THE STRUCTURE OF ATTENTION: CENTRALITY AND BOTTLENECKS IN THE DIFFUSION OF INNOVATIONS

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Abstract

Few of us have the time or resources to acquire even a fraction of the new, innovative ideas that may be relevant to our lives. This simple fact has a profound effect on the diffusion of innovations within organizations. This paper puts forward a process model of the diffusion of innovations, offering a causal explanation for the time-varying adoption behavior of actors in an organization by taking explicit account of the effects of limited resources on an actor's ability to adopt and diffuse multiple innovations. We explicate a simple process model of diffusion and then, through computer simulation, demonstrate that an actor's ability to take advantage of its structural position in a network is moderated by the degree of slack available to that actor and its intermediaries.

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"Participants within an organization are constrained by the amount of time they can devote to the various things demanding attention." Cohen, March and Olsen (1972)

INTRODUCTION

The study of the diffusion of innovations enjoys a long history in the social sciences. Disciplines as disparate as sociology, organizations, marketing and communication have all examined the spread or adoption of innovations within a population of actors, be they people, organizations, communities or schools (Mansfield, 1961; Bass, 1969; Teece, 1980; DiMaggio and Powell, 1983; Rogers, 1976; Tolbert and Zucker, 1983). Most of these studies have examined the predictors of the adoption of a *particular* innovation over time, arguing that certain characteristics of the innovation or of the actors affect the pattern and timing of diffusion within the group that is studied.

A subset of these researchers has extended the study of general processes of diffusion to examining the role of social networks on patterns of adoption. In their classic study, Coleman, Katz and Menzel (1966) examined the influence of networks—the extant relations between actors—on the diffusion of an innovation through a population of doctors. They proposed that the doctors in their study adopted innovations previously adopted by other doctors with whom they had direct social ties—what has been termed cohesion. Burt (1987), in re-examining and extending the Coleman et. al. study, proposed instead that doctors adopted innovations previously adopted by doctors who were in a similar social position—that is, their structural equivalent in the network of social relations. Others have since carried on the tradition by examining the diffusion of a single innovation through networks of doctors (Strang and Tuma, 1993), corporate directors (Davis, 1991), managers (Galaskiewicz and Wasserman, 1989), and even cities (Knoke, 1982).

This network perspective has led others to examine the influence of network structure and actor position on the diffusion of innovations and knowledge more generally. For example, the importance of boundary spanners (Tushman, 1977), gatekeepers (Allen, 1978) and brokers (Burt, 1992; Hargadon and Sutton, 1997) in diffusing innova-

tions has been hypothesized and examined. The importance of these actors is said to derive from their position in the network, connecting two or more otherwise unconnected populations of actors and, thus, "enabling the flow of existing solutions between those that have such knowledge and those that do not" (Hargadon and Sutton, 1997: 728). Similarly, actors who occupy a "central" position within the network are said to play an important role in the movement of innovations, either because of their many direct connections to other actors (Czepiel, 1974; Rogers, 1974), their connection to well-connected or poorly-connected other actors (Bonacich, 1987) or their position between other actors (Freeman, 1978). Finally, the structure of the entire network has been examined in terms of its centrality. In highly central networks, where a few actors have relatively strong central positions compared to all other actors within the network, central actors are expected to play an even more dominate role in the diffusion of innovations (Freeman, 1978).

As distinguished as this stream of research is, we agree with Rogers (1976) when he calls for the increased study of the processes underlying diffusion, claiming, "(Diffusion researchers) lack concepts and propositions that reflect a process orientation" (p.294). This paper puts forward a process model of the diffusion of innovations. Our model offers a causal explanation for the time-varying adoption behavior of actors in a population by taking explicit account of the effects of limited resources on an actor"s ability to adopt and diffuse innovations.

Following Van de Ven (1986) and Abrahamson & Rosenkopf"s (1997) call for understanding the dynamics of systems where limitations in resources inhibit the adoption of all innovations, we consider the diffusion of *multiple* innovations, where innovations must compete for limited resources. New ideas proliferate in organizations, yet, very few innovative ideas are diffused throughout the entire organization. Abrahamson and Rosenkopf offer an explanation for the limited extent of innovation diffusion based on threshold models of adoption, where an actor"s resistance to adopt new innovations must be overcome by the "bandwagon" effects of adjacent adoptions. We extend this explanation of the limits of diffusion by introducing competition for the limited resources of actors. We couch this work in the area of organizations, although it is applicable to any group of actors who can be positioned within a social network.

To summarize, we propose to extend current research in two important ways. First, we will develop a process model that offers a causal explanation for the time-varying adoption behavior of actors within a network. Second, we will consider the diffusion of multiple innovations simultaneously which in turn will compete for limited resources. These extensions are important not only because they provide an alternative description of the adoption behavior of actors within a social network, but also because they have important implications for how we characterize gatekeepers, boundary spanners and central actors within social networks, and how we conceptualize outcomes associated with the structure of the network itself. We will pursue these goals by explicating a simple process model of diffusion and then, through computer simulation, demonstrating that an actor"s ability to take advantage of its structural position in the network is moderated by the degree of slack available to that actor and its intermediaries.

THE PROCESS OF DIFFUSION

The concept of organizational slack, the difference between the demand for resources and their supply, is not new. Cyert and March (1992; first published in 1963) recognized that slack could have an influence on the degree of experimentation within organizations. Nohria and Gulati (1996) tried to make sense of the subsequent literature by offering the hypothesis that "the relationship between organizational slack and innovation is inverse U-shaped," reflecting the tradeoff between greater experimentation and diminishing levels of discipline resulting from increased levels of organizational slack (p. 1250). However, most of this literature, either explicitly or implicitly, deals with the *creation* of innovative ideas and not explicitly with their *diffusion*. Although the constructs of organizational slack have been used in a few empirical studies of the adoption of innovations (cf. Ghoshal and Bartlett, 1988), it has yet to be explicitly incorporated into a process model to offer a causal explanation for the timing and extent of diffusion. In situations where innovations "compete" for the limited resources of actors, slack becomes a critical concept in understanding diffusion through a network.

In this paper we focus on the diffusion of innovations and not their creation from within or adoption from outside the population. That is, we take innovations as given en-

tities that "arrive" over time to actors within the focal population[1]. What is of interest to us is their subsequent diffusion to the rest of the population of actors. Because multiple innovations are simultaneously diffusing throughout the population over time, innovations compete for the limited resources of the actors within the network. We believe that a multiple-innovation model more accurately reflects what happens in populations of actors than does any single-innovation model. As Van de Ven (1986) points out, in current research a sample bias exists in the study of innovations in that only ideas that are deemed "successful" by an organization are studied as innovations. However in reality, actors typically must deal with multiple innovations concurrently, and these innovations must compete for limited resources if they are to diffuse throughout the population of actors. Not all innovations successfully compete. Many simply fade away before they diffuse throughout the entire population.

The Resource Requirements of Diffusion

Our fundamental premise is that the adoption of an innovation by an actor—whether it be a person, sub-unit or organization—requires the commitment of limited resources for some duration of time, during which certain resources are unavailable to commit to other activities. Resources may be required to resolve the ambiguity surrounding an innovation and to actually implement the innovation in the actor"s local setting (Arrow, 1969). To the extent that information about an innovation is codified, a potential adopter might easily adopt an innovation through access to documentation or broadcast media. For example, Burt (1987) could assume that information on tetracycline was widely and freely available to all of the doctors within the Coleman, et al. (1966) study, and thus, that the direct involvement of a previous adopter in the adoption of an innovation by an "adjacent" actor was unnecessary.

