representing a complete firm. For an industry analysis, however, the nodes could be individual firms and the network the entire market.

This approach places the study of the diffusion of new technologies within the large class of the study of networks in economics. Two important aspects of networks are particularly relevant here. The first is that the structure of a network may be determined by the individual actions of nodes within the network, and not by the directed efforts of a "manager" overseeing the entire network. It may not be true that the actions that result in better outcomes for agents at the nodes will also result in structures that work best for the entire group (Jackson & Wolinsky, 1996; Dutta & Mutuswami, 1997). The second is that the problem of finding the optimal network for a given situation can be computationally demanding, even to the point where it is unrealistic to assume that a "manager" could actually solve this problem (Decanio et al, 1998).

Due to these two aspects of networks, it is not credible to assume that the networks that form in an economy will necessarily be the ones that optimize the flow of information. This analysis will rely on an alternative presumption: an evolutionary process drives the development of networks (DeCanio et al, 1998; Kirman, 1997). The types of networks that emerge in the long run are determined by how the evolutionary dynamics of the system drives the behavior of the individual nodes within the network. Using techniques from evolutionary game theory (Weibull, 1995), it will be shown that evolutionary convergence to the optimal network structure is typically the exception rather than the rule.

An important innovation in this analysis is to show how the institutional environment shapes the evolutionary outcome. Given that the evolutionary outcome can not be guaranteed to be optimal, it is helpful to know the effectiveness of different institutional regimes (measured by how close the evolutionary outcome under a given regime is to the optimal structure). The two components of the model that determine evolutionary outcomes are the payoff structure (the net benefits of different strategy profiles) and the evolutionary dynamics. Varying the characteristics of the payoff structure (while retaining a commonly used and representative dynamic, the replicator dynamic) provides insight into the expected outcomes for different institutional settings.

In the network model, different institutional regimes can be represented by different distributions of the costs and benefits of information processing. Four polar cases span the spectrum of possibilities. In the completely “private” case, each individual node bears the full costs and full benefits of the chosen information processing strategy; this corresponds to the nodes representing individual firms operating within a competitive market with no collusion. At the opposite extreme, the completely “public” case, each individual node equally shares the costs and benefits of the behavior of all of the other nodes. A network with this arrangement might represent a particular firms, with employees of the firm at the nodes. The other two cases are a mixture: “public” costs and “private” benefits, or “private” costs and “public” benefits.

The last case is particularly important for policy analysis of the diffusion of new socially beneficial technologies throughout a market place. Individual firms must bear the information processing costs, but everyone benefits from adopting the new technology. This describes the situation for a number of energy-saving technologies, particularly when there is a negative externality associated with energy production. The insight developed here will improve the analysis of diffusion for these technologies and clarify the policy interventions that can be most effective in speeding up or expanding this process.

The next section of the paper lays out the model in detail; this includes relevant details from the evolutionary game theory literature and previous work on the diffusion of new technologies, as well as the introduction of institutional regimes for the distribution of costs and benefits. Section 3 presents some general propositions in the first part, followed by a detailed analysis of a specific example (small organizations with three nodes). Discussion of the results appears in section 4, including policy implications and links to related research. Section 5 concludes the paper with some suggestions for future research.

## *2. The model*

*2.1. Evolutionary game theory background.* Before delving into the specifics of the technology diffusion network model, it will be useful to layout some notation and a result from evolutionary game theory. The nodes of the organizations to be modeled below will be identified as players in an $n$-person symmetric game. The set $S$ contains the pure strategies available for each player (for symmetric games, $S$ is the same for all players). The players belong to a large population, from which $n$ members are randomly selected for each iteration of play. The population state is defined by the proportion of the population playing each pure strategy, so the space of population states is the unit simplex, $\Delta$, in $n$ dimensions. Each population state, $x$, could also be interpreted as a mixed strategy played by all players. Payoffs are defined by the function $u(x)$, which identifies the payoff for any player when all players choose the mixed strategy *x*.

The set of symmetric Nash Equilibrium for this game will be denoted $x^N$. These points are strategy profiles for which no individual agent would receive a higher payoff from a different strategy, given the same strategy played by the others. As such, these are points that are individually rational. For the entire collection of *n* agents, however, the total payoff could be higher with some alternative strategy profile. The highest possible total payoff is achieved at the *optimal* population state:

*Definition 1 (D1):* The set of *optimal* population states, $x^*$, is the collection of points that maximize the *total* payoff for all agents, or, equivalently, the *average* payoff for all players: $x^* = \{x \in \Delta \mid u(x) \geq u(y),\ \forall\, y \in \Delta\}$.

It is worth noting here that it may be possible for more than one state to achieve the unique maximal payoff in a given game. Nevertheless, the discussion presented here will, for the sake of clear exposition, refer to an optimal *state*.

