CHAPTER

8

Viscosity Models and the Diffusion of Controversial Innovation

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As March has indicated in his foreword to this book, the promise of computational models in organizational theory has not been fulfilled. One reason is that too much was promised, such that computational models could not possibly deliver. I have argued elsewhere that computational models are particularly good at developing theory—that is, suggesting the logical consequences of a set of assumptions (Krackhardt, 2000). Most human-generated theories are limited to hopelessly simplistic linear additive assumptions about social phenomena, phenomena we all accept to be complex, dynamic, with feedback loops that make systemic behaviors very difficult to predict from a linear model. But, computational models do not prove these theories they help develop; they are not empirical by that standard. They merely help the researcher to answer logical "what if" questions. Expectations that computational models can *demonstrate* or *prove* anything beyond theory building is asking too much of them and will lead to disappointment.

The other downfall of computational models has been that they have often concluded the obvious, conclusions that could have been derived easily by a human's limited linear thinking. However, there have been historical examples to counter this problem, such as March and Cohen's Garbage Can model. It is in this spirit, of developing a theory of diffusion of innovation that incorporates nonlinear dynamics and of developing a theory that has nonintuitive implications for the diffusion process, that I write this chapter.

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It has long been acknowledged that the diffusion of innovations is a social process. That is, new ideas, new technologies, new management practices are diffused through a set of relationships that exist or emerge among actors within an organization or social system (Allen 1977, Price 1965). As Rogers (1982) noted in his comprehensive review, thousands of studies have been conducted on innovation diffusion, but there have been relatively few that have shown *how* the social structure affects the diffusion process.

There have been notable exceptions to this main thrust, however (Coleman, Katz, and Menzel 1966; Becker 1970; Burt 1973; Burt 1980; Carley 1990).These seminal pieces have emphasized how diffusion can be mapped out through structural features of the social system. For example, Coleman, et al., found that diffusion of a prescription drug was heavily influenced by direct social ties among physicians. Burt (1987), on the other hand, reanalyzed the same data and concluded that the diffusion mechanism was better explained by physicians mimicking each other when they were structurally equivalent (connected to the same set of third parties) rather than connected to each other directly.

A different stream of research has explored a "threshold" model of diffusion (Granovetter 1978). In these models, it is assumed that individuals influence each other toward adopting but that they have different thresholds—that is, some individuals will adopt after only a small proportion of their alters has adopted, while others will not adopt until a large proportion of their alters has adopted. With such a set of assumptions, one can model the diffusion process and recreate the standard "S" curve that is commonly associated with the diffusion process (Granovetter 1983, Granovetter 1978, Granovetter and Soog 1988). T. W. Valente's (1996) recent work in this area is an excellent adaptation of this approach. His approach focused on the ego network for predicting adoption rather than on the density of adoptions throughout the overall network.

Valente empirically showed that early adopters were much more likely to adopt in the face of few neighbors adopting, and conversely "laggards" adopted only after a relatively high proportion of neighbors had adopted. Again, diffusion is mapped out as a function of the structure of relationships among the adopters of various types.

A third stream of work that has hallmarked the diffusion literature has employed computer simulation as a modeling technique. The advantage of the computer is that one can model very complex systems that analytic or simple theoretical models cannot handle (Krackhardt, 1999). Thus, one can conclude that, if a set of assumptions holds (and is modeled appropriately), the diffusion rate should take on a particular shape. This work is epitomized by Carley's structuralism models of group formation and diffusion (Carley 1991, Kaufer and Carley 1990, Carley and Wendt 1991). These models assume that knowledge and beliefs diffuse as a function of what the actors have learned from each other in the course of structured interactions. Carley has found that interesting and complex dynamics can result by restricting access between two groups of individuals (Carley 1991). Another stream of work that explores structural features of diffusion success is that of Abrahamson and Rosenkopf (1993, 1997). They have used computer simulations to explore how structural conditions affect the adoption rates of innovations that have negative consequences for the organization.

A common theme among all of this diffusion research has been to assume that innovations will eventually diffuse throughout the population. Indeed, it is common to explicitly restrict the realm of interest in diffusion studies to cases in which the innovation successfully dominated the organization:

> The diffusion of innovations is the process by which a few members of a social system initially adopt an innovation, then over time more individuals adopt until all (or most) members adopt the new idea.... [Valente, 1996:70]

Innovations do not always succeed in diffusing, however. One of the most notorious examples of a "good" idea that refused to diffuse was the original PC, first proposed by a group of R&D engineers at IBM long before any commercial versions were available. The PC promoters were housed in the guts of IBM's research center in Tennessee. Twice they tried to promote the idea within IBM's structure, and twice they were defeated, allowing Apple to gain a substantial advantage in the market. It was not until years later when the PC developers were transplanted to a separate location in Florida that the PC flourished as an IBM product. Following on the work of Abrhamson and Rosenkopf mentioned earlier, the question I would like to propose is, why do some innovations succeed when others fail to diffuse in a social system? More specifically, under what conditions will such innovations diffuse and under what conditions will such innovations be stopped?

The Nature of Innovation Diffusions

Before specifying what conditions might be influential in this process, it is useful to differentiate types of innovation diffusion processes based on the ease with which they are accepted and adopted. First of all, consistent with Carley's work, I consider innovations to be inherently ideational. That is, actors adopt innovations because they come to believe that it is beneficial to do so. Therefore, the process of innovation diffusion is one of converting people into the belief that the innovation is in fact a good idea.

Given this ideational premise, I suggest that there are two forces that can lead to such a conversion. First, there is the exogenous inherent quality of the innovation itself. This force stems from the intrinsic strength (or failing) of the innovation. It is exogenous in that the evaluation that leads to possible conversion is not the result of political, influential, or other endogenous social forces; rather, that the decision to adopt or not is based solely on the intrinsic merits of the innovation itself. That is, conversion happens because each person independently and objectively recognizes a better mousetrap when one sees it. I will refer to this evaluation/conversion process as "rational" to emphasize its objective and nonsocial process of evaluation (I do not mean to imply anything about the decision maker's utility function here). This "rational" evaluation results in one of two extreme behaviors: either those who are made aware of the innovation immediately see the superior value in the innovation and adopt it; or, those who are made aware of the innovation immediately see its inferior value and reject it in favor of the status quo or some other alternative.

The other force is a social one, wherein the innovation's value is not so clearly determined by external or objective measures. This force suggests either that the quality of the innovation is ambiguous or that even if it is objectively demonstrable people can be swayed through a social or political process to a counter position. Thus, in such cases, innovations are valued through a dynamic social process, wherein people influence each other as to their evaluation of the "true" value and as to whether the innovation should be adopted. Innovations that are subject to this process of evaluation and conversion may be termed *controversial*. The conversion force is quite different from the "rational" ones because potential adopters' minds can be changed back and forth as they are exposed to different social forces from supporters on one side to the detractors on the other.

