Social Network Effects on the Extent of Innovation Diffusion: A Computer Simulation

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Network theory, like some other branches of organizational sociology, has developed its own specialized terminology and technology. An unfortunate result has been that many non-specialists have lost touch with advances and debates in this branch. Not the least of the merits of this article by Abrahamson and Rosenkopf is that they have succeeded in bridging this gap. They show the power of network theory and modeling in analyzing a process of central interest to our field, the diffusion of innovations.

Paul S. Adler

Abstract

Theories of innovation diffusion no longer focus exclusively on explaining the rate at which innovations diffuse or the sequence in which they are adopted. They also focus on explaining why certain innovations diffuse extensively, becoming *de facto* standards, whereas others do so partially or not at all. Many of these theories specify a bandwagon process: a positive feedback loop in which increases in the number of adopters create stronger bandwagon pressures, and stronger bandwagon pressures, in turn, cause increases in the number of adopters. Factors affecting if and how many times this feedback loop cycles explain if and how many potential adopters jump on a bandwagon. We argue that one important factor has not yet been incorporated into theories explaining bandwagons' extent: the structure of social networks through which potential adopters of innovations find out information about these innovations which can cause them to adopt these innovations. We advance a theory of how the structure of social networks affects bandwagons' extent. We propose that both the number of network links, as well as small, seemingly insignificant idiosyncracies of their structures, can have very large effects on the extent of an innovation's diffusion among members of a social network.

(*Innovation Diffusion*; *Institutional Theory*; *Network Externalities*; *Social Networks*)

Introduction

Consider the following three short vignettes. Between 1979 and 1981, Gaetan Dugas, a flight attendant for Air Canada, infected four sexual partners in New York City (NYC) and four in Los Angeles (LA) with Acquired Immune Deficiency Syndrome (AIDS). Dugas, or Patient 0 as the Center for Disease Control later called him, is believed to have introduced AIDS into both NYC and LA gay-men networks, triggering epidemics in these two cities that have and are decimating thousands (Klovdahl 1985). Mortality, however, has differed substantially across communities within these cities. AIDS has decimated entire networks of needle-swapping intravenous drug users, for example, but continues to leave certain other networks virtually untouched.

Somewhat like new viruses, the introduction of innovative ideas, techniques, technologies or products into new segments of social networks can trigger the partial diffusion of these innovations throughout parts of these networks. Following World War II, Dr. W. Edwards Deming had little stature in the U.S., and his Total Quality Management (TQM) approach did not diffuse there. On a trip to Japan in the late 1940s, he convinced Ichiro Ichikawa of the soundness of TQM tech-

1047-7039/97/0803/0289/$05.00

niques. Ichikawa, a well-known scholar in Japanese business circles, subsequently convinced several key Japanese industrialists who spread TQM throughout their extensive social networks (Halberstam 1986). From there, TQM diffused in a fadlike fashion to broad segments of Japanese and, later, U.S. industry. Like the diffusion of AIDS, however, the diffusion of TQM will most likely remain partial. TQM will probably never make broad inroads into U.S. academia and small law firms, for example, or into many countries with little appetite for management fads.

More generally, the introduction of innovations into new segments of social networks does not guarantee these innovations' diffusions in these segments. This is the case even for highly beneficial innovations (Rogers 1995). Incontrovertible evidence that lime juice cured scurvy, for example, was presented first in 1601 by James Lancaster, an English sea captain, and again in 1747 by James Lind, a British Navy physician. This cure was ignored until 1795, however, at which point its diffusion virtually eradicated scurvy from the British Navy. Neither Lancaster nor Lind were prominent in British Navy social networks, which may explain why their radical cure was ignored for almost two centuries (Mosteller 1981).

These vignettes highlight four points. First, many innovations, whether they be new diseases, new cures, or new techniques and technologies, diffuse through social networks linking individuals or organizations. Second, these networks are segmented by internal boundaries which can form at geographic, status, cultural, or industry lines. Third, these boundaries can limit the diffusion of innovations, so that innovations frequently do not diffuse to all potential adopters. Fourth, when and how extensively an innovation diffuses through social networks can be greatly affected by apparently insignificant events occurring at these networks' internal boundaries. Edward Deming convinced one prominent actor at such a boundary, diffusing TQM broadly, whereas James Lancaster did not, and we know of a cure for scurvy only because it diffused two centuries later. Our central argument, in this article, is that such social-network effects must be incorporated into theories that explain when and to what extent innovations diffuse.