In an evolutionary game, the population state changes over time according to the payoffs received by the agents. The *dynamics* of the evolutionary game define how these changes occur by relating the growth rates of particular strategies to the corresponding payoffs. For the general results derived in this section, attention will be restricted to *weakly payoff positive* (and non-stochastic) dynamics. These are dynamics for which the proportion of the population playing a strategy that does better than average grows, and the proportion playing a strategy that does worse than average shrinks (see Weibull (1995, p. 151) for a precise definition). In later sections, attention will be further restricted to a particular member of this class of dynamics, the *replicator dynamics*, where the growth rate of the subpopulation playing a particular strategy is exactly equal to the difference between the payoff for that strategy and the average population payoff.

For an initial population state $x_0$, the dynamics of the game completely determine the population state at time *t*, denoted $x_t(x_0)$. For weakly payoff positive dynamics, the population state will eventually converge to either a *limit point*, $\bar{x}(x_0) = \lim_{t \to \infty} x_t(x_0)$, or to a set of points called a *limit cycle*. The *basin of attraction* for a limit point is the set of initial states that lead to convergence to that limit point: $X^i = \left\{ x_0 \in \Delta \mid \bar{x}(x_0) = x^i \right\}$. Of special interest is the basin of attraction for optimal points,

$X^* = \left\{ x_0 \in \Delta \mid \exists\, x \in x^* \text{ such that } \bar{x}(x_0) = x \right\}$.

The following theorem follows directly from standard results in the evolutionary game theory literature and will be very useful in what follows:

*Proposition 1 (P1):* For weakly payoff positive (WPP) dynamics,

$$\forall x_0 \in \Delta, \text{ if } \bar{x}(x_0) \text{ exists then } \bar{x}(x_0) \in x^N.$$

*Proof omitted* (this proposition is just a restatement of Theorem 5.2c from Weibull (1995, p. 208)).

*Corollary 1 (P1.1):* For WPP dynamics, $X^* = \Delta \Rightarrow x^* \subset x^N$

*Corollary 2 (P1.2):* For WPP dynamics, $x^* \cap x^N = \varnothing \Rightarrow X^* = \varnothing$

From a social efficiency perspective, it would be comforting to know that the system always converges to an optimal point, regardless of the starting point. At the very least, it would help to know that some of the starting points converge to an optimum. These two conditions are formalized for future reference:

*Definition 2 (D2):* An evolutionary game is *strongly efficient* if all the interior starting points converge to an optimum: $X^* = \Delta$.

*Definition 2 (D3):* An evolutionary game is *weakly efficient* if there exists a non-empty set of interior starting points that converge to an optimum: $X^* \neq \varnothing$.

Proposition 1 states that within the large class of weakly payoff positive evolutionary dynamics, it is necessary that each of the optimal points also be Nash Equilibrium points in order for a game to be strongly efficient. There is no particular reason for this correspondence to exist in a particular game. The Prisoner's Dilemma is the quintessential example of a game where this condition does not hold; the Nash Equilibrium (and, in fact, strictly dominant) strategy profile does not provide the highest total surplus. With *P1*, establishing that a socially optimal point is not a Nash Equilibrium rules out the possibility that the game is strongly efficient. Furthermore, if all of the socially optimal points are not Nash Equilibrium then the game is not even weakly efficient.

*2.2. The technology adoption model as an n-person game.* This section describes the network model of technology adoption, represented within the framework of a game.

For the technology adoption model, individual agents can represent firms within a market, managers within a firm, or even individual employees within a particular production unit. The collection of agents within a group of *n* agents play an *n*-person non-cooperative game. Each agent selects how many connections to make to other agents; this is a strategy. Making a connection provides an agent with access to information held by another agent.

The strategy profile for all the players in a group defines the type of organization that forms, which determines the success of the technology adoption process and thus the payoff to the individual players. For this model, the strategy set is defined to contain choices only over the number of connections, without specifying to which other agents the connections are made[1]. The actual organization that occurs is then a random draw from a small set of possible networks determined by the number of connections chosen by each player. Once this draw occurs, the network remains the same until the group is disbanded.

For example, in 3-agent organizations, the strategy set is $\{0,1,2\}$. If all members of the group choose the strategy "2 connections", then a fully connected group would form (with probability one). On the other hand, suppose each member of the group chooses

[1] This arrangement means that the strategies of the players are independent of their position within the organization, so this could be referred to as the *position independent* network technology adoption game. It would also be possible to define *relative position* strategies (such as connect with the "next" 2 nodes), or more generally *position dependent* strategies (such as, connect to node 2 if in position 1). These would require an additional component to the model to arrange the position of the players, and allow more complex structures to be considered. In the absence of compelling reasons to extend the model along those lines, this general analysis considers only the position independent game. The main advantage of this arrangement is that there are fewer strategies to consider (only $n-1$, as opposed to $2^{n-1}$ for the relative position game, or $n2^{n-1}$ for the position dependent game), so the results are easier to develop and interpret.

strategy “1 connection”. Two possible groups could form, each with probability *0.50*. These two groups are depicted in figure 1.