However, while codified information can be useful in some cases, critical aspects of the innovation may remain tacit (Nelson and Winter, 1982), and tacit knowledge is more difficult to impart (Winter, 1987). The transfer of technical knowledge often involves both transmission and absorption costs (Teece, 1977), and if an actor is to enable

[1] These arrivals could represent either innovative developments by the actor itself or adoption of innovations from sources external to the focal population.

"the flow of existing solutions between those that have such knowledge and those that do not" (Hargadon and Sutton, 1997: 728), it may have to expend resources not only on adopting innovations but on diffusing them as well. Much of the information used in technical problem solving is "costly to acquire, transfer and use in a new location" and when this "sticky information" resides in more than one location, "the locus of problem solving may *iterate* among these sites as problem solving proceeds" (Von Hippel 1994: 429, emphasis added).

Thus, we cannot assume that all relevant information is freely available to all potential adopters for all innovations, or that this information will be readily transferable to potential adopters in codified form. Instead, the information exchange and influence processes that are critical to diffusion are likely to be iterative processes, requiring the resources of both the broker—the previous adopter who is influencing the potential adopter—and the potential adopter. Thus, although influence may arise from an actor"s position within the network, for many innovations the actor will have to utilize its limited resources to effect this influence—in turn reducing the resources available to adopt and diffuse other innovations. This can have a significant impact on how innovations diffuse throughout a network. To be a source of influence is to incur a cost in terms of resource requirements. The type and quantity of resources required for any one innovation may vary with many factors—including the complexity, compatibility and relative advantage of the innovation—but over the long run, and thus, over many innovations, the resource costs of influence are unavoidable.

Social Networks, Salience and Attention

In his early treatise on decision making in organizations, Simon (1976; first published in 1945) wrote:

> "All behavior involves conscious or unconscious selection of particular actions out of all those which are physically possible to the actor and to those persons over whom he exercises influence and authority. The term "selection" is used here without any implication of a conscious or deliberate process. It refers simply to the fact that, if the individual follows one particular

course of action, there are other courses of action that he thereby forgoes" (p. 3).

We adopt a similar view. Because many demands are placed on an actor"s limited resources, either by other innovations or by day-to-day task requirements, an explicit or implicit prioritization of the commitment of resources emerges. The resulting prioritization, which is dynamically changing over time, is simply a manifestation of how the various demands compete for resources—the allocation of resources need not be the result of rational calculation (Simon, 1976; March and Simon, 1958; Cyert and March, 1992). .

Many factors can influence timing and resource allocation decisions in the adoption of innovations. However, we focus our attention on the influence of social relations among actors within the population. Our fundamental premise is that under constraints of limited resources, attention mechanisms play a critical role in determining the diffusion of innovations, and attention is strongly affected by social relations. That is, the more salient an actor is to a potential adopter, the greater the salience of innovations previously adopted by that actor. Although bandwagon theories of diffusion often assume that adoption by adjacent actors within the network will be sufficient to entice an actor to adopt, we assume only that this will make the innovation more salient to the potential adopter.

Simply put, our basic assumption is that the relative salience of adjacent actors who adopt an innovation will somehow influence the prioritization of that innovation relative to other innovations. All else being equal, innovations with greater salience will be attended to before innovations with less salience. Of course, all else is never equal and so we will introduce a stochastic element to the priority given to any one innovation. This stochastic element incorporates the many other factors likely to influence the relative priority of a particular innovation at a particular actor—factors that we take as unspecified, random perturbations in our parsimonious model.

Similar to previous research on the diffusion of innovations within networks, this characterization of the population reflects the notion that the salience of actors to other actors exhibits some regularity and is not solely dependent upon the ad hoc characteristics of particular innovations or adoption events. For example, subsidiaries within a multina-

tional corporation may be more likely, consistently, to notice innovations adopted by a headquarters operation than to notice innovations adopted by another distant subsidiary (Ghoshal and Bartlett, 1988 and 1990). Or doctors may be more likely to attend regularly to the prescription practices of other doctors of equal status than to doctors they perceive as having less status (Burt, 1987).

In this paper, we are not primarily interested in whether processes such as cohesion or structural equivalence are the underlying causes of salience. Our focus is on the salience relations themselves. That is, we start at the level of salience relations as given among actors and examine the influence of the structure of these salience relations on the diffusion of innovations within a population. Once organizations understand the importance of the structure of salience relations they can then begin to concentrate on the mechanisms that give rise to these relations.

Within this framework, the commitment of sufficient resources to any particular innovation may be delayed—possibly for a very long time—before any decisions are made regarding adoption. In fact, explicit decisions about the adoption of an innovation can be delayed indefinitely, explaining why an actor may never adopt some innovations even though an explicit decision to reject the innovation was never made. The salience of adoption events by adjacent actors, and thus, of the innovation itself, simply fades away with time (Strang and Tuma, 1993).

A SIMULATION MODEL OF DIFFUSION

We are interested in modeling the diffusion of multiple innovations through a network of salience relations among a population of N actors. For this simulation, we assume that innovations "arrive" to the focal population—that is, the network of actors—according to some random arrival process. Each innovation arrives to only a single actor within the network, although different innovations can arrive to different actors. For each actor $n = 1,\ldots,N$, we denote the mean external arrival rate of innovations to this actor as λ_n, and assume that this arrival rate is stationary over time—that is, the mean external arrival rate of innovations to each actor neither increases nor decreases over the time horizon of interest. Thus, innovations "arrive" to the network randomly, with an av-

erage arrival rate $\lambda = \sum_n \lambda_n$, where the average innovation arrival rate to any actor n, λ_n, may vary, depending on many factors, including the actor"s network position or level of slack resources.

Our assumptions for this model imply that innovations arrive to the focal population independently of one another and that no one innovation will arrive to more than one actor. Thus, the diffusion of an innovation is always assumed to occur from a single initial actor within the population. Furthermore, we assume that these innovations are independent of one another in the sense that they are neither substitutes nor compliments of one another. The adoption of one innovation by an actor neither precludes nor enhances the adoption of any other innovation by that same actor. Therefore, innovations compete with each other only for the attention of the actors.[2]

Modeling the Resource Requirements of Adoption and Diffusion

Since our objective is to explore how network structure and slack interact to affect the diffusion of multiple innovations, actors in these networks must have some fixed capacity for processing innovations—that is, limited resources. In our simple model there is only one type of resource at each actor, *time*, and each innovation requires some random amount of time at each actor before it can be adopted.

Specifically, when an innovation first gains access to the resources of the potential adopter, due to the availability of slack resources and the innovation"s priority relative to other innovations, the innovation occupies the resources of this actor for a randomly-distributed amount of time. During this time, the potential adopter must forego other activities (either operational or innovative) while it begins to "figure out" the innovation. However, for many innovations, diffusion may entail both transmission and adsorption costs, and "the locus of problem solving may iterate among [actors] as problem solving proceeds" (Von Hippel, 1994: 429). Thus, resource demands may iterate between the potential adopter and the broker—that is, previous adopter. Although it is possible that

[2] Although incorporating the effects of network position and organizational slack on the rate of external innovation arrivals and allowing for multiple, competing or enhancing innovations would prove interesting, we believe that these extensions would unnecessarily complicate the model and obscure the implications of the process model on diffusion. We leave this for future research.

the number of iterations and the time required to diffuse an innovation could depend on the previous number of adoptions of that innovation—as well as many other factors—we assume them to be independent in our model.[3]

Thus, with probability P, the potential adopter will require the resources of the actor from whom the innovation came (the broker), to understand further and to adopt the innovation. In effect, the innovation "returns" to the brokering actor from whom it "came," occupying its resources for a randomly distributed amount of time as well. At each stage, this *iterative problem solving* continues with probability P. Equivalently, with probability $(1-P)$ at any stage, the potential adopter requires no further resources from itself or from the brokering actor in either considering or adopting the innovation. So as not to introduce potentially confounding variables on diffusion, we typically assume that all innovations that have made it this far in the process are "adopted" by the potential adopter. Thus, the only factors affecting diffusion in most of our simulations are network structure and slack.