From Diffusion Rate to Diffusion Extent

Traditionally, the literature on the diffusion of innovations has examined innovations that diffused fully, meaning that every potential adopter adopted them. The focus has not been on explaining why these innovations diffused fully when they did, but rather on explaining the rate at which these innovations diffused or the order in which they were adopted (Rogers 1995). More recently, scholars have begun to ask a very different type of question: why, at particular points in time, do certain innovations diffuse fully and become the *de facto* standard or dominant design, whereas other innovations diffuse partially or not at all? (Granovetter 1978; Arthur 1983; David 1985, 1991; Granovetter and Soong 1986, 1988; Abrahamson and Rosenkopf 1990, 1993a).

The burgeoning literature exploring the diffusion-extent question has yielded a host of counterintuitive propositions. Extremely small differences in the initial distribution of preferences about an innovation can have extremely large effects on the extent of its diffusion (Granovetter 1978). One variant of an innovation may prevail completely over another due to small, random factors prompting a few more adoptions early in the diffusion of the innovation that prevailed (Arthur 1983, David 1991). The widespread diffusion of a less technically-efficient variant can "lock it in," forestalling the diffusion of a more technically-efficient variant (David 1985, Cowan 1990). Innovations can diffuse extensively across potential adopters, even when the vast majority of these potential adopters were quite certain, initially, that the innovation would produce a loss (Abrahamson and Rosenkopf 1993a), and even if they subsequently learned information reinforcing this impression (Abrahamson and Rosenkopf 1991; paper available from the first author upon request).

This literature on diffusion extent has focused on how information about costs, returns, risk, efficiency, and legitimacy influences the extent of innovation diffusion. These theories largely ignore, however, the possibility that this information is channeled by social networks only to certain potential adopters. Consequently, we still know little about when and how the structure of social networks can influence the extent of an innovation's diffusion by determining which network participants can become aware of information about this innovation and adopt it (Granovetter 1985, 1992).

This article has three sections. In the first, we distinguish three broad types of theories explaining the diffusion of single innovations. We discuss which of these theories can be enriched by a social networks perspective in order to explain the extent of innovation diffusion. In the second section, we develop propositions about how the structure of social networks can influence the extent of diffusion of an innovation—that is, how many potential adopters adopt this innovation. Our central argument is that small, apparently insignificant idiosyncracies of these networks' structures can exert major influences on diffusion extent. Consequently, it is essential to examine the precise structure of social networks in order to develop propositions about when and how extensively an innovation will diffuse through them. We develop these propositions using models of how the distribution of potential adopters' resistances to adopting—their adoption thresholds—influences the extent of diffusion through varying network structures (Granovetter 1978; Granovetter and Soong 1986, 1988; Valente and Rogers 1993). We use computer simulation of these threshold models to develop propositions because the diffusion of innovations through networks of potential adopters with differing thresholds is both dynamic and complex and, thus, difficult to anticipate.

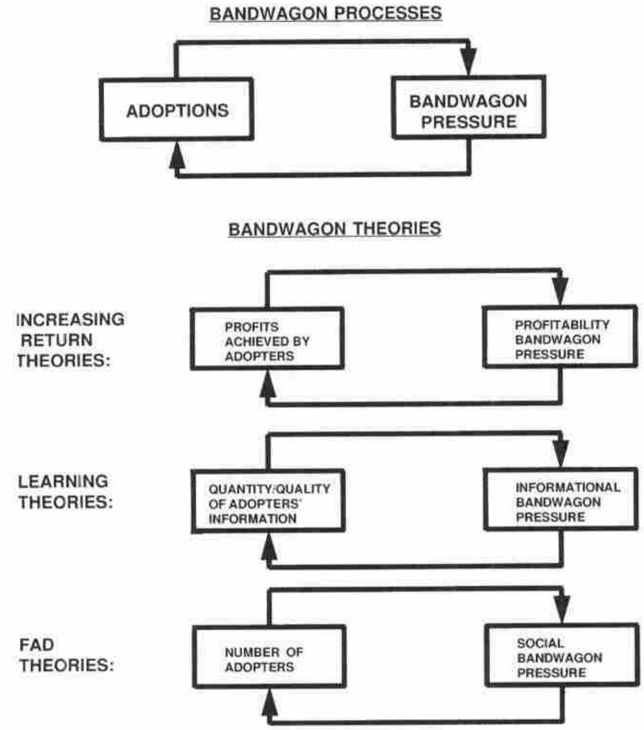
In the final section, we discuss how our abstract model of innovation diffusion applies to the diffusion of a broad range of innovations: administrative, technological, and product innovations and ideas. Moreover, we consider how it generalizes to diffusion across different types of potential adopters (both organizations and individuals), in different types of networks (both island networks as well as core-periphery networks), and with different types of diffusion processes (both diffusion by cohesion and by structural equivalence). We illustrate the utility of our model not only when most members of social networks believe initially that they should not adopt an innovation, but also when most believe that they should. More generally, we ask, when will a focus on social networks enrich theories and models of the extent of innovation diffusion?