While it is an empirical question beyond the scope of this chapter to verify, I will go boldly out on a limb to suggest that most innovations fall into this latter, controversial category. Most innovations have identifiable advantages, which supporters of the innovation can point to, addressing some need or shortfall in the status quo. But the flip side is that these innovations threaten the status quo. Consequently, there will be detractors. Few innovations are so clearly and markedly inferior or superior to the status quo as to overcome this inherent conflict. Thus, most innovations are controversial and subject to a social process of convincing others of their superiority over the status quo.

Early information processing models (e.g., March and Simon, 1958) have made similar claims. Organizations accrue competencies by executing stable routines to perform frequently-encountered tasks. People learn by doing; they get stuck in this rut. Innovation based on a new technology they are unfamiliar with becomes a threat to their knowledge base. Thus, even in cases where technological superiority can be easily recognized by an outsider, the innovation may be resisted by the insider whose job must change because of it. For example, France has proven to be one of the slowest among developed countries to adopt the internet. The reason for this is probably that the country has had Minitel since the early 1980s, which is in many ways a lesser technology. However, people have experience using Minitel and trust it to perform many of the functions that the web offers, and so adoption of the web has been slow.

Others have made similar claims. For example, Cohen and Levinthal's notion of absorptive capacity suggests that innovation occurs not simply because the technology is superior but because the firm has invested in R&D's ability to understand and absorb (or perhaps accept) this new technology. Another example is the work of Brian Arthur and his colleagues whose collective work has underscored the critical role of social structure and context in the diffusion process even though the innovation may have clear technological superiority. Thus, a strong argument can be made that most innovations are in fact controversial, despite their apparent objective appeal.

Having said that, it may still be that some innovations are more likely to be seen as controversial than others. Indeed, innovations on organizational procedures and routines, such as re-engineering and TQM, are almost universally regarded as controversial. Other more technologically based innovations, such as the Xerox™ photocopying process, may appear as less controversial. While these distinctions are not hard and fast, I will restrict myself in the remainder of this chapter to controversial innovations as the main focus of interest.

We can plot the progression of all three types of innovation diffusion patterns resulting from both rational and social forces in terms of the rapidity with which they diffuse or retreat. To do this, we note that for any given time period, *t*, there will exist a proportion of the population that will "agree" with the innovation—that is, they hold the belief that the innovation is a good idea. Since we are concerned here with ideational aspects of innovation, I will call such people adopters and not differentiate them from people who agree with the innovation but have not yet behaviorally acted on it. Further, I will assume for the purposes of simplicity that people either agree or disagree with the innovation; that is, I assume everyone can be classified as either an adopter or a nonadopter.

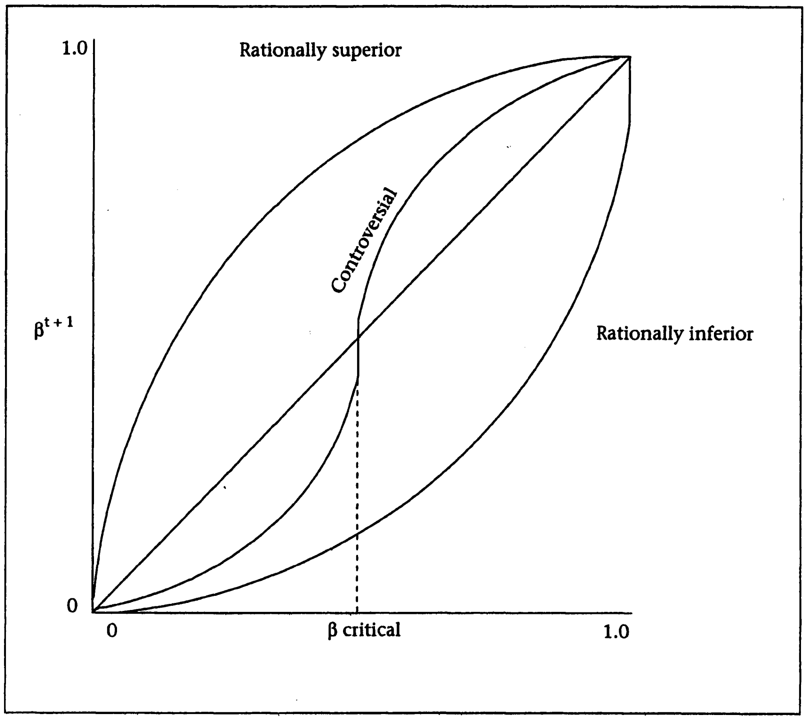

Figure 1. A plot of the progression of all three types of innovation diffusion patterns.

If we designate the proportion at time t who are adopters as β^t then we can plot the dynamics of this process for all three innovation types as in figure 1. The proportion of adopters at time t (β^t) is represented on the horizontal axis, while the proportion of adopters at time $t + 1$ (β^{t+1}) is represented on the vertical axis. Any point along the 45° line would represent a steady state solution, where no changes occur in the proportion of adopters in the population from one time period to the next. Points above the line would indicate that the proportion of adopters was increasing over time; points below the line would indicate that the proportion of adopters was decreasing over time.

In this figure, we see the fundamental difference between rational and controversial innovation diffusion processes. In the top curve, the "rationally superior" innovation is plotted. In this case, no matter what proportion of believers you start with (as long as there is at least one adopter in the population), each subsequent time period will have a higher proportion of converts to the innovation, until everyone is an adopter. The bottom curve represents the "rationally inferior" innovation. In this case, no matter what proportion of exogenously-determined adopters you start with, there will be fewer during the next time period, until all the adopters have converted to nonadopters.

The controversial innovation, however, has no automatic outcome. In this case, there are three possible outcomes, as represented in the S curve in the middle of figure 1. There is a saddle point on the curve, marked β^t_{crit}, located on the 45° line, indicating that each subsequent time period will have the same proportion of adopters. In this case, people may convert from adopters to nonadopters, but to the extent that they do they will be exactly balanced by the conversion rate of nonadopters to adopters, so that no net gain or loss in adoption proportions is observed. The intuition here is that, since adoption is a function of the social forces around you (rather than personal and objective experience with the innovation itself), the number of proponents and the number of opponents of the innovation are precisely balanced at β^t_{crit} so that neither side has the ability to convert more than the other side. Thus, an unstable equilibrium (standoff) is reached wherein both sides retain the same strength of support.

But, as we move off of β^t_{crit} we see that there is a pronounced effect on the outcome. Any starting point below β^t_{crit} results in successively fewer adopters in each time period, until extinction is reached. Any starting point above β^t_{crit} results in successively more adopters in each time period, until saturation is reached. Thus, the success of the innovation depends not on the quality of the innovation itself but rather the ability of the innovators to establish a critical mass of support for the innovation, β^t_{crit} after which they are virtually certain that the innovation will eventually dominate the social system.