If we let τ denote the average time a single iteration occupies an actor, then τ and P can be considered as *resource cost parameters* for diffusion within the network. Larger values of τ might reflect environments with more complex or difficult-to-implement innovations. Larger values of P could reflect environments where information about most innovations is not freely available and thus, previous adopters must provide the main source of information. In these environments, diffusion costs for brokering actors can be as significant as adoption costs. Not only do innovations compete for the resources of the potential adopting actor; if $P > 0$ then potential adopting actors compete for the resources of the brokering actor. These resource costs have significant implications for the ability of central actors to influence the diffusion of innovations in a network.

Salience and Innovation Prioritization

We are interested in how the structure of salience relations, whatever their cause, influences the diffusion of these multiple innovations through a population of N actors.

[3] The stochastic nature of the number of iterations and the time required reflect the fact that these variables may be influenced by many factors—factors that we take as random perturbations in our model.

Thus, we examine the diffusion of innovations through a network, represented by a possibly asymmetric $N \times N$ matrix R (for relations), where $r_{n,m}$ reflects the relative salience of actor m to actor n. We take these salience relations as given. For simplicity, we assume that the network of salience relations remains constant over the time horizon of interest. Because the matrix R represents *relative* salience relations, we normalize the salience relations at each actor in the network, so that for each actor, $n=1,...,N$,

$$\sum_{m=1}^{N} r_{n,m} = 1 .$$

To illustrate, consider the three-actor network depicted in Figure 1. An arrow from actor B to actor A reflects the fact that actor A is salient to actor B—that is, actor B "looks to" actor A for innovations. Actor A is salient to actors B and C, but actors B and C do not look to each other for innovations ($r_{BC} = r_{CB} = 0$). Perhaps actor A is a supervisor to actors B and C, or actor A is a headquarters unit in an organization where subsidiaries are virtually unknown to each other. Both actors B and C are salient to actor A but actor B is relatively more salient to actor A ($r_{AB} = 0.75$) than is actor C ($r_{AC} = 0.25$).

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INSERT FIGURE 1 ABOUT HERE

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Consistent with previous research on the diffusion of innovations within social networks, we assume that the greater the salience of adjacent adopters and the greater the number of adjacent actors to adopt a given innovation, the greater will be the likelihood that a potential adopter will allocate resources to that innovation, all else being equal. Thus, innovations adopted by many actors such as facilities within a multinational organization or doctors within a local community are more likely to be adopted than those only adopted by a few. We must also introduce a random error term reflecting important, but unspecified factors that will also influence a given innovation"s relative priority.

Specifically, if we let $p_{i,n}(t)$ denote the relative priority of innovation i at actor n at time t, and $A_i(t)$ the set of actors that have adopted innovation i by time t, then we want

$p_{i,n}(t)$ to be a stochastically increasing function of $\{r_{n,m} : m \in A_i(t)\}$. That is, the greater the salience to actor n of actors who have already adopted innovation i, the greater the priority innovation i is likely to have with actor n, all else being equal. The actor then allocates whatever free resources it has—organizational slack—to those innovations with the greatest priority first.

Following on the work of Strang and Tuma (1993), we require that $p_{i,n}(t)$ be stochastically decreasing in the time since previous adoptions of innovation i. Specifically, that the "impact of each prior event falls off exponentially with the length of time since its occurrence" (Strang and Tuma, 1993: 621). This is consistent with the belief that over time, either the innovation itself or the information concerning the innovation becomes less salient to the potential adopter.

We propose the following additive formulation to model the effect of previous adoptions on the priority of innovation i to actor n at time t:

$$p_{i,n}(t) = \sum_{m \in A_i(t)} [r_{n,m} + e_{i,n,m}] \exp(\zeta (t_{i,m} - t)) , \tag{1}$$

where

$p_{i,n}(t)$ = the relative priority of innovation i at actor n at time t,

$A_i(t)$ = the set of actors that have adopted innovation i by time t,

$r_{n,m}$ = the relative salience of actor m to actor n,

$e_{i,n,m}$ = a $(0,\sigma)$-normal random perturbation reflecting the many unidentified factors affecting the salience of innovation i to actor n due to adoption by actor m,

$t_{i,m}$ = the time at which actor m adopts innovation i, and

ζ = a constant that reflects the proportional rate of decrease in the salience of an adoption event over time.

The additive formulation in (1) reflects situations where the combined salience of adjacent adopters determines the "expected" priority of the innovation but unspecified factors may increase or decrease its priority equally. That is, the perturbation, $e_{i,n,m}$, in (1) reflects the fact that the priority of an innovation is likely to be influenced by other factors besides the salience of adjacent adopters—factors that we incorporate as independent,

random perturbations. The larger the variance of these perturbations, the more these other factors not included in the model will influence the priority of a particular innovation at a particular actor.

Furthermore, we specify a lower bound, $p_{min}>0$, on the absolute level of priority required to attract the attention of an actor. This is consistent with assuming that there is a certain threshold salience level below which an innovation will not be detected from the daily demands on an actor"s attention. For example, a threshold level of 0.14 would be consistent with the statement that, on average, an actor could not spread its attention equally among more than 7 other actors and still be likely to notice innovation adoption events at each actor. Also, innovations whose adoption events have not attracted the attention of an actor after some period of time, and thus, have exponentially declined in salience, eventually disappear from the actor"s horizon, having no chance of adoption regardless of what else the actor may or may not be doing at the time.

One should note that the salience of actor m to actor n, $r_{n,m}$, does not represent the fraction of time or resources that actor n allocates to innovations adopted by actor m. It simply represents the importance, or salience of actor m to actor n, *relative* to other actors. The fraction of time or resources that actor n allocates to innovations adopted by actor m will certainly depend on the level of salience of actor m to actor n, $r_{n,m}$, relative to other actors, but it will also depend on actor m"s relative overall innovative activity—that is, its overall rate of innovation adoption.

If, for example, actor B in Figure 1 adopted very few innovations over time while actor C adopted many, then even though the few innovations adopted by actor B might have higher priority at actor A—due to actor B"s greater salience to actor A—actor A could still have considerable slack left over to allocate to the many innovations adopted by actor C. Thus, in the end, actor A might actually allocate more resources to the many innovations adopted by actor C than to the few adopted by actor B. However, if one were to reverse the situation, with actor B adopting many innovations over time, then it is clear that actor B could monopolize much of the attention of actor A to the exclusion of actor C.

AN ILLUSTRATIVE EXAMPLE

In this section we examine the diffusion of innovations within the simple three-actor network depicted in Figure 1. This example explicates our process model and illustrates the importance of the structure of attention and slack on the diffusion of innovations. The results arising from this very simple example will lead us to more closely examine the concept of network structure and actor position in the following section.

Actor *A* in Figure 1 clearly acts as a broker to actors *B* and *C* in that actor *A* enables the flow of innovations from actor *B* to *C*, and vice versa. Due to its central position, actor *A* will be a source of influence for the diffusion of innovations to each of the other actors. This influence, however, comes at a cost in terms of the resources required of *A*, and this cost has an effect on the diffusion of innovations in the network.