*Figure 1:* Two organizations that could form with strategy profile {1,1,1}

The payoff for a given strategy profile is determined by the information processing network model. Payoffs are a combination of costs (which are determined by the number of connections) and benefits (which are determined by the speed of adoption). Each network lasts long enough to face a long string of new innovations. The expected value of net benefits from this sequence of innovations (with the expectation taken over the different organizations that could form with a given strategy profile) determines a payoff vector for each strategy profile.[2]

In the technology adoption model, an agent from the group is selected as the start node, which adopts the technology in the first period.. Each node that has a link to the start node adopts the new technology in the second period. Each node that has a connection to any of the previous adopters will then adopt in the third period, and so on. Thus, the time of adoption for every particular node is determined by the distance (measured in the minimum number of links) from the start node. The value of technology adoption is denoted by a parameter *A*. The benefit of adoption is this value discounted according time the time that the adoption occurs. The time of adoption for node *i*, $t^i$ depends on the group structure, *G*, and the start node *a*. The adoption benefit is calculated for a particular agent using each of the nodes as the start node, then the average gives the benefit for that agent. The expectation taken over the possible structures that could be created from a given strategy profile, *x*, determines the benefit for node *i*:

$$B^i(x) = E_{G|x}\, \tfrac{1}{n} \sum_{a=1}^{n} \frac{A}{(1+r)^{t^i(G,a)}} \qquad (1)$$

The cost of connections is a convex function of the number of connections for node *i*:

$$C^i(x) = E_{s^i|x} \sum_{t=1}^{\infty} \frac{c^{s^i}}{(1+r)^t} = E_{s|x}\, c^{s^i} \big/ r \qquad (2)$$

where *c* is a cost parameter, *r* is the discount rate, and $s^i$ is the number of connections for node *i* (the strategy chosen by agent *i*) .

Net benefits for each agent are contingent upon the prevailing institutional arrangement for the distribution of costs and benefits, but the optimal strategy profiles (or population states) are independent of the distributional arrangements. The following result will help simplify the analysis in later sections:

*2.3. Institutions (distributional arrangements)*. There are many ways that the costs and benefits of each agents actions may be distributed through the group. If the

[2] An alternative, but equivalent, approach is to assume that the random draw for the organizational form occurs anew with each new innovation (while the strategies of the members of the organization stay the

organization under study is a firm, then the individual nodes are simply employees of the firm. The firm as a whole bears the costs of actions taken by employees and the firm as a whole reaps the benefits. The net benefit then accrues to the shareholders of the firm, but, in general, a profitable firm confers benefits to employees that unprofitable firms do not. In fact, when all of the net benefits go back to the employees, then all costs and all benefits are completely shared. An employee-owned firm is a good example of this category. At the other extreme, consider a competitive industry with many interacting firms. Individual network nodes in this case correspond to firms, not individuals. Each firm incurs the cost of establishing information links on its own, and each firm will capture the benefit on its own. This is the case of completely private costs and benefits.

The other two cases are mixtures. Many industries have professional organizations that serve has information hubs. Within these organizations, the cost of information transfer is often born by the organization as a whole (consider trade conferences), but the benefits accrue to individual firms that are members of the organization. This is the case of shared costs and private benefits. On the other hand, consider an industry that does not have a professional organization but for which some network externality exists (from standardization, for example). This would be the case of shared benefits and private costs. This case is also important for the diffusion of new technologies that have a positive externality. Energy-saving technologies, for example, benefit not only the firm adopting the technology, but also other firms due to decreased environmental damage from the production of energy.

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same). In expectation, the payoffs are equivalent to the model described in the text.

| | | Costs | |
|---|---|---|---|
| | | Shared | Private |
| Benefits | Shared | *I*<br>employees in a firm | *II*<br>environmentally sound technology |
| | Private | *III*<br>professional group | *IV*<br>firms in a market |

*Table 1.* Institutional arrangements for distribution of costs and benefits

Using this framework for different institutional arrangements, the payoff for individual nodes can be represented symbolically as follows:

$$u^i_{(b,g)}(x) = \left[ bB^i(x) + (1-b)\tfrac{1}{n}\sum_{j=1}^{n} B^j(x) \right] - \left[ gC^i(x) + (1-g)\tfrac{1}{n}\sum_{j=1}^{n} C^j(x) \right] \quad (3)$$

$$I:\ (b, g) = (0,0) \qquad II:\ (b, g) = (0,1)$$

$$III:\ (b, g) = (1,0) \qquad IV:\ (b, g) = (1,1)$$

The Nash Equilibria for institutional parameters $(b, g)$ will be denoted $x^N_{(b,g)}$, and the basin of attraction for the optimal point will be denoted $X^*_{(b,g)}$.