Bandwagon Theories

Theories bearing on innovation diffusion typically specify one of three types of bandwagon processes that have the underlying structure depicted in Figure 1. Increases in the number of adopters of an innovation generate new information about the innovation, creating stronger bandwagon pressures to adopt it. Stronger bandwagon pressures, in turn, prompt increases in the number of adopters of the innovation. These three bandwagon theories differ according to the assumptions they make about the ambiguity of information concerning innovations. After discussing this ambiguity concept, we review each of the three types of bandwagon theories in turn.

Uncertainty and Ambiguity. Certain decision-making models assume that potential adopters of an innovation receive information about the innovation which leaves them uncertain about its profitability. Under

Figure 1 **Bandwagon Processes and Theories**



such conditions of uncertainty, the decision situation is represented by a subjective probability distribution of possible outcomes from adopting an innovation. The basic decision rule is that decision makers assess the profitability of adopting the innovation by summing the products of probabilities of each possible dollar outcome and this outcome, and adopting if this sum exceeds some threshold. As decision maker who adopts when assessed returns exceed 0 and who assesses a 0.4 chance of making \$10 and a 0.6 chance of losing \$5 would adopt because the sum of the product of probabilities and outcomes ((\$10*0.4) + (−\$5*0.6) = \$1) exceeds zero.

A number of scholars have found that greater environmental turbulence and complexity causes information about innovations to be ambiguous (Aldrich 1979, Dess and Beard 1984, Milliken 1987, Pfeffer and Salancik 1978, Wholey and Brittain 1989). Ambiguity differs from uncertainty. Milliken (1987) distinguished three types of ambiguity. State ambiguity denotes the degree of ignorance, on the part of decision-makers, about possible future environmental states. Effect ambiguity denotes the degree of ignorance about the effect of environmental states, whether or not those states are clear. Response ambiguity denotes a lack of clarity about the outcomes of choices in response to environmental states, regardless of their clarity. State, effect and response ambiguity make the range of choice alternatives unclear. Moreover, state, effect and response ambiguity obscure both the range of possible outcomes from making a choice and the probability of these outcomes occurring. Finally, state, effect and response ambiguity can obscure which type of outcome should be maximized. Thus, under conditions of uncertainty, the range of alternatives, the range of outcomes for each alternative, and the probability of each outcome are assumed to be clear. Under conditions of ambiguity, one or all of these are unclear, and the model of decision-making under conditions of uncertainty cannot be assumed (March and Olsen 1976).

Increasing Returns Theories of Bandwagons generally assume that the profitability of innovations is unambiguous. Information about the innovation's costs is apparent from its price, whereas information about its returns is either apparent from the innovation itself or easily obtainable from an accurate and credible external source. Consequently, potential adopters can decide to adopt based on a simple cost-benefit analysis (David 1969, Davies 1979).

Increasing Return theories suggest that as the number of adopters of an innovation increases, so does its profitability, causing more potential adopters to adopt. One variant of this type assumes that returns increase with the number of adopters because of positive externalities, such as the "network externalities" case where the more potential adopters adopt a communication standard, the greater the returns to each adopter because it can communicate with more adopters (Farrell and Saloner 1985; Katz and Shapiro 1985, 1994). Another variant assumes negative externalities, where returns to any adopter decline with the number of adopters, yet the innovation's profitability increases with the number of adopters because costs decline the later the adoption date (Reinganum 1981, Fudenberg and Tirole 1985, Quirmbach 1986).