The Simulation

To illustrate, we simulate the diffusion of multiple innovations that arrive to this network according to a Poisson arrival process with rate λ=1 per unit of time. Each arrival is randomly assigned to one of the three actors with equal probability, at which time the innovation arrives or is "adopted" for purposes of diffusing to the other actors within the network. This initial adoption does not compete for the actor"s slack resources and is not considered as an adoption for purposes of tallying the extent of diffusion—we are interested only in the subsequent diffusion of the innovation after its introduction into the network.

The cumulative effect of previous adoptions on the salience of an innovation to a particular actor is determined by the relations described in Figure 1, using equation (1) with an exponential decay at rate of 10% per unit of time ($\zeta = 0.10$) and a normally distributed error term with standard deviation $\sigma = 0.05$. This error term is rather small in that it implies that the difference in salience of actors *B* and *C* to actor *A*,

$$r_{AB} - r_{AC} = 0.75 - 0.25 = 0.5,$$

is ten standard deviations apart. Thus, the network relations play a significant role in determining the priority of innovations at each actor. In addition, a minimum salience level $p_{min} = 0.05$ is assumed. This minimum salience level is four standard deviations from the

smallest attention relation ($r_{AC} = 0.25$). Thus, each innovation adoption event is likely to be above the minimum salience level of every adjacent actor. This gives each innovation ample opportunity for diffusion in the network.

Each actor has 20% of its resources—that is, time—available to allocate to the adoption and diffusion of innovations. Whether or not this is sufficient to allow for the complete diffusion of all innovations depends on the arrival rate of innovations to the network and on the resource cost parameters of diffusion. We have already noted that the average arrival rate of innovations to the network is λ=1 per unit of time. Furthermore, we assume average resource cost parameters of $\tau = 0.2$ time units and $P = 0.5$. That is, if and when an innovation first gains the attention of an actor, it will occupy that actor for an exponentially distributed length of time with mean $\tau = 0.20$. After each iteration, the probability that an innovation will require an additional iteration is $P = 0.50$. Thus, half of all innovations do not require more than a single iteration—that is, the adoption of the innovation does not require the resources of the brokering actor—and the average number of iterations for each innovation is two—that is, one iteration at the potential adopting actor and one at the brokering actor. All innovations that complete processing are assumed adopted. This allows us to isolate the effects of network structure and slack on the diffusion of innovations without introducing extraneous reasons for why an innovation was not adopted by a particular actor.

Given the above assumptions, the minimum available resources (slack) necessary to allow complete diffusion of all innovations arriving to the network over time is[4]

$$W = (N-1)\frac{\lambda\tau}{(1-P)}$$
$$= (3-1)\frac{1(0.2)}{(1-.5)} = 0.8$$

or, on average, 0.8/3 = 26.67% per actor. However, each actor has only 20% of its time available to allocate to innovative activities. Thus, the network has a capacity to diffuse,

[4] We ignore the resource cost of the initial adoption of an innovation when it arrives to the network. Our model simply assumes that innovations "appear" in the network because we are interested only in the subsequent diffusion of innovations after their introduction into the network.

at most, 75% of the innovations arriving to it over time. This does not mean that no innovation will diffuse to 100% of the actors within the population. It only means that, on average, 75% of all adoptions that are possible can occur in the long run. Typically, however, due to congestion and the tendency of innovation adoption events to lose salience over time, many fewer adoptions will take place than what is theoretically predicted.

We have yet to fully describe the model because we have not addressed the specific prioritization given by brokers to potential adopters in need of assistance. That is, when an innovation iterates back to the broker, with probability *P*, what priority is it given vis-à-vis not-yet-adopted innovations? One could approach this in many ways, but we opt to consider only two extreme cases. Actors are said to give priority to *diffusing* innovations when each actor gives priority to innovations iterating back from potential adopters who need help or convincing. Similarly, actors are said to give priority to *adopting* innovations when they give priority to not-yet-adopted innovations over requests from potential adopters.

Results

Tables 1-3 present results for a computer simulation of diffusion assuming that actors give priority to diffusing innovations. As we might have expected given actor *A*"s central position, innovations originating at actor *A* have the greatest extent of diffusion (92%), while those originating at actor *C* have the least (19%). However, actor *A*"s centrality does not carry over to the adoption of innovations in this case. In fact, because actor *A* gives priority to diffusion, and it is in an ideal position to diffuse innovations, actor *A* ends up adopting the *fewest* innovations (36%), while actor *C* adopts the most (72%). This is simply due to the fact that each actor has only 20% of its time available to adopt *and* to diffuse innovations. To the extent that actor *A* takes advantage of its central position to diffuse innovations, it has fewer resources remaining to adopt innovations.

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INSERT TABLE 1 ABOUT HERE

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This is clearly illustrated in Table 2 which shows the percentage of time allocated to adoption and diffusion activities for each actor. Actor *A* allocates the most time to diffusion activities (12% for actor *A* versus 1% for actor *C*) and the least time to adoption activities (8% for actor *A* versus 13% for actor *C*). Actor *A* has no unused slack left over for further innovation adoption. However, actors *B* and *C* do have unused slack (7% and 6%, respectively) even though there are many innovations still to be adopted. Actor *A* causes this phenomenon by limiting the number of innovations each actor sees. Thus, although actors *B* and *C* have unused slack left over to allocate to the further adoption and diffusion of innovations, actor *A* is constraining their ability to do so. As a result, the total extent of diffusion in the network, as depicted in Table 1, is only 54%, significantly less than the theoretical limit of 75%.

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INSERT TABLE 2 ABOUT HERE

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Table 3 presents a final look at the simulation results. Here we examine the average time—in the general time units of the computer simulation—to the first and second adoption for innovations originating from each of the three actors. As we might expect, average times to first and second adoption are always shorter for innovations originating from actor *A* (5.6 and 14.0, respectively) than for those from actors *B* and *C* (8.2-8.6 and 17.8-18.6, respectively).

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INSERT TABLE 3 ABOUT HERE

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However, it is more interesting to examine the time to first adoption from actors *B* and *C* as presented in Table 3. This first adoption is always by actor *A* and the average time until actor *A* adopts the innovation does not differ greatly between innovations originating from actors *B* or *C*, even though their relative salience to actor *A* differs markedly. This reflects the "window of opportunity" created by the combination of the temporal decline in salience of adoption events with the minimum salience or priority, p_{min}, required to be noticed.[5] Thus, innovations from actor *C* that get diffused are those that are lucky enough to quickly gain the attention of actor *A*, and thus, are diffused about as quickly as those from actor *B*. Unfortunately, fewer of them get noticed (172 for actor *B* versus 66 for actor *C*). This has significant implications with respect to the sampling bias previously mentioned by Van de Ven (1986). If we only sample those innovations that are successfully diffused throughout a population, innovations originating from actors *B* and *C* may look quite similar. We must also examine the innovations that do not diffuse to differentiate between the actors.

Results from computer simulations of diffusion assuming that actors give priority to *adopting* innovations give exactly symmetric results. That is, actor *A* adopts the most innovations while diffusing the least. Actor *A* still acts as a bottleneck, but this time because it spends so much time adopting innovations that it does not diffuse enough innovations to actors *B* and *C*. In fact, the total extent of diffusion is not statistically significantly different than the 54% achieved in the prior simulation.