## *3. Results*

*3.1. General results.* Given the framework developed in the previous section, it is straightforward to identify some universal properties of the technology adoption game. The primary thrust of these general results is negative; these propositions identify limitations to what can be assumed about evolutionary convergence. In particular, Proposition 2 shows that convergence to an optimal point cannot be assumed, no matter what institutional arrangement holds for the organizations. Moreover, knowing that convergence to an optimal point occurs under one institutional arrangement is not enough to ensure that this occurs under an alternative regime, as is stated in Proposition 3.

*Proposition 2 (P2):* None of the institutional arrangements considered here result in a strongly efficient game for all technology adoption parameter values; i.e. $\forall \left(b,\ g\right) \in \{0,1\} \times \{0,1\},\ \exists \left(A, r, c\right)$ such that $\mathrm{X}^*_{(b,g)} \neq \Delta$

*Proof (incomplete):* According to *P1*, it is sufficient to identify parameter values for which an optimal point is not a Nash Equilibrium (examples for size 3 are identified below in section *3.2*). The structure of the proof is to start with a set of parameter values exists for which NE and optimal coincide, then show that gradually changing a parameter eventually knocks out the optimality property without changing the NE property.

*Proposition 3 (P3):* For any pair of the four institutional arrangements listed here, there exist technology parameters such that the game is strongly efficient for one but not even weakly efficient for the other; i.e.

$\forall \left(b_1,\ g_1\right) \in \{0,1\} \times \{0,1\}$, and $\left(b_2,\ g_2\right) \in \{0,1\} \times \{0,1\}$, with

$\left(b_1,\ g_1\right) \neq \left(b_2,\ g_2\right),\ \exists \left(A, r, c\right)$ such that $X^*_{(b_1, g_1)} = \Delta$ and $X^*_{(b_1, g_2)} = \varnothing$

*Proof (incomplete):* the structure of this proof is similar to that for P2.

That fact that individual agents do not always act together to create an efficient outcome (*P2*) is not particularly surprising. There are many instances in economics where externalities inhibit efficiency. In this model, the interdependence of agents within the information processing structure creates the externality. Sometimes the evolutionary model will still converge to an optimal point, but this is merely a fortuitous coincidence. What is more surprising, but equally common, is the importance of the specification for the institutional arrangement (*P3*). Evidently the distribution of costs and benefits is quite important in characterizing the effect of the externalities in this model, and a misspecification in this regard could lead to the exact opposite of the correct conclusion.

*3.1.1 Additional conjectures.* A brief diversion into a more general model of institutional arrangements is also considered here. Extending the parameter space for $(b, g)$ to the unit interval provides for an infinite variety of distributional arrangements. It seems likely that the arguments used to prove Proposition 2 could be extended as well, suggesting the following (unproved) conjecture:

*Conjecture 1 (C1):* $\forall(b, g) \in [0,1] \times [0,1]$, $\exists(A, r, c)$ such that $X^*_{(b,g)} \neq \Delta$.

Likewise, there may be a parallel version of *P3* asserting that each pair of distribution parameters has some small space around it for which strong efficiency under some set of technology adoption parameters carries over to other distribution parameters:

*Conjecture 2 (C2):* For any institutional parameters, there exist "similar" parameters such that strong efficiency in the first case implies strong efficiency in all nearby cases, and weak efficiency in a wider space; i.e.

Given $(A,r,c)$, $\forall(b,\ g)\in\{0,1\}\times\{0,1\}$, $\exists e_1 > e_2 > 0$, such that

$$\left\|(b,\ g)-(\hat{b},\ \hat{g})\right\| < e_2 \Rightarrow \left\{X^*_{(b,\ g)} = \Delta \Rightarrow X^*_{(\hat{b},\hat{g})} = \Delta\right\} \text{ and}$$

$$\left\|(b,\ g)-\left(\hat{\hat{b}},\ \hat{\hat{g}}\right)\right\| < e_1 \Rightarrow \left\{X^*_{(b,\ g)} = \Delta \Rightarrow X^*_{\left(\hat{\hat{b}},\hat{\hat{g}}\right)} \neq \varnothing\right\}$$

Finally, the specific examples developed in the next section will show that the Nash Equilibrium for different institutional arrangements can surround the optimal point This suggests an optimistic conjecture, that for a given technology adoption game an arrangement within this continuous space exists that guarantees convergence:

*Conjecture 3 (C3):* For any set of technology adoption parameter values, there exist at least one pair of distribution parameters such that convergence to optimal is guaranteed; i.e. $\forall(A,r,c)$, $\exists(b,\ g)$ such that $X^*_{(b,\ g)} = \Delta$.