Learning Theories of Bandwagons assume incomplete information (Mansfield 1961). As a result, an innovation's profitability can be conceived of as ambiguous, and potential adopters must learn about the innovation before deciding to adopt it. As more potential adopters of an innovation adopt it, however, they generate more information bearing on the innovation's profitability (Rogers 1995; Valente and Rogers 1993). Information about innovations tends to cause potential adopters to learn and revise their assessed profits either upward, causing more adoptions, or downward, forestalling such adoptions (Feder and O'Mara 1982, Oren and Schwartz 1988, Lattin and Roberts 1989, Chatterjee and Eliashberg 1990, Valente and Rogers 1993).

Fad Theories of Bandwagons assume not only that profitability is ambiguous, but that updated information about innovations' profitability either does not flow from earlier to later adopters or does not influence their adoption decisions. Under these conditions, it is information about who has adopted the innovation, rather than about the innovation itself, that generates a social bandwagon pressure to conform, causing more potential adopters to adopt, thereby reinforcing the bandwagon pressure. One sociological variant of fad theories specifies institutional bandwagon pressures on potential adopters, arising from the threat of lost legitimacy. In these theories, the more potential adopters adopt an innovation, the more it becomes taken for granted that it is normal, or even legitimate, for potential adopters to use this innovation (Meyer and Rowan 1977). When this happens, potential adopters that do not use the innovation tend to appear abnormal and illegitimate to their stakeholders; these potential adopters tend to adopt the innovation because of the fear of lost legitimacy and stakeholder support (Tolbert and Zucker 1983, Pennings and Harianto 1992, Abrahamson and Rosenkopf 1993a, Wade 1995). A similar variant from the field of economics assumes that potential adopters tend to adopt an innovation the more other potential adopters have adopted it because these potential adopters will be evaluated more favorably if they do what other adopters are doing (Sharfstein and Stein 1990). A second variant of fad theories describes competitive bandwagon pressures—pressures on potential adopters arising from the threat of lost competitive advantage. Bandwagon pressures occur because as the proportion of adopters increases, potential adopters experience a growing risk that if the innovation is a success, their performance will fall well below the average performance of other potential adopters; they adopt to avoid running this risk (Abrahamson and Rosenkopf 1990, 1993a). Still a third variant of fad theories assumes that potential adopters adopt an innovation the more other potential adopters have already adopted it because the number of adopters is taken as evidence that these adopters must know something that the potential adopter does not know (Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992).

Both learning and fad theories of innovation diffusion assume that the profitability of innovations is ambiguous. This assumption adds realism when explaining the diffusion of innovations, such as administrative innovations or technological innovations in turbulent complex environments, whose profitability is quite ambiguous (Kimberly 1981, Abrahamson 1991). We argue in the next section that Fad and Learning bandwagon theories must extend this greater realism by considering the impact of social networks in explaining the extent of diffusion of innovations with ambiguous profitabilities.

Ambiguous Profitability and Social Networks

Despite their differences, most Increasing Returns, Learning, and Fad theories of bandwagons' extent resemble each other in one fundamental way. They assume that all potential adopters experience the same bandwagon pressure to adopt an innovation in each cycle of a bandwagon process. That is, each potential adopter experiences the same pressure to adopt an innovation because of its price, perceived efficiency, or legitimacy. What these theories rarely recognize, however, is that this assumption is realistic only when all potential adopters receive the same information about an innovation. Indeed, if potential adopters receive different information, then they will tend to experience bandwagon pressures of differing strength.

The assumption of equal information and bandwagon pressure is not necessarily reasonable when the profitability of innovations is ambiguous. Under these conditions, the question—should I adopt this innovation?—cannot be answered by pointing only to concrete aspects of the innovation or to its price. Social-comparison theory suggests that, when confronted with such empirically ambiguous questions, decision makers tend to base their decisions on social cues, such as, how many of their close contacts have adopted this innovation or what do they have to say about it (Festinger et al. 1950, Festinger 1954, Coleman et al. 1966; Burt 1987). What each potential adopter finds out about an innovation, therefore, depends on the structure of the social network that disseminates the information about this innovation and on this potential adopter's position in that network. Network structure can cause certain potential adopters to find out more information and, therefore, to experience a different bandwagon pressure than potential adopters who find out less or different information. In sum, network structure influences the strength of bandwagon pressure on each potential adopter, whether or not they adopt and, consequently, the extent of innovation diffusion.