The relative centrality of actor *A* in Figure 1 is unambiguous in terms of degree—the number of direct ties; closeness—how "far" it is from all other actors in the network; and betweenness—its ability to facilitate and inhibit the flow of innovations between all other actors in the network (Freeman 1978). This centrality manifests itself in actor *A*"s ability to either diffuse or adopt innovations according to its preference—but not necessarily both at the same time. As a broker between actors *B* and *C*, actor *A* certainly enables the flow of innovations between them. However, due to the extra demands placed on it as a broker, actor *A* soon runs out of slack and thus, inhibits the flow of innovations between actors *B* and *C*. When an actor is both in a position to inhibit innova-

[5] We borrow the term "window of opportunity" from Tyre, M. and W. J. Orlikowski (1997).

tions and has insufficient slack to fulfill its role as intermediary, that actor will become a *bottleneck*, limiting the extent of diffusion within the network.

Actor *A* must have more slack than actors *B* and *C* in order to compensate for its brokering activities. Table 4 shows the extent of diffusion for simulations when actor *A*"s slack is increased to 50% as compared to the 20% slack for actors *B* and *C*. As expected, the total extent of diffusion in the network increases from 54% to 81%. Actor *A* is no longer constraining the ability of actors *B* and *C* to see innovations. Now, actors *B* and *C* constrain actor *A*"s ability to diffuse innovations. This is evident in Table 5, which gives a breakdown of the activity levels for each actor. It shows that actor *A* has excess resources with which it could diffuse more innovations to actors *B* and *C*, but actors *B* and *C* have no further available slack with which to adopt these innovations. Obviously, the network is still unbalanced in terms of slack, but now with actors *B* and *C* having insufficient resources to allocate to innovative activities.

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INSERT TABLE 4 ABOUT HERE

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INSERT TABLE 5 ABOUT HERE

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IMPLICATIONS OF THE PROCESS MODEL OF DIFFUSION

In examining the diffusion of innovations within a network of salience relations, one must consider both the structure of the network and the extent of slack in the network. Because innovations "move" throughout the network, becoming salient to actors only after adjacent actors have adopted the innovation, an actor"s ability to adopt or diffuse innovations is increased by having adjacent actors who themselves are in a good po-

sition to adopt or diffuse innovations. This is similar to many previous conceptions of centrality (c.f. Bonacich, 1972).

However, an actor"s position within the network is moderated both by the extent of its own slack and the extent of slack in the network. First, whether a particular level of salience leads to high prioritization and eventual adoption depends on the level of congestion at the actor in question. If there are very few innovations competing for an actor"s attention relative to its available slack, then any adoption event whose salience exceeds some minimum threshold level, p_{min}, is likely to gain the actor"s attention. As the level of congestion increases—either due to reduced slack or increased innovative workload—the probability that a low-salience event will gain the actor"s attention decreases.

Second, having adjacent actors who themselves are well positioned to adopt or diffuse innovations may not be sufficient if these adjacent actors are too busy to adopt innovations or to diffuse the innovations that they do adopt. Under low slack conditions, having adjacent actors who have many adoption alternatives will decrease an actor"s ability to diffuse innovations. Similarly, adjacent actors with many diffusion alternatives will decrease one"s ability to adopt innovations. This is similar to conceptions of centrality where relations represent negotiation for limited resources (Cook et al 1983; Bonacich 1987).

The difficulty is that all of these processes happen simultaneously. We hope to illustrate some of the implications of our process model on interpreting an actor"s centrality and its effect on the diffusion of innovations. Towards this end, we examine the three conceptualizations and associated measures of actor centrality proposed by Freeman (1978): (i) centrality as activity, with the associated measure of degree; (ii) centrality as independence, with the associated measure of closeness; and (iii) centrality as control, with the associated measure of betweeness. Although not all of the specific measures put forward by Freeman are particularly well-suited to our process model of diffusion, his conceptualizations of centrality as activity, independence and control provide an excellent framework for discussing the moderating influence of slack on network structure.

Activity Centrality

According to Freeman, an actor"s activity is the extent to which its centrality is based on direct ties to other actors. That is, an actor"s activity reflects the number of its direct ties, or degree in the network. In our process model of adoption and diffusion, we have not attributed any direct "cost" to maintaining direct salience relations. That is, a greater number of direct ties does not directly consume more slack resources. Only the innovations themselves consume slack resources. However, there are two forms of indirect costs of maintaining many direct ties: those associated with an actor"s in-degree—the number of actors that look to the focal actor for innovations—and those associated with an actor"s out-degree—the number of actors to whom one looks for innovations.

In-Degree. Increasing one"s in-degree, or increasing the number of actors who are attentive, increases one"s ability to directly influence the innovation adoptions by adjacent actors. However, this direct influence comes at a cost in terms of the resources required to effect this influence. That is, if an actor is to use its in-degree to diffuse innovations, it must commit resources to this activity. If slack resources are tight, then these resources are not available to use in adopting innovations. This was illustrated in the three-actor network described in Figure 1. Actor *A*"s in-degree allows it to directly influence the innovation adoptions of actors *B* and *C*. However, as we saw in the simulations described in Tables 1-3, actor *A*"s role as broker between actors *B* and *C* cost actor *A* in terms of the resources expended on diffusing innovations rather than adopting them. As a result, actor *A* was over-loaded and became a bottleneck in the diffusion of innovations within the network.

Within organizations, increasing the number of people or subunits that report to a central unit, for example, probably would increase the central unit"s in-degree. It would be able to influence the actions—the innovation adoption—of the other units. But this increase could only be utilized if enough slack were present. If organizational slack were low, this in-degree centralization would result in a bottleneck—slowing the flow of innovations between units.

Out Degree. The effects of out-degree, the number of actors to whom a focal actor attends, are more subtle than for in-degree. To illustrate, consider actor *n* depicted in

Figure 2. Actor n has zero in-degree and its out-degree can range from one to five. If we assume that each of the other five actors depicted in Figure 2 brings non-redundant innovations into this sub-population, then the greater the out-degree of actor n—that is, the more actors to which actor n attends—the greater the number of unique innovations actor n might "see."

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INSERT FIGURE 2 ABOUT HERE

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One might expect, in this simple case, that as actor n"s out-degree increases, so would the number of innovations to which it attends, and thus, adopts over time. But, depending on the level of slack at the actor, this is not necessarily so. Because the salience of adoption events are attenuated over time and because less salient events are pushed aside by more salient events, the impact of any one attention relation will be moderated by the amount of congestion at actor n. The greater the innovative demands placed on the actor in relation to its available slack, the less effective will be marginal relationships—that is, relationships with small values of $r_{n,m}$—in gaining actor n"s attention.

This is illustrated in Figure 3, which graphs results of a series of simulations for high, medium and low levels of slack, and out-degrees of one and five at actor n. As the figure demonstrates, under conditions of low slack, actor n actually attends to more innovations when attending to a single actor than when attending to several. This effect is due to the negative consequences of spreading one"s attention too thinly under conditions of low slack. As actor n spreads its attention over more actors, the probability that innovation events will fall under its minimum salience level increases—that is, the actor is more likely to ignore innovations it might otherwise attend to. At low slack conditions, this probability increases with out-degree faster than its ability to attend to the new sources of innovations.

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INSERT FIGURE 3 ABOUT HERE

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If spreading one"s attention too thinly over *unique* sources of innovation reduces one"s adoption centrality, what happens when the sources of innovation are not unique? To illustrate, consider the situation of actor *n* depicted in Figure 4. Here, the five actors potentially adjacent to actor *n* all receive their innovations from the same source: actor *0*. Whether actor *n* is better off—that is, more central in terms of adoption—having many or only a few relationships in this situation depends on the consequences of the reinforcing stimuli provided by its adjacent actors. Because all five actors receive their innovations from the same source, each new adjacent actor only brings a potential source of reinforcing stimuli in terms of the adoption of the same innovations. Of course, once actor *n* adopts an innovation, reinforcing events become redundant. Their usefulness lies in their ability to reinforce one another for the attention of actor *n* for each innovation. This reinforcement occurs in two ways.