*3.2. Comprehensive analysis for n=3, with replicator dynamics.* This section describes detailed results for a specific case: when the number of nodes in the network is three, and when the evolutionary dynamics are the replicator dynamics. This specific case illustrates some of the pertinent implications of the general results, and reveals some intriguing and unexpected complications. Recall that the replicator dynamic is defined as follows: the growth rate for each strategy is exactly equal to the relative payoff of that strategy compared to the population average. Qualitatively, the results will be the same for any WPP dynamic.

The results were obtained by selecting specific parameter values, evaluating the corresponding game for Nash Equilibria (for each of the four institutional structures), and then identifying the basin of attraction for each NE. Within this class of games, the only available pure strategies are (0, 1, 2), and all NE are either pure strategies or a mixture between (0,1) or (1,2). In other words, there is no mixed strategy NE with a support that contains both 0 and 2. Thus, all of the equilibria can be represented by a point on the interval [0,2]. In the event that multiple equilibria occur, then the average value was taken, weighted by the relative size of the basin of attraction for each NE. This average can be interpreted as an expectation of the outcome, when the prior distribution for initial starting values is uniform. Figures 2 and 3 demonstrates this procedure for a particular set of parameter values The parameter values represent a range of possible situations. Using a fixed adoption benefit of $A = 100$, and a fixed discount rate of $r = 10\%$, the cost of establishing a link is varied from $c = 1.1$ to $c = 7$.

The results are displayed in Figures 4 and 5. The first graph, Figure 4, depicts the actual strategies of the equilibrium, demonstrating the action of the expected long run outcome. The vertical axis represents the strategy and the horizontal axis represents the cost of establishing links. First, note that no matter what the cost, the four different institutional arrangements always follow the same order, in terms of the number of links chosen at equilibrium. The fewest links are chosen in II, when individual nodes must bear the cost of communication, but share the benefit, and the most links are chosen in III, when the situation is reversed. Occupying the middle ground are IV and I; there are fewer links when all costs and benefits are private (IV), and more when all costs and benefits are shared (I). Second, note that none of the institutions match the optimal strategy profile for all of the parameter values. In almost all cases, in fact, the equilibrium strategy has too many or too few links.

Differences in strategies, however, are not identical to differences in payoffs. Figure 5 shows the average payoff of the expected equilibrium strategy. At a communication cost of $c = 1.5$, for example, the type IV institution (fully private) is closer in strategy to the optimal than the type II (private costs, shared benefits), but has a much lower payoff. In the type IV case, agents reduce the number of connections (from what would be optimal), they bear the full cost of making connections, but the lure of the benefit is still strong. When the benefit is shared, as in the type II case, each agent tries to free ride, and reduces the number of connections further. This turns out to be advantageous; when the rest of the network is not chipping in with the optimal strategy then it is better to drop down to a secondary local optimum. Note additionally that each of the institutions performs very poorly at some parameter values (compared to the optimal payoff), but the area of poor performance varies. The fully private case performs poorly when communication costs are low, but the fully public case performs poorly when communication costs are high.

*4. Results*

As expected, the results of both the theoretical analysis and the simulation of a specific case indicate that convergence to an optimal outcome is the exception rather than the rule for evolving networks. Before continuing with some more general comments, let us focus specifically on the situation for the diffusion of environmentally sound technologies, using the simulation results to guide the discussion.

*4.1. Discussion of results for Type II institutions.* As mentioned earlier, the diffusion of an environmentally sound is best represented by the Type II institutions. It is clear from Figure 5 that there are situation where this institution will perform poorly, particularly when communication costs are moderate. At very low communication costs, the tendency to free ride is small and the outcome is very close to optimal. At moderate costs, the free riding causes such a drop in the chosen number of links that no communication occurs at all. When costs are high enough, this no communication outcome is actually optimal.

There is another interesting result for the type II institutions that is not evident from the figures. For the range of communications costs $c = 1.7$ to $c = 2.7$, the poor outcomes actually consist of a mixture of two pure strategy equilibria; one of the equilibria is to choose 1 link, and the other is to choose 0 links. The initial conditions determine which equilibria occurs in the long run. As costs increase, the basin of attraction for the bad equilibrium, everyone chooses 0 links, increases, even though the optimal outcome remains everyone choose 1 link. This suggests an interesting possibility for intervention. Policy could change the starting values (in other words, encourage more communication links at the very beginning). Also, policy could temporarily alter the institutional framework (perhaps by forcing shared costs), which would change the dynamic and encourage movement towards the good outcome. When the population is sufficiently close to the good outcome, then a shift back to a type II institution will not be harmful. Either way, there could be a permanent positive outcome from just a temporary policy intervention.

*4.2 Discussion of results in general.* The results developed within this paper can be viewed from both a positive perspective or a normative perspective. From a positive perspective, these results could begin to explain the existence of different institutional arrangements. It is evident from the simulation results and from the theoretical work, that the relative value of costs and benefits of communication are very important for determining which of the institutional frameworks will perform well. It is possible to conjecture a larger evolutionary picture, where different markets are evolving under different institutional structures for the same underlying parameters. Those markets for which the institution is best suited to the parameter values will be more successful.