As an aside, it should be noted that diffusion channeled through communication networks is often called diffusion by "cohesion." Diffusion can, however, also occur by "structural equivalence" (Abrahamson and Fombrun 1994, Burt 1987, Friedkin 1984, Lorraine and White 1971). The structural equivalence argument suggests that the more similar the pattern of linkages binding actors to a network—that is the more structurally equivalent the network position of these actors—the more intensely they will compete, and the more likely each is to adopt an innovation adopted by its competitor, even if they do not communicate with each other. We focus on diffusion by cohesion in the body of this article and we show, in the article's conclusion, that our argument generalizes to diffusion by structural equivalence.

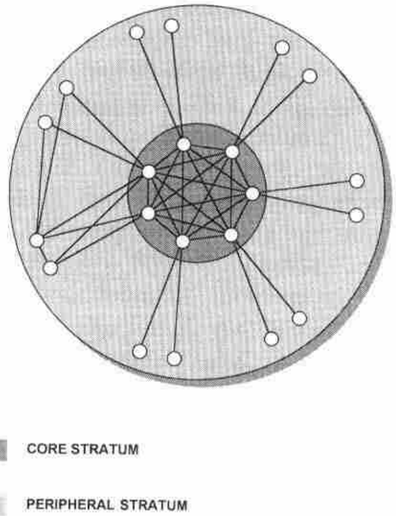
Empirical Evidence

Tests of social comparison theory suggest that the structure of communication networks influences the **order** in which potential adopters receive information about an innovation and, therefore, the order in which they adopt. We review this research in this section. We note, however, that this research does not examine how network structure influences the **extent** of diffusion. We turn to this question in the following section.

Research about social network effects on the temporal order of adoptions usually tests so-called "mixed-influence" theories of innovation diffusion (Mahajan and Peterson 1985). The term "mixed-influence" is used because diffusion is explained by a mix of influences emanating not only from influencers, such as the mass-media, located outside the set of potential adopters, but also from internal influences that these potential adopters exert on each other.

Imagine, for instance, a social network with the core-periphery structure depicted in Figure 2. A densely-interlinked core stratum of potential adopters has relatively few links with a weakly-interlinked peripheral stratum of potential adopters. The diffusion of innovations tends to follow the well-known "two-step flow" hypothesis (Lazarsfeld et al. 1944). In the first step, external actors, such as the mass media, make potential adopters aware of an innovation and may affect their evaluations of the innovation as well. But these external influences are not strong enough to push all adopters over their adoption thresholds. It is largely internal influences that potential adopters exert on each other in a second step that persuades them to adopt (Abrahamson 1996a; Coleman et al. 1965; Rogers 1995; Valente and Rogers 1993). More specifically,

Figure 2 Core-periphery Network



in what Abrahamson and Fombrun (1994) called a "trickle-down process," adoptions by potential adopters in the core strata of social networks tend to trigger imitations by members in these networks' peripheral strata (Rogers 1995, DiMaggio and Powell 1983). Rogers (1995) reviews many studies which reveal trickle-down diffusion processes among individuals. More recently, researchers have found trickle-down diffusion among organizations (Walker 1969, Galaskiewicz and Wasserman 1989, Davis 1991, Mizruchi 1992, Burns and Wholey 1993, Haunschild 1993, Haveman 1993, Palmer et al. 1993).

More rarely, trickle-up processes can also occur, whereby adoptions in peripheral strata trigger adoptions in core strata. Becker (1970) reviews studies that have revealed trickle-up diffusion processes. These studies indicate that whereas trickle-down processes tend to diffuse innovations congruent with network norms, trickle-up processes, to the contrary, tend to diffuse contra-normative innovations. The explanation offered is that potential adopters at the core of networks tend to have higher reputations, and that they do not adopt contra-normative innovations first because doing so violates norms and puts their reputations at risk. Potential adopters at the network's periphery, however, have lower reputations and are willing to take the risk of appearing deviant by adopting a contra-normative innovation in return for a chance to improve their reputations if the innovation succeeds (Becker 1970, Burt 1981, Kimberly 1981, Rogers 1995). Under certain conditions, they can push higher-reputation potential adopters, at the core of social networks, to adopt, and the innovation trickles up from peripheral to core strata. A number of observers have noted, however, that these trickle-up processes are rare. Most often, incumbents fail to adopt contra-normative or competence-destroying innovations, and it is new members of social networks, instead, who adopt and exploit such innovations (Tushman and Anderson 1986, Bower and Christensen 1995).