The first source of reinforcement comes from the fact that multiple adjacent actors offer multiple "opportunities" to attend to the innovation. For example, if an adoption by an adjacent actor happens to occur when actor *n* is quite busy, actor *n* will be unable to attend to the innovation before its salience falls below actor *n*"s minimum threshold. The adoption of the same innovation by another adjacent actor might come at a time when actor *n* is not quite so busy and thus, can attend to the innovation. The second, and more commonly referred to source of reinforcement is the increase in salience of the innovation with every adoption event by an adjacent actor. As expressed in equation (1), this salience is assumed additive, but with the contribution of each adoption event tapering off over time since that event.

This reinforcement, in effect, reduces the "cost" of spreading one"s attention under the low slack condition because one is spreading their attention over reinforcing sources of stimuli. However, at the same time, the benefits are reduced because one is

not increasing their access to unique innovations by increasing their out-degree—that is, each new adjacent actor offers access to the same innovations. The cumulative effect of these reinforcing adoption events depends on their relative timing to one another. Because of the decreasing salience of adoption events over time, adoption events that are close together have a more significant impact than those spread out over time. The "farther" one"s intermediaries are from the source of the original innovation, or the greater the variability in the diffusion process, the more spread out these adoption events are likely to be and thus, the less likely one"s adjacent actors will reinforce each other.

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INSERT FIGURE 4 ABOUT HERE

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Figure 5 illustrates how the adoption centrality of actor *n* in Figure 4 changes with out-degree. The results in Figure 5 are not statistically significantly different than those presented in Figure 3—that is, the reinforcing effect of adjacent actors does not significantly reduce the cost of spreading one"s attention too thinly under low slack conditions.

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INSERT FIGURE 5 ABOUT HERE

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Independence Centrality

An actor is *independent* to the extent that it need not rely on others in the network as intermediaries. Thus, actors who are close to all other actors are independent in the sense that they have few intervening actors between them and all other actors. Because of the dual nature of our network, an actor"s independence centrality will have two components: (i) *adoption independence*—the access the actor has to all other innovations

adopted by other actors in the network; and (ii) *diffusion independence*—the access other actors have to innovations adopted by the actor. These concepts are similar to previous concepts of centrality and prestige, respectively (c.f. Knoke and Burt 1983). However, we propose that an actor"s independence centrality must reflect the available slack in the network. Specifically, intermediaries with low available slack should prove to be poor intermediaries, thus causing an actor to be "farther away" form other actors in the network than they would be otherwise.

To illustrate, consider the six-actor network depicted in Figure 6. Here, attention relations are only unidirectional. For example, actors 1 and 2 are salient to actors 3a and 3b, but not vice versa. Similarly, actors 3a and 3b are salient to actors 4a and 4b, respectively, but actors 4a and 4b are salient to no one. Actors 3a and 3a have similar positions within the network of salience relations, as do actors 4a and 4b. However, actors 3a and 3b are *asymmetric* with respect to available slack (30% for actor 3a and only 10% for actor 3b). This reduction in the level of slack at actor 3b affects its ability to diffuse innovations and thus, the ability of actor 4b to adopt innovations.

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INSERT FIGURE 6 ABOUT HERE

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This is apparent in the results of the simulations of diffusions for this network, as presented in Table 6. Actor 4b, though symmetric to actor 4a in terms of the salience relations, adopts considerably fewer innovations than does actor 4a (24% for actor 4b versus 61% for actor 4a). In a very real sense, actor 4b is much farther away from the other actors in the network than is actor 4a due to its intermediary"s low level of slack resources.

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INSERT TABLE 6 ABOUT HERE

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Control Centrality

Finally, actors have *control* to the extent that they can intervene between other actors in the network. An actor who is between other actors in the network is an intermediary, or broker and as such, can facilitate or inhibit the diffusion of innovations within the network. However, an actor in a position of control can quickly turn from broker to bottleneck if their slack resources are overloaded with innovative activities. This is especially likely when control is achieved through direct contact—degree—rather than through strategic use of intermediary actors.

To illustrate, consider the four possible network structures presented in Figure 7. Each are based on a stylized representation of the Philips corporate network described in Ghoshal and Bartlett (1990). To simplify the network representation, we assume that an arc between two actors implies that each actor is salient to the other, and that salience is equally divided among all adjacent actors—that is, an actor who has four adjacent actors gives each equal salience of 0.25.

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INSERT FIGURE 7 ABOUT HERE

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Actor 1, which represents Philips headquarters in Holland, is concerned about its ability to control—that is, inhibit and facilitate—the diffusion of innovations in the network.. Headquarters has low control in networks one and three, but relatively higher control in networks two and four. Comparing networks two and four, we see that headquarters (actor 1) achieves control in network two through its strategic use of actors 2a-2c, which represent regional subsidiaries, as intermediaries, but relies on direct ties to all actors to achieve control in network four. Its many direct ties in network four give the headquarters actor greater independence along with greater control but at a cost of greater activity. As we will demonstrate in the simulations, this greater activity overloads the headquarters actor, thus creating a bottleneck to the diffusion of innovations.

When might headquarters care about its independence? Two possible scenarios are: (i) the regional subsidiaries may be overloaded and thus, would make poor intermediaries; and (ii) the regional subsidiaries share different interpretations of what are "good" and "bad" innovations (not-invented-here syndrome). To further illustrate this later point, consider the diffusion of innovations that are characterized by two attributes. The first attribute of an innovation is a binary decision variable (yes, no) that determines whether headquarters deems the innovation suitable for the corporation. The second attribute is a similar decision variable that determines whether the regional subsidiaries deem the innovation suitable for the corporation. We assume that all other actors will adopt any innovation if given the chance. Thus, there are four possible characterizations for each innovation arriving to the corporate network:

i. (N,Y) = The headquarters (actor 1) does not consider the innovation suitable while the regional subsidiaries (actors 2a-2c) do;

ii. (N,N) = neither headquarters nor regional subsidiaries consider the innovation suitable (recall that all other actors will consider these innovations suitable) ;

iii. (Y,N) = headquarters considers the innovation suitable, but the regional subsidiaries do not; and

iv. (Y,Y) = headquarters and regional subsidiaries both consider the innovation suitable.

The relative diffusion of each type of innovation will depend on the relative control and independence of headquarters to the regional subsidiaries.

Table 7 presents results of simulations of each of the four networks shown in Figure 7. Headquarters" (actor 1) control centrality affects the diffusion of innovations that it does not deem as fit for the organization. When headquarters" control is low, 48% of the (N,Y) innovations diffuse while only 26-27% diffuse when its control is high. Similarly, when headquarters" independence centrality is low, only 13-14% of (Y,N) innovations diffuse while 24-26% diffuse when its independence centrality is high. However, greater control and independence centrality for headquarters comes at a cost to the organization. Because of limited resources (actors are assumed to have 20% of their time as slack), the resulting high activity centrality, combined with headquarters" high control

centrality, turns headquarters" from a broker to a bottleneck, limiting the diffusion of (Y, Y) innovations to the lowest of the four network structures (44%).

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INSERT TABLE 7 ABOUT HERE

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CONCLUSION

This paper began with the premise that actors within organizations have limited resources with which to do all the things that they could or perhaps should do in a world with no resource constraints. This fundamental idea has a profound influence on the adoption and diffusion of innovations within organizations. Because actors within organizations are busy and multiple innovation vie for adoption, the role of salience relations, and the pursuant structure of those relations, becomes prominently important when these multiple innovations compete for limited resources. We offer a simple process model that expands previous models of the diffusion of innovations by examining the diffusion process in a new context: that of multiple innovations in a resource-constrained environment. Our model assumes that the adoption and diffusion of innovations may require resources from both the potential adopter and the brokering actor, and that these resources are limited.