From a normative perspective, it has already been noted that the optimal outcome is far from guaranteed by the evolutionary process, and some specific policy interventions are briefly suggested in the previous section. More generally, this work opens the way for better qualitative analysis of a wide variety of policy options, including policies that change the relevant institutional framework, as well as those which affect the parameter values. Finally, and perhaps most importantly, it should be noted that this work helps explain why some policies are *not* effective.

Consider a subsidy for adopting a new technology, for example. This is equivalent to raising the benefit (the $A$ parameter). While Figures 4 and 5 only show what happens when the cost is changed (the $c$ parameter), it is not difficult to imagine similar results for changes in benefits. It is apparent that in many cases, when the situation has already evolved to a long run equilibrium, changing the parameter values incrementally will not result in any change in the outcome whatsoever.

## *5. Conclusion*

The results developed in this paper provide a foundation for further research on networks that spans both theoretical and applied work. The propositions fill in some of the gaps for easier theoretical development, while the conjectures point the way that future theoretical development might proceed. The simulations demonstrate how the model can be put to practical use. It is shown that the long run outcome is quite dependent on the relevant institutional regime (arrangement for distributing costs and benefits). Also, a specific case demonstrates how different relative costs and benefits imply better or worse performance for different institutions.

Continued work with simulations would help augment the results shown here. First priority for further work along these lines would be to consider larger organizations. While the techniques used here become impractical as the size of the organization increases, it is not difficult to create alternatives. With the evolutionary dynamic fixed (in this case, the replicator dynamic), the actual evolution could be simulated several times from a full range of starting values to indicate long-run equilibria.

A significant gap still exists between theory and practice in this research area. This model presents some clear results. If the components of the model could be mapped into real world situations, then these results would be testable hypotheses. That endeavor would complete the loop for this research area by providing substantive tests of the model against actual economic data.

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| 100. | 0.1 | 2.2 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 0. | 0. | 0. | 30.3 | 30.3 | 30.3 | 10. | 10. | 10. | 60.91 | |
| 0. | 0. | 1. | 30.3 | 30.3 | 44.08 | 10. | 10. | 22. | 62.68 | |
| 0. | 0. | 2. | 30.3 | 30.3 | 85.4 | 10. | 10. | 48.4 | 77.61 | |
| 0. | 1. | 1. | 30.3 | 64.11 | 64.11 | 10. | 22. | 22. | 104.53 | |
| 0. | 1. | 2. | 30.3 | 70.37 | 85.4 | 10. | 22. | 48.4 | 105.68 | |
| 0. | 2. | 2. | 30.3 | 85.4 | 85.4 | 10. | 48.4 | 48.4 | 94.3 | |
| 1. | 1. | 1. | 70.37 | 70.37 | 70.37 | 22. | 22. | 22. | 145.12 | p = 0.95 |
| 1. | 1. | 2. | 76.63 | 76.63 | 85.4 | 22. | 22. | 48.4 | 146.27 | |
| 1. | 2. | 2. | 82.9 | 85.4 | 85.4 | 22. | 48.4 | 48.4 | 134.89 | |
| 2. | 2. | 2. | 85.4 | 85.4 | 85.4 | 48.4 | 48.4 | 48.4 | 111. | |

Complete sharing

| | 0. | 1. | 2. |
|---|---|---|---|
| p0p0 | 20.3 | 20.89 | 25.87 |
| p0p1 | 20.89 | 34.84 | 35.23 |
| p0p2 | 25.87 | 35.23 | 31.43 |
| p1p1 | 34.84 | 48.37 | 48.76 |
| p1p2 | 35.23 | 48.76 | 44.96 |
| p2p2 | 31.43 | 44.96 | 37. |

x = (0, p, 1-p) p = 0.95

Complete private

| | 0. | 1. | 2. |
|---|---|---|---|
| p0p0 | 20.3 | 22.08 | 37. |
| p0p1 | 20.3 | 42.11 | 37. |
| p0p2 | 20.3 | 48.37 | 37. |
| p1p1 | 20.3 | 48.37 | 37. |
| p1p2 | 20.3 | 54.63 | 37. |
| p2p2 | 20.3 | 60.9 | 37. |

x = (0, 1, 0)