One important observation should be made here: Once a critical threshold of density of adopters is reached, one could argue that the remaining people are simply acting "rationally" by adopting, seeing that the result is inevitable and not wanting to be left out of the wave of the future. While this is indubitably possible, such a process is outside the scope of the model I am proposing in this chapter. For simplicity's sake, this model incorporates only a local conversion process, as a function of who interacts with whom.

In terms of dynamics and equilibria, the two rational innovations are trivial in their solution. The controversial innovation, on the other hand, is both interesting and complex. But the question left unanswered is, how is it possible for the adopters to attain β^t_{crit} short of a massive infusion of exogenously determined support for the innovation? That is, is it possible for a smaller group of adopters to reach β^t_{crit} and "take over" the organization? The rest of this chapter is devoted to the answer to this question. Without relying on any assumptions of political motives or moves on the part of any of the actors in the system, I demonstrate that the. structure of interactions among the participants can itself lead to surprisingly stable and counter-intuitive results To demonstrate this, I draw heavily from the work of Boorman and Levitt (1980}, who asked a similar question about how is it possible for altruistic genes to propagate in a population of animals when the gene itself puts the host at greater risk for survival. While it is not my intent to explicate their model in this chapter, the curious reader will find their work to have a similar mathematical basis and very similar results to those I uncover for this problem.[1]

The Model

I start with a set of simple axioms about the diffusion process at the micro level in our social system. I will use the organization as a metaphor for any social system to which this diffusion may apply. The organization is populated by an arbitrarily large number of two kinds of persons, adopters (those who currently believe in the innovation) and nonadopters (those who currently do not believe in the innovation). Within any given time period, each person actively seeks out a set of others within the local part of the organization in which they currently find themselves and confers with those others on their beliefs about the innovation. If among those others they find agreement with them on the value of the innovation, they will retain their own belief about it. If, on the other hand, they find themselves surrounded by those who disagree with them, then they will tend to convert to the other belief (change from being an adopter to being a nonadopter, or vice versa).

To formalize this model, let us make the following assumptions:

Assumption 1: Each individual adopter (a person who believes in the value of the innovation) searches randomly through L_a others to find another like-minded individual. Each individual nonadopter (a person who believes that the innovation does not have value) searches randomly through L_n others to find another like-minded individual. I assume that the innovators are more likely to proselytize the status-quo oriented nonadopters than the converse; therefore, $L_a > L_n$.[3]

Assumption 2: (The Asch assumption): If in the process of this search, an individual finds at least one other individual who agrees with them (i.e., an adopter interacts with one other adopter, or a nonadopter interacts with one other nonadopter), then the individual will retain their current belief. This assumption acknowledges the work of Asch

{1951}, who found that it only required one person to agree with the subjects of his experiments to allow them to retain their beliefs, no matter how many confederates disagreed with the subjects.

Assumption 3: If an adopter fails to find at least one other adopter in the course of their search, then the adopter will convert to being a nonadopter with probability σ. This is the probability of conversion from adopter to nonadopter for those adopters who find themselves isolated. Again, Asch's work supports this assumption.

Assumption 4: If a nonadopter fails to find at least one other nonadopter in the course of their search, then the nonadopter will convert to being an adopter with probability τ. This is the probability of conversion from nonadopter to adopter for those nonadopters who find themselves isolated.

These four assumptions are all that are necessary to drive the shape of the S curve (the "controversial innovation" curve) in figure 1. In particular, these values will determine how large the threshold β^t_{crit} is. The larger the threshold to be surmounted, the more difficult it will be to successfully diffuse the innovation throughout the entire organization. The larger L_a is relative to L_n, the lower will be β^t_{crit} the larger τ is, the lower will be β^t_{crit} the larger σ is, the higher will be β^t_{crit}. But, no reasonable values of these parameters will permit an arbitrarily small minority of innovators to convert, through this minimalist process, the entire organization.

Organizational Viscosity

I now introduce the idea of structure into our organization. Embedded in the prior set of assumptions is the notion that each individual performs a random search through the entire organization. In fact, people are usually confined in their interactions to those more locally accessible (Simon 1962). It has been argued elsewhere that structural differentiation can easily affect the diffusion process (Hagerstrand 1967), although our argument will rely on social structural forces rather than spatial ones such as Hagerstrand used. For simplicity, I will assume the organization can be partitioned into subsets, which I will call groups, and that people only search within their own group. Again, for simplicity, each group will be assumed to contain the same number of people. Diffusion within each group, then, simply becomes a smaller problem of the one tackled earlier. Within any group, if the proportion of adopters exceeds β^t_{crit} then the adopters will win over that group; otherwise, they will become extinct within that group.

Carley (1991), in her study of signal analysis, showed that the presence or absence of migratory links between groups, and the length of the chain connecting two groups, determined the rate and pattern of adoption. Likewise, if we assume some small degree of mobility among groups, we offer the opportunity of the problem becoming much more complex and interesting than one encounters in the case where everyone is free to interact with everyone else in the organization.

The restrictions on mobility will be monitored through two mechanisms. First, only certain pairs of groups will be characterized as exchanging individuals at all. The pattern of these exchange possibilities will constitute the structure of the permissible flow of people in the organization. Second, the rate at which individuals are allowed to migrate along these exchange paths from group to group will be controlled by a parameter (v), a rate which reveals the extent of organizational *viscosity.*[4] For purposes of this chapter, we will restrict ourselves to some simplifying assumptions:

Assumption 5: For each period t, prior to individuals searching for like-minded others, a certain fraction of the group's inhabitants will migrate to another group. The migration rate from group i to group j will be given as $M_{ij} = vS_{ij}$, where S_{ij} is a symmetric adjacency matrix designating the structure of possible exchange relations between all group pairs, and v is the fraction of the group that migrates to the adjacent group each period.

It is important to point out that people are not being modeled individually here. Rather, the group is the unit of analysis, and the measure of interest is the proportion of adopters within the group. Moreover, all groups are assumed to be the same size, and this size does not change over time since movement between groups occurs equally in both directions.

Dynamic Details

There are two steps in the model. First, a certain proportion of individuals migrate to their new groups. Second, after a migration has taken place, a certain proportion of individuals may convert to being either adopters or nonadopters.

Step 1: Migration

We now have enough information to determine the dynamics of this diffusion process. Let β_i^t be the proportion of adopters in group i. Let M_{ij} be the proportion of group i that migrates to group j in one period (and vice versa). I will refer to all groups that directly exchange people with group i as groups *adjacent* to i (i.e., all groups j such that $M_{ij} \neq 0$).