Having many relationships can have a cost, especially for those with little slack. If an actor is busy—that is, it has too little slack relative to the innovative demands placed on it—and it has dense relationships—that is, its attention is spread too thinly over several competing sources of events—then it will have difficulty in attending to the many adoption events of adjacent actors. This is consistent with common experience. Actors who are both busy and have many events competing for their attention will likely attend only to those events fortunate enough to gain their attention quickly. Otherwise, events soon fall below the actor"s minimum salience level, never to be returned to again unless, and until, there is another event of a similar nature. If, at the same time, the actor has a

great deal of control centrality, then this actor can become a bottleneck, limiting the diffusion of innovations within the network.

Alternatively, actors with a great deal of slack, but who are surrounded by actors with very little slack, are much better off with many direct ties, thus avoiding any dependence on poorly-suited intermediaries: how close or how far one is from other actors in the network in terms of the diffusion of innovations depends not only on the network of salience relations, but also on the amount of slack available to various intermediaries.

By putting forward a process model of diffusion, this paper examines how the structure of a network, defined by the relative salience of actors to one another, impact the timing and extent of diffusion within a network. We find that centrality, a concept often-examined in diffusion studies, cannot simply be examined as a uniform construct. Different treatments of centrality have fundamentally different interpretations in the context of the diffusion of innovations in a resource-constrained network. Generally, being central can be costly. As was demonstrated in our concluding example, a highly central network can be hindered in its ability to disseminate effectively innovations to all actors. Brokers must be chosen wisely, or bottlenecks will result.

Acknowledgements

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FIGURES AND TABLES

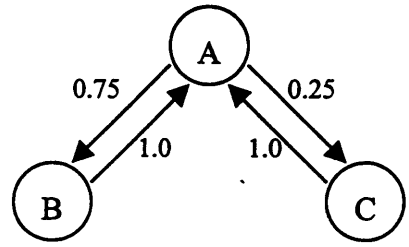

Figure 1: A simple three-actor network.

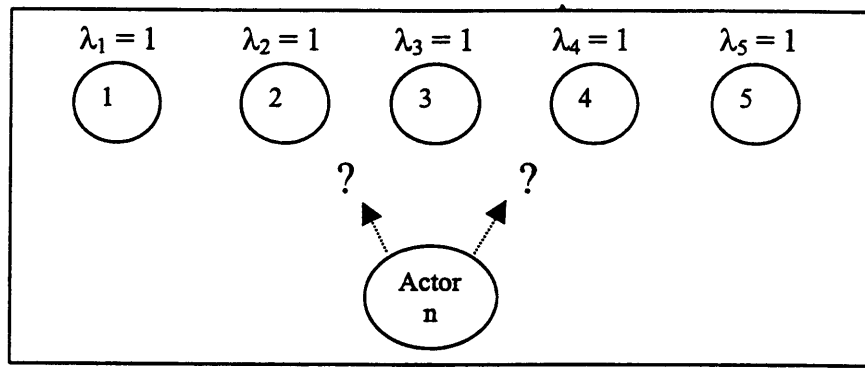

Figure 2: Non-redundant sources of innovation for actor *n*.

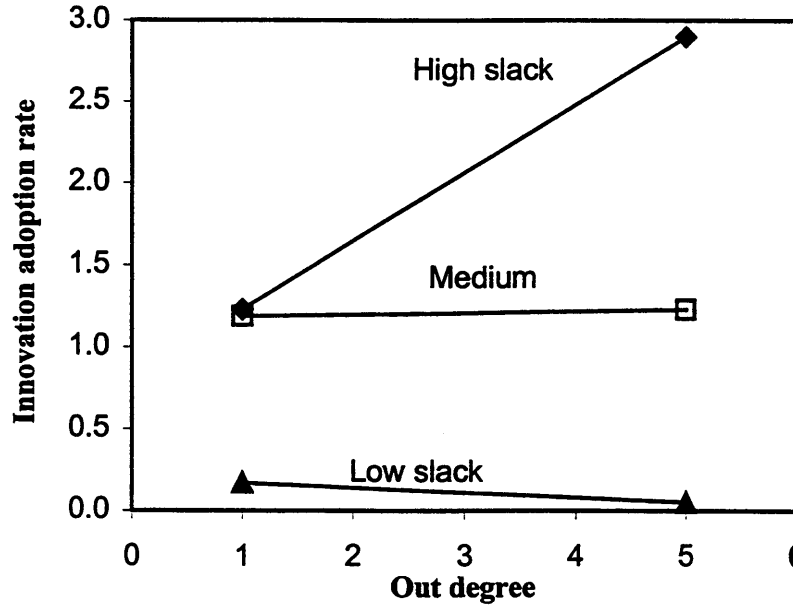

Figure 3: The effect of out degree on the adoption rate of actor *n* when salience is spread equally over adjacent *non-redundant* actors.

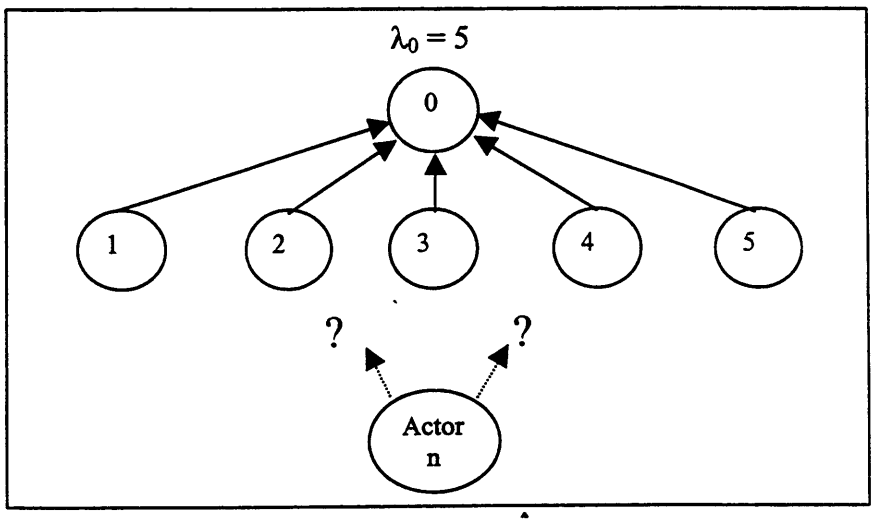

Figure 4: Reinforcing sources of innovation for actor *n*.

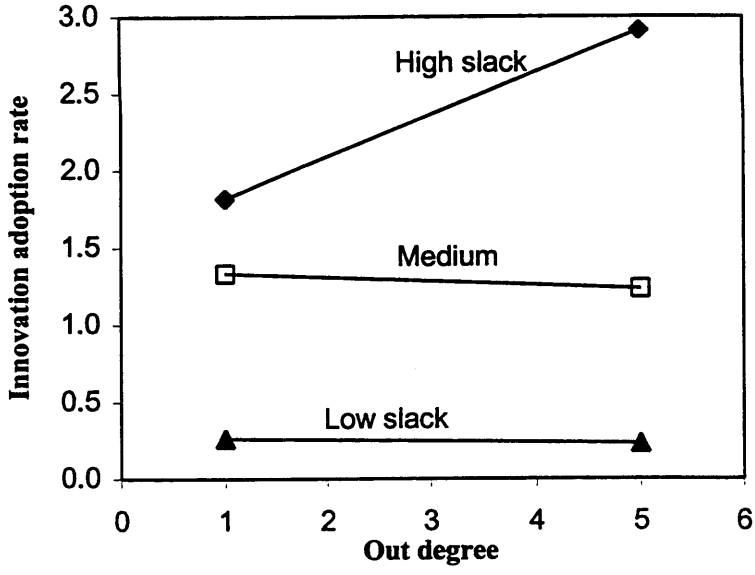

Figure 5: The effect of out degree on the adoption rate of actor *n* when salience is spread equally over adjacent *reinforcing* actors.