Private benefits, shared cost

| | 0. | 1. | 2. |
|---|---|---|---|
| p0p0 | 20.3 | 30.08 | 62.6 |
| p0p1 | 16.3 | 46.11 | 58.6 |
| p0p2 | 7.5 | 43.57 | 49.8 |
| p1p1 | 12.3 | 48.37 | 54.6 |
| p1p2 | 3.5 | 45.83 | 45.8 |
| p2p2 | -5.3 | 43.3 | 37. |

x = (0, p, 1-p) p = 0.5

Shared benefit, private cost

| | 0. | 1. | 2. |
|---|---|---|---|
| p0p0 | 20.3 | 12.89 | 0.27 |
| p0p1 | 24.89 | 30.84 | 13.63 |
| p0p2 | 38.67 | 40.03 | 18.63 |
| p1p1 | 42.84 | 48.37 | 31.16 |
| p1p2 | 52.03 | 57.56 | 36.16 |
| p2p2 | 57.03 | 62.56 | 37. |

x = (1, 0, 0)
x = (0, 1, 0) p = 0.66

Optimal is: (0, 0.95, 0.05)

**Figure 2: Sample data sheet**

Private benefits, shared cost

| | 0. | 1. | 2. |
|---|---|---|---|
| p0p0 | 20.3 | 30.08 | 62.6 |
| p0p1 | 16.3 | 46.11 | 58.6 |
| p0p2 | 7.5 | 43.57 | 49.8 |
| p1p1 | 12.3 | 48.37 | 54.6 |
| p1p2 | 3.5 | 45.83 | 45.8 |
| p2p2 | -5.3 | 43.3 | 37. |

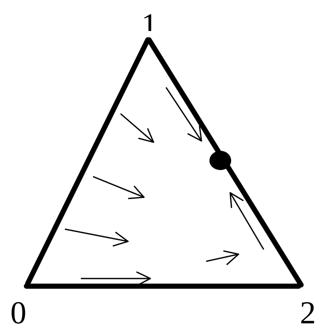
x = (0, p, 1-p)      p = 0.5

Shared benefit, private cost

| | 0. | 1. | 2. |
|---|---|---|---|
| p0p0 | 20.3 | 12.89 | 0.27 |
| p0p1 | 24.89 | 30.84 | 13.63 |
| p0p2 | 38.67 | 40.03 | 18.63 |
| p1p1 | 42.84 | 48.37 | 31.16 |
| p1p2 | 52.03 | 57.56 | 36.16 |
| p2p2 | 57.03 | 62.56 | 37. |

x = (1, 0, 0)