The fraction of adopters who left due to migration is the sum of the product of migration rate for each adjacent group and the proportion of adopters who originally occupied the group (= $\sum_j M_{ij}\beta_i^t$), and the fraction who remain is one minus this sum. The fraction of adopters who are added through immigration is simply the sum of the products of the migration rates of adjacent groups and the proportion of adopters in those locations (= $\sum_j M_{ij}\beta_j^t$). Combined, these two factors give the proportion of adopters who occupy group i at the succeeding time period but before any conversion takes place:

$$B_i^t = \left(1 - \sum_j M_{ij}\beta_i^t\right) + \left(\sum_j M_{ij}\beta_i^t\right) \tag{1}$$

Since all persons are either adopters or nonadopters, then the proportion of nonadopters in group i at a successive time period is $1 - \beta_i^{t'}$.

This completes the process of migration. The next step is to consider what happens to these adopters and nonadopters once migration is completed, that is, what proportion of adopters and nonadopters are converted nonadopters and adopters, respectively.

Step 2: Conversion

By assumption 2, we know that conversion only occurs when an individual is unable to find another like-minded individual in the process of their search through L others. I assume random searching within the confines of the group. The rate of conversion, then, is a function of the probability that the individual will not encounter a like-minded individual among the L others.

If the probability of not finding such a person in one encounter is p, then the joint probability of not finding such a person in a search among L others is p^L. The probability of not finding such a person in one encounter is 1 minus the proportion of like-minded others. Substituting this proportion for adopters (equation 1) we can derive the following probability of adopters not encountering another adopter in a given time period following migration:

$$\begin{aligned} p_i(\bar{a}) &= \left(1 - \beta_i^{t'}\right)^{La} \\ &= \left(1 - \left(\left(1 - \sum_j M_{ij}\beta_i^t\right) + \sum_j M_{ji}\beta_j^t\right)\right)^{La} \end{aligned} \tag{2}$$

For nonadopters, we can substitute their particular search parameter L_n and their own probability of not finding another like-minded nonadopter:

$$\begin{aligned} p_i(\bar{n}) &= \left(\beta_i^{t'}\right)^{Ln} \\ &= \left(\left(1 - \sum_j M_{ij}\beta_i^t\right) + \sum_j M_{ji}\beta_j^t\right)^{Ln} \end{aligned} \tag{3}$$

The net overall conversion rate, then, is the probability of being isolat-

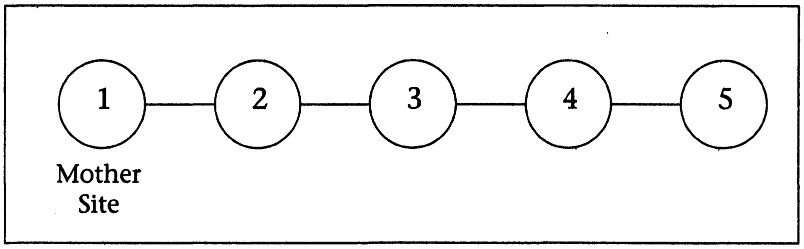

Figure 2. An organization, composed of five groups in a chain.

ed from like-minded others (p) times the probability of converting given this isolation (σ or τ) times the proportion in the group after migration $\beta^{t'}$ or $1 - \beta^{t'}$). For adopters, this conversion rate is

$$C_i(a) = \sigma\beta_i^{t'} p_i(\bar{a}) \tag{4}$$

and for nonadopters this conversion rate is

$$C_i(n) = \tau(1 - \beta_i^{t'}) p_i(n) \tag{5}$$

Thus, combining these equations, we find the proportion of adopters that reside within group i after migration and conversion to be

$$\beta_i^{t+1} = \beta_i^{t'} - C_i(a) + C_i(n) \tag{6}$$

From these mathematical drivers, it is a straightforward task to create simulations of this system to determine the effects of various parameters and the overall structure. In the following section, I present simulation results and generate some overriding principles of behavior of these diffusion systems.

Results

Our intent here is to uncover some conditions under which a small minority of innovators could overcome the majority in a system where the only process that matters is conversion due to social isolation. I start with a simple example that demonstrates how such is possible.

Consider the organization depicted in figure 2. This organization is composed of five groups, arranged in a chain. The links among the groups represent the avenues of migration. In each simulation, I will start by assuming that the adopters dominate one and only one of the groups. That is, in the initial conditions, one group will contain 100 percent adopters; all other groups will contain 0 percent adopters. I will call the site that contains 100 percent adopters the "Mother site" (again, borrowing from Boorman and Levitt). In the

Iteration	β_1	β_2	β_3	β_4	$\beta 5$
1	0.9656	0.0469	0.0000	0.0000	0.0000
2	0.9473	0.0779	0.0001	0.0000	0.0000
3	0.9369	0.1012	0.0004	0.0000	0.0000
4	0.9311	0.1203	0.0006	0.0000	0.0000
5	0.9283	0.1367	0.0009	0.0000	0.0000
6	0.9276	0.1515	0.0012	0.0000	0.0000
7	0.9282	0.1653	0.0015	0.0000	0.0000
8	0.9299	0.1784	0.0018	0.0000	0.0000
9	0.9323	0.1914	0.0021	0.0000	0.0000
10	0.9351	0.2042	0.0025	0.0000	0.0000
20	0.9658	0.3529	0.0085	0.0000	0.0000
30	0.9875	0.5687	0.0272	0.0000	0.0000
40	0.9984	0.8409	0.0886	0.0004	0.0000
50	0.9999	0.9500	0.2169	0.0028	0.0000
100	1.0000	1.0000	0.9775	0.4199	0.0136
134	1.0000	1.0000	1.0000	1.0000	1.0000

Table 1. Chain graph.
Parameters for this simulation: $\nu = 0.1$; σ, $\tau = 1.00$; $L_a = 6.0$; $L_n = 4.0$

current example in figure 2, group #1 is the Mother site.

The fate of the adopters, and the subsequent fate of the innovation itself, depends on the parameters set for the structure. As an illustration, I will assign the Mother site to group #1; I will assign a 100 percent conversion rate for those faced with unanimous opposition to their current beliefs; I will assign modest searching values of 6 and 4 for the adopters and nonadopters; and I will assign a migration rate of .1 for those groups who are adjacent to other groups. That is, I will assign the following parameter values: $L_a = 6$; $L_n = 4$; $\sigma = 1.0$; $\tau = 1.0$; $\nu = .10$. The simulation results are given in table 1.

Listed in this table are the β's for each group, that is the proportion of adopters in each group, after a number of time periods. For example, after the first time period, the fraction of adopters in the Mother site drops to .9656, while it increases in group #2 from 0 to .0469. The proportion of adopters in the Mother site drops slowly until period 7 and continues to increase from then on. By the end of period 50, the Mother site is virtually all adopters, group #2 is almost all adopters, and group three is rapidly increasing its proportion of adopters. By the end of 134 periods, equilibrium is reached[4] and all five groups become completely converted to the innovation.