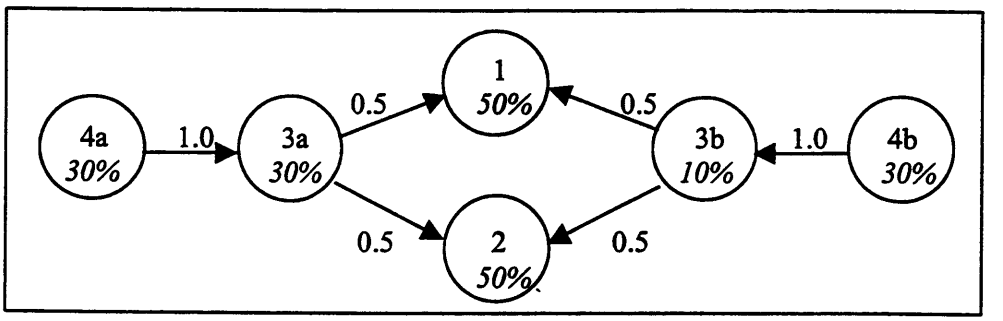

Figure 6: Symmetric six-actor network with asymmetric slack.

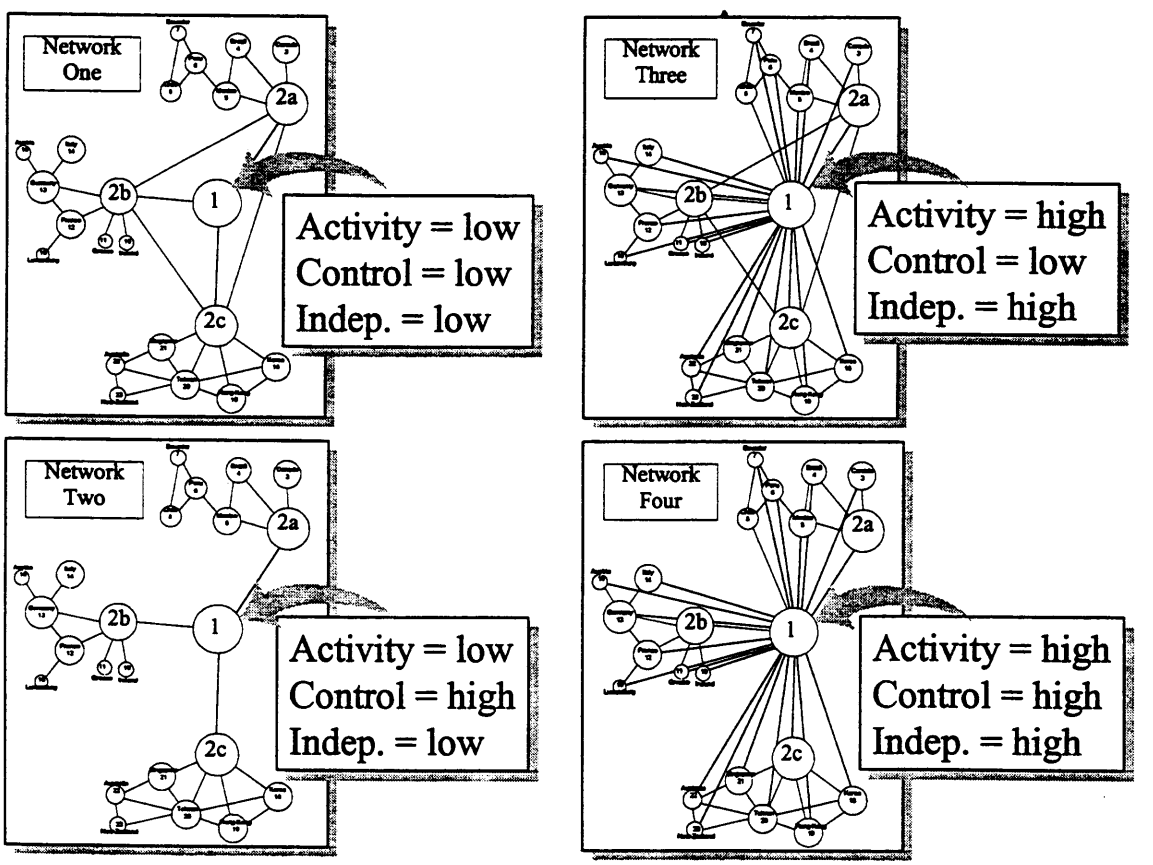

Figure 7: Four alternative network structures.

Originating at Actor	Adopted by Actor A	B	C	Extent of Diffusion
A	-	90%	95%	92%
B	51%	-	48%	50%
C	20%	17%	-	19%
Extent of Adoption	36%	54%	72%	54%

Table 1: Diffusion results for the three-actor network depicted in Figure 1 when diffusion is given priority over adoption at each actor.

Actor	Slack	Adoption activities	Diffusion activities	Unused
A	20%	8%	12%	<1%
B	20%	10%	3%	7%
C	20%	13%	1%	6%

Table 2: Percentage of time actors spend on innovative activities for the three-actor network depicted in Figure 1 when diffusion is given priority.

Originating at Actor	*First Adoption*		*Second Adoption*	
	Number	*Average Time*	*Number*	*Average Time*
A	328	5.6	290	14.0
B	172	8.6	163	17.8
C	66	8.2	55	18.6

Table 3: Average diffusion times for innovations originating at each actor depicted in Figure 1 when diffusion is given priority.

Originating at Actor	**Adopted by Actor**			**Extent of Diffusion**
	A	**B**	**C**	
A	-	65%	79%	72%
B	100%	-	79%	89%
C	99%	63%	-	81%
Extent of Adoption	99%	64%	79%	81%

Table 4: Diffusion results for the three-actor network depicted in Figure 1 when actor *A* has 50% slack time.

Actor	Slack	Adoption activities	Diffusion activities	Unused
A	50%	18%	13%	19%
B	20%	13%	6%	< 1%
C	20%	15%	4%	< 1%

Table 5: Percentage of time actors spend on innovative activities for the three-actor network depicted in Figure 1 when actor *A* has 50% slack time.

Originating at Actor	Adopted by Actor 3a	3b	4a	4b	Extent of Diffusion
1	100%	49%	100%	45%	57%
2	100%	53%	100%	50%	58%
3a			100%		20%
3b				87%	12%
Extent of Adoption	40%	23%	61%	24%	25%

Table 6: Diffusion results for the six-actor network depicted in Figure 4.

	Node 1 Centrality			*Adopt Innovation? (Headquarters, Region)*			
Network	*Activity*	*Control*	*Indep dence*	*(N,Y)*	*(N,N)*	*(Y,N)*	*(Y,Y)*
One	low	low	low	48%	14%	13%	55%
Two	low	high	low	26%	14%	14%	59%
Three	high	low	high	48%	13%	26%	61%
Four	high	high	high	27%	14%	24%	44%

Table 7: The effects of network structure and bottlenecks on the diffusion of innovations.