x = (0, 1, 0)      p = 0.66



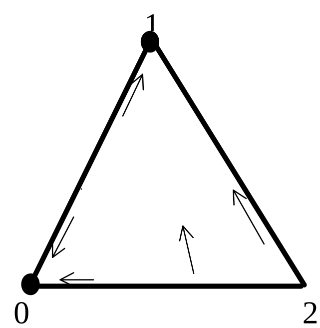




**Figure 3: Sample data analysis**

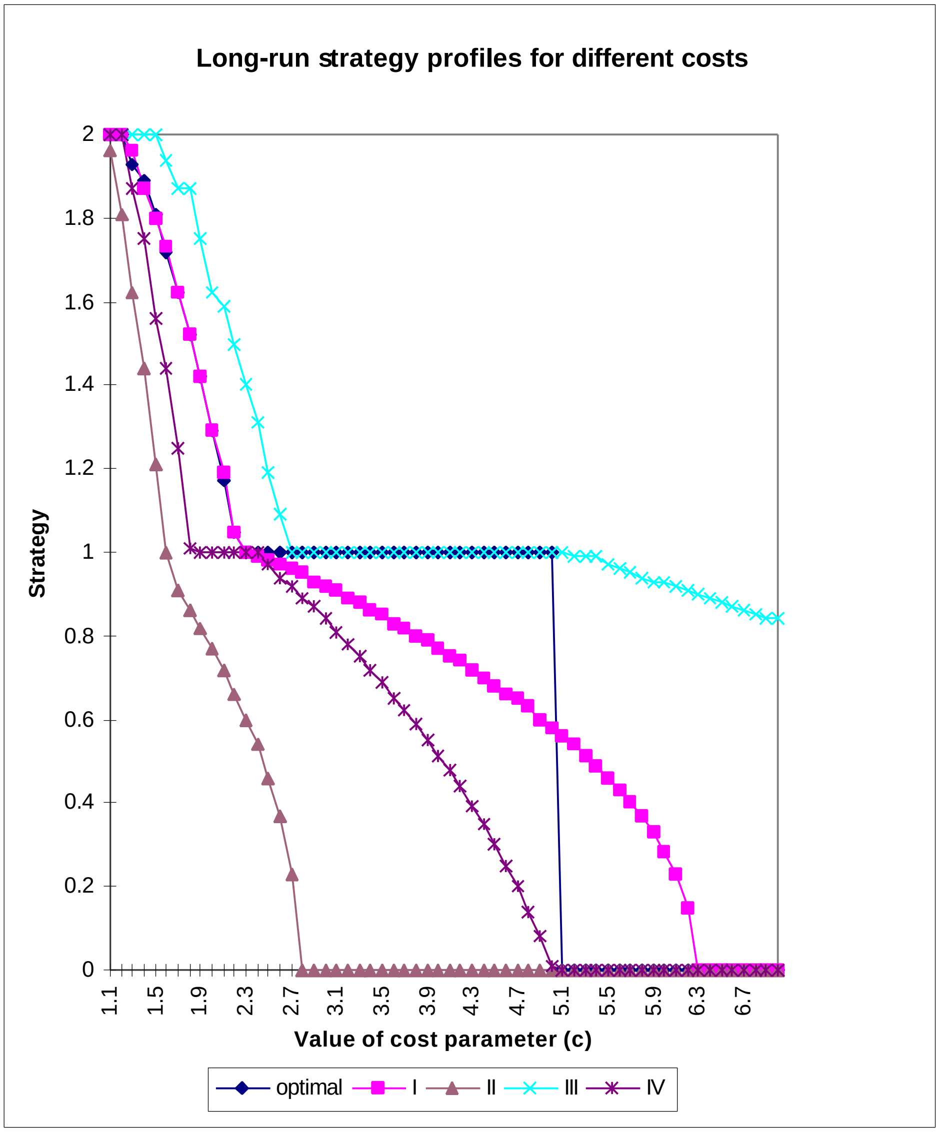



**Figure 4: Size 3 organizations, strategy graph**

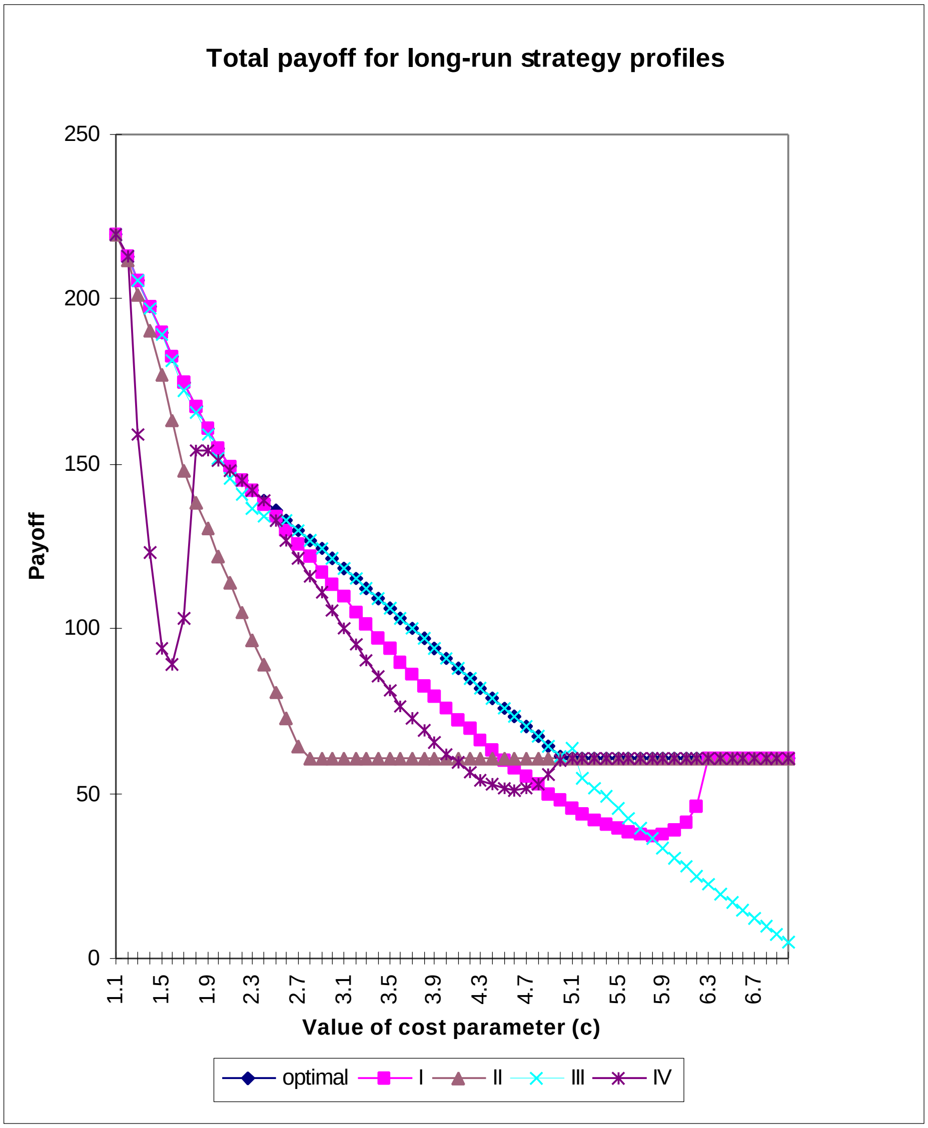



**Figure 5: Size 3 organizations, payoff graph**