In sum, tests of social comparison theory reveal that trickle-up and -down diffusion process channel diffusion through core-periphery networks. This research does not indicate, however, when, or to what extent trickle-up and -down diffusion occurs. It leaves open the question of how variations in the structure of core-periphery networks determine whether innovations diffuse fully, becoming *de facto* standards, or whether they do so partially or not at all? We explore this question in the next section. We attempt to show, in particular, that apparently insignificant idiosyncracies of the structure of core-periphery networks can exert major influences on the extent of innovation diffusion. Consequently, it is essential to examine the precise structure of social networks in order to develop propositions about when and how extensively innovations will diffuse through them.

Network Influences on Diffusion Extent

This section has three parts. In the first, we explain why we use threshold models in order to explore how social-network structure influences the extent of innovation diffusion. In the second, we focus on a threshold model of innovation diffusion we advanced in another article (Abrahamson and Rosenkopf 1993a) because it assumes that the profitability of innovations is ambiguous, though it does not consider how social networks affect diffusion extent. In the third part, we modify this model so as to incorporate the effects of variations in core-periphery social network structures on the extent of innovation diffusion. We use computer simulation of this modified model to verify propositions about diffusion extent.

From Rate to Threshold Models

Rate Models. Rate-oriented models of innovation diffusion are not designed to explain the timing and extent of innovation diffusion. These models are variants of the generic model,

$$R_t = b * n_t * [N - n_t], \qquad (1)$$

where R_t is the rate of diffusion at time t, n_t is the number of adopters at time t, N is the total number of potential adopters, and b is a constant (Mahajan and Peterson 1985). Integrating Eq. (1) produces the well-known logistic S-curve for the cumulative number of adopters over time. This model is not designed to explain *when* diffusion occurs. It is apparent from Eq. (1) that when the number of adopters, n_t, equals 0, so does the rate of diffusion, R_t. What, then, starts the diffusion process? These models also are not designed to help researchers forecast how many adoptions a diffusion process will cause. According to Eq. (1), once diffusion has started, the adoption rate, R_t, is greater than 0, and diffusion ends only when the total number of potential adopters N equals the number of adopters, n_t, that is, when 100 percent of potential adopters have adopted. What, then, causes a situation of partial diffusion? Rate-oriented models of innovation diffusion do not answer this question.

Threshold Models. Bandwagons have a positive feedback loop in which information generated by more adoptions creates a stronger bandwagon pressure, and a stronger bandwagon pressure prompts more adoptions. Yet each potential adopter need not necessarily succumb to the bandwagon pressure. Threshold models of innovation diffusion assume that potential adopters have varying predispositions against adopting an innovation. A potential adopter will give in to a bandwagon pressure to adopt only if it exceeds this potential adopter's *threshold*—the point at which the strength of the bandwagon pressure to adopt is greater than the potential adopter's predisposition against adopting (David 1969). Therefore, a potential adopter with a high threshold adopts only in response to a strong bandwagon pressure, whereas it only takes a weak bandwagon pressure to cause a potential adopter with a low threshold to adopt, and it takes no bandwagon pressure for a potential adopter with a zero threshold to do so.

Threshold models can easily describe complex processes that cause bandwagons to start and various proportions of potential adopters to adopt. Potential adopters with zero thresholds have no predisposition against adopting and they adopt first. Their adoptions cause the strength of the bandwagon pressure to increase. Potential adopters whose threshold is exceeded by this increase in the bandwagon pressure adopt, further raising the strength of the bandwagon pressure, and possibly prompting still more adoptions. There can be repeated cycles of this process in which more adoptions raise the strength of the bandwagon pressure and the strength of the bandwagon pressure causes more adoptions. This cycle stops whenever the increase in the bandwagon pressure, in one cycle of the process, is insufficient to prompt the non-adopter with the lowest threshold to adopt. A bandwagon's extent equals the number of adopters when the bandwagon cycle stops. Note that threshold models can explain why a bandwagon would stop before all potential adopters had adopted. Indeed, if at any stage of a bandwagon, all non-adopters have a threshold that exceeds the bandwagon pressure, the bandwagon stops.

A Threshold Model Ignoring Social Network Structure

We have advanced a threshold model for the diffusion of innovations that have ambiguous profitability (Abrahamson and Rosenkopf 1993a). We made assumptions, common to most threshold models of bandwagons, that a potential adopter's threshold is determined by the profits (losses) it assesses from adopting and that profitability assessments differ across potential adopters. By "assessing profits" we mean establishing a probability distribution of different outcomes of which "profit" is the sum of the products of possible profitability outcomes and their probabilities.