Iteration	β_1	β_2	β_3	β_4	$\beta 5$
1	0.9656	0.0469	0.0000	0.0000	0.0000
2	0.9473	0.0779	0.0001	0.0000	0.0000
3	0.9369	0.1012	0.0004	0.0000	0.0000
4	0.9311	0.1203	0.0006	0.0000	0.0000
5	0.9283	0.1367	0.0009	0.0000	0.0000
6	0.9276	0.1515	0.0012	0.0000	0.0000
7	0.9282	0.1653	0.0015	0.0000	0.0000
8	0.9299	0.1784	0.0018	0.0000	0.0000
9	0.9323	0.1914	0.0021	0.0000	0.0000
10	0.9351	0.2042	0.0025	0.0000	0.0000
20	0.9658	0.3529	0.0085	0.0000	0.0000
30	0.9875	0.5687	0.0272	0.0000	0.0000
40	0.9984	0.8409	0.0886	0.0004	0.0000
50	0.9999	0.9500	0.2169	0.0028	0.0000
100	1.0000	1.0000	0.9775	0.4199	0.0136
134	1.0000	1.0000	1.0000	1.0000	1.0000

Table 2. Chain graph.
Parameters for this simulation: $\nu = 0.2$; σ, $\tau = 1.00$; $L_a = 6.0$; $L_n = 4.0$

The dynamic here is important to emphasize. Migration has allowed the innovation adopters to spread their innovation to an adjacent group. But, while they are making inroads into this neighboring group, they are losing out initially in their home base to the nonadopters who have replaced them. This struggle continues until one of two things happens: either the rate of depletion/conversion of adopters in the Mother site overtakes the depletion/conversion rate of nonadopters in the neighboring sites, or the converse. In the former case, the innovation adopters will eventually dominate the system. In the latter case, the nonadopters will eventually dominate the system. In this simulated organization, the adopters win.

Principle of Optimal Viscosity

This outcome is determined by the system and its parameters. But, the system is surprisingly insensitive to many parameters. For example, if we change the search parameters to any number of values from 2 to 20 (retaining the constraint imposed by assumption 1 that $L_a > L_n$), the same results hold—that is, in equilibrium the adopters dominate the entire organization. Moreover, the system is relatively insensitive to values of the conversion rates, *a* and *t,* which can vary from 0 to 1. without affecting the eventual outcome (as long as they do not differ markedly from each other).[6]

However, the outcome is quite sensitive to viscosity. Table 2 shows the results of a simulation with exactly the same parameters and starting conditions as provided in table 1 but with $v = .2$ instead of .1. In this case, we can see that by the end of period 23 all of the adopters have been eliminated from all groups.

Note in particular, that at the beginning of this dynamic process in rounds 1 and 2, the total number of adopters is increasing. It is only after round 3 that the proportion of adopters in the system starts to decline. This curvilinear result is in sharp contrast to the dynamic characterized by figure 1, where the long term result is consistent once you establish a starting point. The difference here is that in figure 1 there is no structure; each individual has an equal chance of interacting with any other individual in the entire population. Without structure, the behavior of the system is simple, deducible without the help of computational methods. But, as I mentioned at the beginning of this chapter, computational models become most interesting when they reveal behavior that is not intuitive. With differential viscosity and structure limiting who gets to migrate where and how quickly, the dynamics become complex and counterintuitive. The adopters start to increase in table 2 because they migrate to neighboring groups that are devoid of adopters. Their migration rate is matched by the migration rate of nonadopters who are invading the mother site of adopters. This counterinvasion eventually cuts off the life line of support, in a sense preventing the adopters from calling in reinforcements to bolster their invasion of the nonadopting groups. While the exact point at which the invasive forces of adopters loses out to the defensive invasion of the nonadopters is determined by the exact parameter values in the model, the overall shape of this result is both counter-intuitive and robust against a wide choice of parameters.

Another outcome is obtained if we use a migration rate of $v = .05$, again retaining the same values for all other parameters. In this case, an equilibrium is reached wherein the Mother site stays dominated by adopters and the other groups remain predominantly nonadopters (see table 3). Note that after 19 time periods, the proportion of adopters at the Mother site has stabilized at .986 and at the adjacent group #2 at .0273 (the remaining groups remained at .0000 for all time periods), producing a *poly-stable* outcome.

Figure 3 plots the effect of v on the equilibrium outcome of the system. The vertical axis indicates the average β for the five groups; the horizontal axis indicates the value of v that produced that β Polystable

Iteration	β_1	β_2	β_3	β_4	β_5	
1	0.9907	0.0133	0.0000	0.0000	0.0000	
2	0.9876	0.0195	0.0000	0.0000	0.0000	
3	0.9865	0.0229	0.0000	0.0000	0.0000	
4	0.9861	0.0246	0.0000	0.0000	0.0000	
5	0.9800	0.0257	0.0000	0.0000	0.0000	
6	0.9860	0.0263	0.0000	0.0000	0.0000	
7	0.9860	0.0267	0.0000	0.0000	0.0000	
8	0.9860	0.0269	0.0000	0.0000	0.0000	
9	0.9860	0.0271	0.0000	0.0000	0.0000	
10	0.9860	0.0271	0.0000	0.0000	0.0000	
19	0.9800	0.0273	0.0000	0.0000	0.0000	(equilibrium

Table 3. Chain graph.
Parameters for this simulation: $v = 0.05$; $\sigma, \tau = 1.00$; $L_a = 6.0$; $L_n = 4.0$

outcomes are represented by an average β of about .2—that is, one of the five groups is dominated by adopters (β= 1); the remaining four groups are dominated by nonadopters ($\beta = 0$). Note that any value of v below .07 will result in a poly-stable outcome with these structural conditions. In such cases, as one would expect, the migration rate is so low that neither position (adopters nor nonadopters) are able to muster enough forces to infiltrate and take over the dominance of the other in their already established groups.

Values of v from .08 to .16 result in an equilibrium wherein adopters dominate ($\beta = 1$ for all groups). But the dynamic above this threshold has an unexpected result. Any value of v greater than .16 will result in the nonadopters dominating the organization at equilibrium ($\beta = 0$ for all groups). That is, there is a *narrow window of opportunity* in which adopters can win, where the migration rate is between the values of .08 and .16. If migration exceeds this window, then all of a sudden the structural advantage that is enjoyed by the adopters disappears.

One might think that conversion rates would influence the shape of this graph. It is obvious that lower conversion rates will result in slower diffusion. But it is not obvious what lower rates of conversion will do to the shape of the equilibrium curve.

Figure 4 demonstrates these effects for five specific values of $s = t$ (= .2, .4, .6, .8, and 1.0). As one can see, lowering the conversion rate has the effect of narrowing the window of opportunity for adopters and shifting this window to the left (that is, lower values of v are required for the adopters to succeed in diffusing to the entire organization). But the ba-

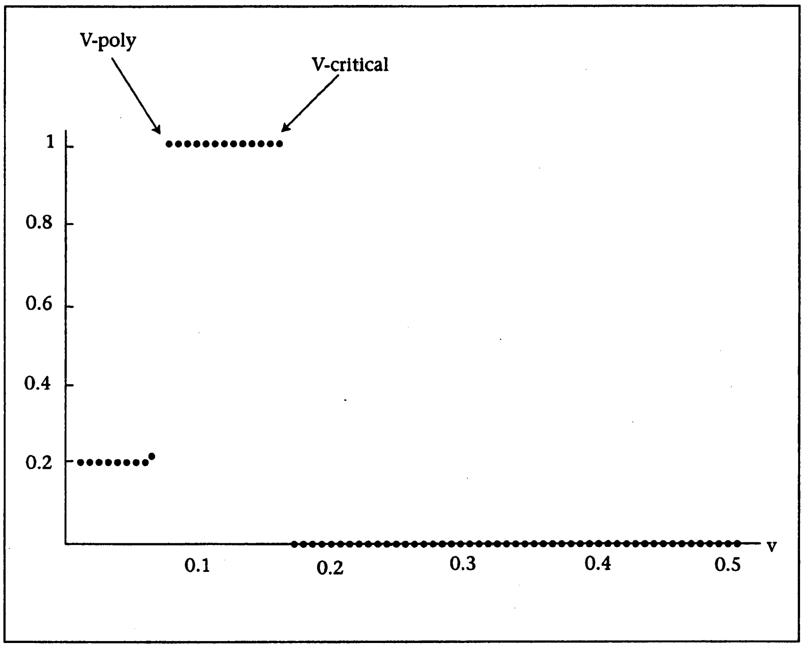

Figure 3. Plot of beta averages for equilibrium states given different viscosities for chain structure.

sic shape of the curve remains the same: there is a lower region of polystable outcomes, followed by a restricted region in which adopters win, followed by a substantial region in which nonadopters win.

These results obtain in any chain structure, independent of the length of the chain. Since this chain can be arbitrarily long, an innovation can come to dominate an organization no matter how small a minority position they hold. All that is necessary is to control the structure and viscosity within the organization.

It is not necessary to start with a chain structure to obtain this result, either. This result is robust over many kinds of structures (although not all) and parameter values. The result is so common that I propose the following general principle, the "Principle of Optimal Viscosity:"

> The degree of viscosity from one group to another has two threshold values, *v*-poly and *v*-critical, where 0 < *v*-poly < *v*-critical < 1. If *v* is below *v*-poly, then the result will be polystable, with the Mother site dominated by adopters and other dominated by nonadapters. If *v* is above *v*-poly but below *v*-critical, then all sites will become dominated by adopters. But, if *v* increases beyond the *v*-critical value, then the adopters will lose out to the nonadopters in equilibrium.

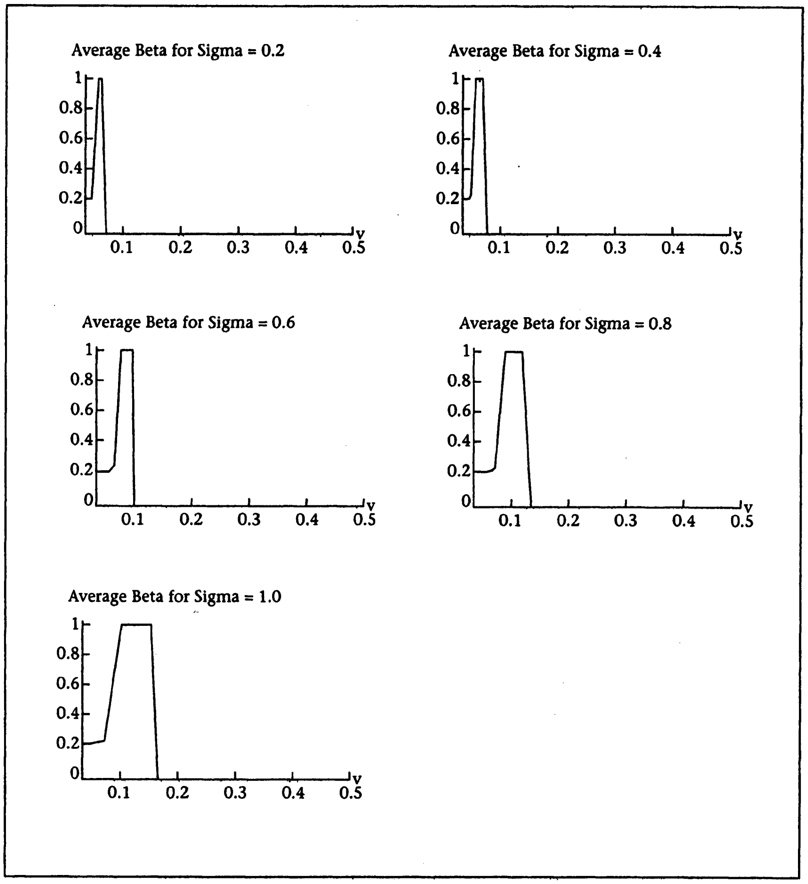

Figure 4. Plot of beta averages for equilibrium states given different sigmas and different viscosities for chain structure.

Principle of Peripheral Dominance

It is not always the case that a structure will permit a successful diffusion of the innovation, no matter what the viscosity. That is, the window of opportunity for adopters is nil (ν-poly = ν-critical). For example, consider figure 5, which depicts an organization the same size as in the previous simulation but structured very differently. In this case, we use the same parameters we used in the prior model: $L_a = 6$; $L_n = 4$; $\sigma = 1.0$; $\tau = 1.0$. The simulation results for $\nu = .05$ are provided in table 4; Table 5 contains the results for $\nu = .10$. In both cases (and in all cases above ν-poly = .03), the nonadopters dominate the organization in equilibri-

Iteration	β_1	β_2	β_3	β_4	β_5	
1	0.8819	0.0133	0.0133	0.0133	0.0133	
2	0.7811	0.0168	0.0168	0.0168	0.0168	
3	0.6845	0.0158	0.0158	0.0158	0.0158	
4	0.5876	0.0129	0.0129	0.0129	0.0129	
5	0.4888	0.0094	0.0094	0.0094	0.0094	
6	0.3877	0.0061	0.0061	0.0061	0.0061	
7	0.2846	0.0036	0.0036	0.0036	0.0036	
8	0.1823	0.0018	0.0018	0.0018	0.0018	
9	0.0900	0.0007	0.0007	0.0007	0.0007	
10	0.0261	0.0002	0.0002	0.0002	0.0002	
14	0.0000	0.0000	0.0000	0.0000	0.0000	(equilibrium)

Table 4. Dense graph.
Parameters for this simulation: $v = 0.05$; σ, $\tau = 1.00$; $L_a = 6.0$; $L_n = 4.0$

um. When v drops below .03, poly-stable outcomes are again observed.