Potential adopters who assess that they will obtain a profit from adopting have no predisposition against adopting (zero threshold) and therefore they adopt. The greater the loss a potential adopter assesses from adopting, the greater its initial predisposition against adopting (the higher its threshold). But why would potential adopters who assess a loss from adopting ever adopt?

Fad theories of innovation diffusion provide one answer. Potential adopters are unsure about their assessed profits calculations. This doubt about assessed profits and losses is called ambiguity, and theories of fads assume that under conditions of ambiguity, the number of potential adopters that have adopted previously influences the remaining potential adopters' adoption decisions (March and Olsen 1976, DiMaggio and Powell 1983). We expressed this relation with the equation,

$$B_{i,k} = I_i + (A_i * P_{k-1}), \qquad (2)$$

where $B_{i,k}$ is potential adopter i's "bandwagon assessment" of the innovation, in bandwagon cycle k (Abrahamson and Rosenkopf 1993a). The bandwagon assessment is a function of both I_i, which denotes potential adopter i's individual assessment of the innovation's profitability and $A_i * P_{k-1}$, which denotes the bandwagon pressure.

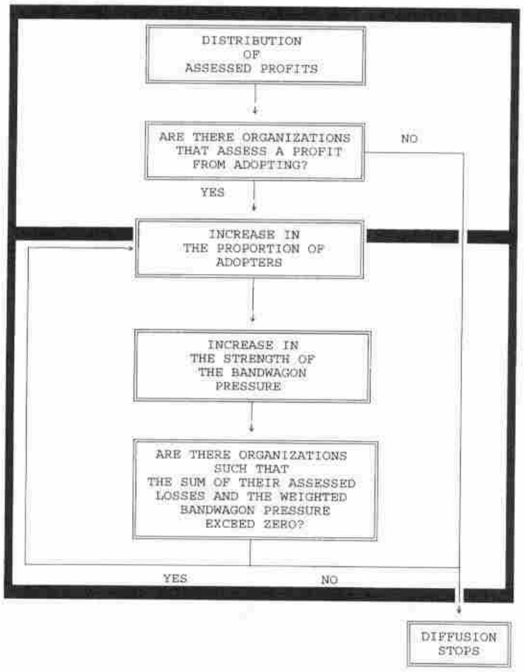
P_{k-1} stands for the information that creates the bandwagon pressure after $k - 1$ cycles. In our modeling of fads, information about the proportion of potential adopters in a collectivity that adopted was assumed to cause the bandwagon pressure (Abrahamson and Rosenkopf 1993a). P_{k-1}, therefore, stood for this proportion. To model a learning process, P_{k-1}, can be made to stand for information about the innovation's profitability learned from other potential adopters that have already adopted it. In learning models, P_{k-1}, is usually calculated as the average of this information across all adopters (e.g., Feder and O'Mara 1982).

A_i denotes how much potential adopter i weights the information represented by P_{k-1}. Social-comparison theory suggests that A will increase with the level of ambiguity about an innovation's profitability (Festinger 1950, DiMaggio and Powell 1983). Put differently, the less a potential adopter is certain about its individual assessment of the innovation, I_i, the more its decision to adopt the innovation will be swayed by information, P_{k-1}. Research indicates that environmental turbulence and complexity generates ambiguity, so that ambiguity and A_is will tend to be the same across potential adopters facing the same environment (Milliken 1987). Yet A_is might differ somewhat if potential adopters in core strata of social networks are less sensitive to social pressures than peripheral-strata potential adopters (Hollander 1976). We explore this possibility below.

Figure 3 depicts how Equation (2) evolves dynamically. If the distribution of assessed profits from adopting is such that certain potential adopters assess a profit from adopting (zero threshold), then these potential adopters adopt. Potential adopters that did not adopt at this point adjust their assessed losses by the bandwagon pressure (Equation (2)). If there is not at least one potential adopter whose adjusted bandwagon assessment, $B_{i,k}$, leads it to assess a profit, then diffusion will stop. If there is such a potential adopter, then it adopts. We call these potential adopters "bandwagon adopters."

The process may not stop there, however. Bandwagon processes animate a feedback loop in which growing bandwagon pressures prompt the number of bandwagon adopters to increase, and increases in the number of bandwagon adopters prompts bandwagon pressures to grow. With each cycle of the feedback loop, the bandwagon pressure grows and prompts adoptions by potential adopters that initially assessed greater losses from adopting. It is even possible that this feedback loop will cycle until potential adopters that initially assessed large losses adopt nonetheless.