What is different about this structure is that the Mother site is located in a central position in the structure.[7] In general, in cases where the Mother site is more centrally located, the window of opportunity for the adopters is smaller than it is when the Mother site is located on the periphery of the structure. This gives rise to the principle of peripheral dominance:

> It is more likely that the innovation will successfully diffuse throughout the organization if the Mother site is located on the periphery of an organization's structure than if the Mother site is located centrally in the organization's structure.

Two additional points should be made here. First, the way we know that there is no "window of opportunity" is by successively cutting the tolerance into smaller and smaller units to ensure that there is no region of successful innovation that may exist between the coarse units reported in table 4. Second, this search for a narrow window would be easier if there were a mathematical solution to the derivation of the equilibrium outcome given a set of parameter values. Unfortunately, one of the characteristics of complex dynamic feedback systems such as modeled here is that they do not behave in mathematically tractable ways. This is precisely why computational models are useful.

Principle of Irreversibility

Another interesting finding in these simulations is that there is an apparent asymmetry in the process governed by Assumption #1 (L_a

Iteration	β_1	β_2	β_3	β_4	β_5	
1	0.6494	0.0469	0.0469	0.0469	0.0469	
2	0.4074	0.0530	0.0530	0.0530	0.0530	
3	0.2276	0.0378	0.0378	0.0378	0.0378	
4	0.0956	0.0168	0.0168	0.0168	0.0168	
5	0.0210	0.0034	0.0034	0.0034	0.0034	
6	0.0011	0.0002	0.0002	0.0002	0.0002	
7	0.0000	0.0000	0.0000	0.0000	0.0000	
8	0.0000	0.0000	0.0000	0.0000	0.0000	
9	0.0000	0.0000	0.0000	0.0000	0.0000	(equilibrium)

Table 5. Dense graph.
Parameters for this simulation: $v = 0.1$; σ, $\tau = 1.00$; $L_a = 6.0$; $L_n = 4.0$

$> L_n$). This asymmetry makes it almost impossible for the nonadopters to retake control of the organization once adopters have dominated it. To be specific, if we were to take an organization dominated by innovators with the exception of the Mother site, which we populate with nonadopters, the nonadopters would not be able to diffuse their belief throughout the organization—even though these are exactly the structural conditions that allowed the adopters to take over in the first place. As long as adopters retain their proselytizing edge, the organization will remain resistant to a return to a preinnovation state.

I call this result the *principle of irreversibility:*

> Once an innovation has been successfully diffused throughout the organization, then it is almost impossible for the process to be reversed to a state where the nonadopters once again dominate the organization.

Discussion

Starting with a few very simple but powerful assumptions, we can uncover interesting dynamics in a process that may account for the diffusion of innovations within a complex social system. But, the results clearly depend on the viability of the assumptions we make at the beginning of this chapter. It is worth discussing how critical and realistic these assumptions are.

First, the model as given in this chapter is deterministic, not stochastic. It assumes that exactly v fraction of each group moves

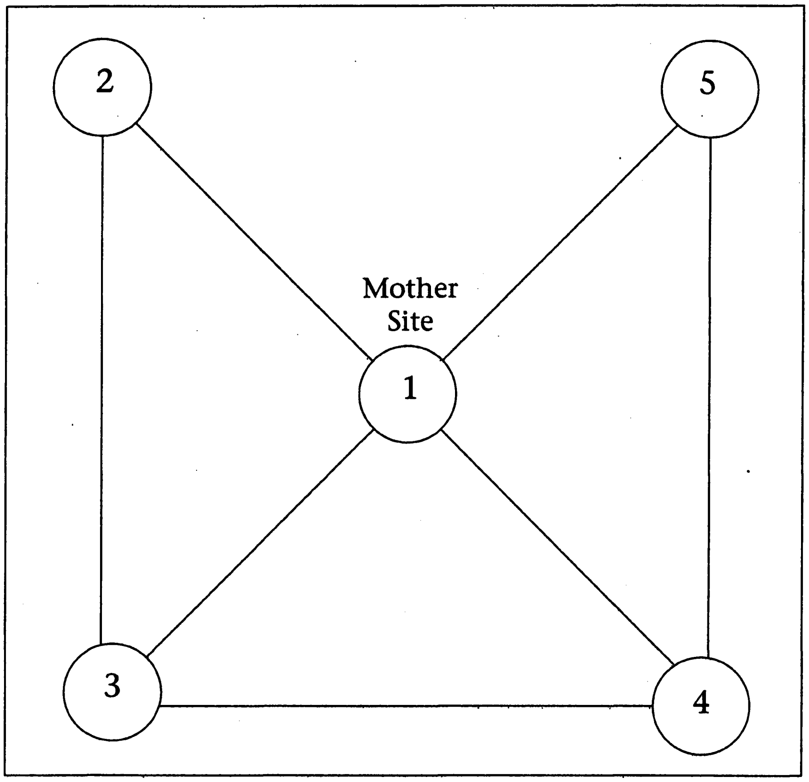

Figure 5. Dense structure with mother site at center.

along the structured paths provided in the model. It assumes each actor engages exactly L others in their search for a like-minded soul. These are not realistic assumptions, perhaps, but they are not critical either. Stochastic models probably better represent reality, but the deterministic counterpart allows one to efficiently model the most likely outcome. Stochastic modeling would require modeling the behavior of each actor individually, making it much more difficult. And perhaps more importantly, deterministic models are appealing because they allow conclusions to be deduced instead of statistically inferred.

Along similar lines, one could play with the modeling assumption that each group has an undetermined number of actors. Rather than keep track of each individual actor in each group at each stage, the simulation recounts simply the proportion of the actors in each group that are adopters vs nonadopters. This simplification makes the results robust and independent of the number of actors that might populate each group. However, it is possible that if each group had a small number of actors, the dynamics might show signs of instability.

Some assumptions can be relaxed naturally by using alternative parameter values. For example, the Asch assumption that conversion occurs primarily in cases where the individual finds no one in her immediate environment who agrees with her, can be relaxed by playing with the sigma and tau parameters. Indeed, it would be an extremely difficult assumption to defend in today's age where anyone can find someone who agrees with them on just about anything by hooking up to the internet. However, while I have not explored all possibilities, figure 4 suggests that the general principles derived in this chapter are not sensitive to a wide variety of parameter values and hence not sensitive to this assumption.

A more serious limitation is in the assumption that the structure of interactions does not change L_a, L_n, v, and the structure M are all invariant over time in this model. This is not only unrealistic but clearly the dynamics would be altered if these parameters were allowed to change over time periods.

In particular, the principle of irreversibility, as noted before, rests on the assumption that $L_a > L_n$ That is, the adopters are assumed to reach out and proselytize to more people than the nonadopters are. Indeed, there is nothing inherent in the nature of the innovation that would dictate this be so; it is simply an assumption of the model that innovators are perhaps more excited, energetic, and likely to reach out to others than noninnovators. However, what makes the process irreversible is that adopters continue this gregarious behavior even after they have become the dominant force inside the organization, the new status quo. One could argue that, once they have reached this dominant position, the nonadopters become the new innovators by suggesting the alternative to the new status quo. One could assume that this would lead them to become more excitable, more energetic, more expansive in their social ties than the old adopters, who are now fat, happy and lazy. This could lead them to a reversal of the $L_a > L_n$ assumption; such a reversal would destroy this irreversibility principle. Indeed, while relaxing this assumption may destroy the irreversibility principle, it may at the same time model more closely the "fashionable innovation" discussed by Macy and Strang (chapter 3).

Thus, as with any model, the predictions are in part sensitive to the veracity of the driving assumptions. One distinct advantage that Carley's structuralism model has over the viscosity model is that it explicitly allows for such changes in parameter values (Carley 1991, Kaufer and Carley 1993). I would not defend the realism of these assumptions about lack of parameter changes. Indeed, an interesting extension of this model would be to incorporate such dynamics in the model to see how the system behaved. But, as a first step, this chapter offers insight into how a system would behave if it *were* fixed.

The actors in this model are undifferentiated. They have no personality, nor differentiated powers, skills, or demographic characteristics. We know that such individual characteristics affect probabilities of ties in various ways (Krackhardt 1992, Krackhardt and Brass 1994, Ibarra 1995). While it was beyond the scope of this chapter, incorporating these kinds of dynamics into the model could provide a richer insight into the relationship between structure and diffusion. The Carley and Hill article in this volume suggest triadic structures that could also influence exchange and diffusion rates. When these triads create cliques, then these structures have both liberating and constraining effects that can profoundly influence change in an organization (Krackhardt 1999). To pursue this even further, the PCANS model provides a framework for describing the complex relationship between people, tasks and resources (Krackhardt and Carley 1999). Including hypothesized structures among these three domains could greatly enhance our ability to understand these dynamics in a much more realistic though complex model.

A related critical issue is that I have included no assumptions about the rationality of the actors in these organizations. These actors did not cajole, persuade, intimidate, or in any other way act to further their own interests or positions. They were passive actors, whose decisions to adopt or not adopt were a formulaic function of the positions taken by others they happened to run into.

Again, this is clearly an unrealistic assumption. Nonetheless, my purpose was not to model strategies that advocates might take to win a controversial battle. Rather, my purpose was to illuminate structural conditions under which changes might easily take place in the absence of such strategic behavior. If the principles uncovered in this chapter work in the absence of purposive behavior on the part of the organizational participants, then how much easier is the job of the purposive actor trying to diffuse the innovation if they could control the structure of organization and the viscosity of its mobile participants?

This last question suggests a use for this modeling procedure. There is a natural tendency to attribute success of a political battle to the attributes of the winner(s). But, as Schelling (1978) has shown, sometimes simpler mechanical rules of micro behavior can adequately explain the phenomena of interest at the macro level. If we can identify structural constraints that by themselves predispose an outcome usually attributed to the wiles of the actors, then perhaps this will force us to look at other sources of (structural) explanations of outcomes that do not rely on dangerous tautologies such as "the innovators won because they had a better idea" or "the innovation diffused because the adopters were better at persuading everyone of the value of their idea". More modeling of this kind may be a useful way to wean us from such easy but uninformative theorizing (Mayhew 1980).

In closing, I quote from Jim March's introduction to this book: "The survival of infant ideas, like the survival of infant humans, requires a social structure that buffers them from short-run and local selection pressures." He is referring to the field of computational modeling, the thrust of this book. But he could easily have been summarizing this article. Indeed, computational modeling *is* a controversial innovation, one that has the potential to diffuse widely. March points to its failure to do so the first time around (some 30 years ago), but perhaps that could be attributed to the fact that it was too central, migrating too quickly from the Carnegie Mellon University mother site. Perhaps this time around, with computational modeling establishing a firm foothold on the periphery, with a few carefully chosen groups forming at selected outposts, with its participants actively reaching out in the literature and academic conferences advocating this new form of scientific inquiry, perhaps this time around it will succeed.

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Notes

1. Interesting extensions of these ideas—especially viscosity-have been made into such varied areas as biology (Pollock 1989a, 1989b), game theory (Myerson, Pollock, and Swinkels 1991, Pollock and Lewis 1993) and school desegregation (Granovetter 1986). The central theme around all of this work is that structuring (restricting) interactions within any system can produce unexpected results that are not possible when the system is unrestricted.

2. I am indebted to conversations with Joel Podolny for contributing this important

insight. Boorman and Levitt (Boorman and Levitt 1980) had used only one L parameter in their exploration of the diffusion of genetic altruism within a species—that is, they assumed that phenotypically nonaltruistic critters did no searching for other nonaltruists. Podolny, in collaboration with Peter Bearman (Bearman and Podolny 1986), explored a model of religious conversion in Medieval Europe using two L parameters, one for each group. They observed dynamics similar to those found by Boorman and Levitt and those reported in this chapter.

3. *Viscosity* is a term drawn from fluid dynamics which refer to the *lack* of ability of a liquid to flow. Thus, a highly viscous fluid moves very slowly. I will use the term in a similar vein, although the parameter v will take on its highest values when mobility is maximized, not minimized. One may think of the parameter v as standing for *velocity* rather than viscosity, strictly speaking.

4. Equilibrium is defined in this chapter operationally as no group changes its β by more than 10^{-6} from the previous iteration.

5. It is true that one can virtually determine the outcome in favor of the adopters or the nonadopters by setting differential conversion probabilities for adopters and nonadopters. If adopters have a high probability of converting and nonadopters do not, then nonadopters will win in spite of any structural advantages. The converse is also true. However, these situations describe "rational" innovations rather than controversial innovations. That is, if an individual is more easily swayed to one position or the other, then it seems reasonable to assume that it was due to some exogenous force, such as the inherent quality of the innovation, rather than social influence.

6. It should be noted that by "central" I mean at a location that minimizes the average path distance to all other nodes—or "closeness" centrality (Freeman 1979). This should not be confused with "degree" centrality, or the number of other groups that are adjacent to the focal group. In fact, this result for "closeness" centrality obtains even when the central node has fewer ties than other nodes, such as in classic "bow tie" structure (Krackhardt and Hanson 1993).

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