Figure 3 Flow Diagram for the Model



Of course, if at any stage of this process, the non-adopter with the highest bandwagon assessment of the innovation's value, $B_{i,k}$, does not adopt, then the cycle ends and diffusion stops.

Diffusion Extent. Threshold models of innovation diffusion suggest that a potential adopter's predisposition against adopting an innovation, measured by its assessed profits from adopting the innovation, affects whether it gives in to a bandwagon pressure and adopts. Therefore, the distribution of assessed profits across potential adopters affects the extent of bandwagon diffusion among these potential adopters. Mathematical models and computer simulations suggest that the mean and variance of these distributions, in particular, have powerful effects on the extent of bandwagon diffusions (Abrahamson and Rosenkopf 1993a, Granovetter 1978, Schelling 1978). This is because distributions of assessed profits determine the difference in assessed profits between the last adopter, and the non-adopter with the lowest threshold, at any time during a bandwagon diffusion. If this difference is such that the increase in bandwagon pressure caused by the last adopter is strong enough to push the lowest-threshold non-adopter to adopt, then the bandwagon keeps on rolling, otherwise it stops and the maximal extent of innovation diffusion is attained.

The greater the mean of the distribution of assessed profits, the more potential adopters will tend to assess a profit and adopt, the greater the bandwagon pressure caused by these adoptions, and the more likely that potential adopters that have not adopted will do so because of the bandwagon pressure. The most interesting cases occur, however, when the mean is negative. Then, most potential adopters assess a loss from adopting. An innovation can nevertheless diffuse widely because of a faddish bandwagon process. Such bandwagons can occur if the variance of the distribution of assessed profits is large enough so that a few potential adopters will tend to assess profits, triggering a faddish bandwagon. High variance, however, also tends to stop bandwagons because it entails large gaps in the distributions of assessed profits. At these gaps, the adoption by the non-adopter with the highest assessed profits creates an added bandwagon pressure which is not powerful enough to cause the non-adopter with the next highest assessed profit to adopt, and the bandwagon stops as a result (Abrahamson and Rosenkopf 1993a). We assume that assessed returns are normally distributed and we examine only such negative-mean scenarios throughout this section. In the following section, we consider positive-mean scenarios.

Threshold Model Considering Social Network Structure
In this part of the article, we modify our previous model so as to incorporate the effect of variations in core-periphery network structures on the extent of innovations' diffusion. We use computer simulation of this modified model to verify propositions about diffusion extent across social networks.

Modified Model. We created an artificial core-periphery network like that depicted in Figure 2. A densely-linked core stratum of seven potential adopters is linked to a weakly-linked peripheral stratum of fourteen potential adopters. Figure 2 shows the specific case of 19 links beyond the core: 16 links between the core and peripheral strata, and 3 links within the peripheral stratum. Note that in a fully-linked network, there would be a maximum of 189 links beyond the core: 98 core-periphery links and 91 periphery-periphery links. For a given number of links beyond the core, random selection among the 189 possible links generated the network structure. Any two potential adopters for which a random link is generated are said to *communicate*.

The diffusion process was initiated by randomly choosing one potential adopter in the *focal* stratum as the initial adopter—we call it the seed—and no adopters in the *non-focal* stratum. To simulate trickle-down diffusions (core/focal to peripheral/non-focal diffusion), we randomly selected one seed in the core stratum and the peripheral stratum was considered non-focal. To the contrary, to simulate trickle-up diffusion (periphery/focal to core/non-focal diffusion), we randomly selected one seed in the peripheral stratum, and the core stratum was considered non-focal.

We also modified Equation (2) in order to reflect our assumptions that different potential adopters received different information depending on their positions in the social network. Other than the seed, for any potential adopter to adopt, it had to find out information about the innovation through the network (i.e., communicate with an adopter), and it had to find the innovation adoptable as a result of finding out this information (i.e., positive $B_{i,k}$). Moreover, while in Equation (2) the information that creates the bandwagon pressure, P_{k-1}, was operationalized as the total number of adopters divided by the total number of potential adopters, we used a measure specific to each potential adopter, $P_{i,k-1}$. This adopter-specific measure was operationalized as the number of adopters of the innovation with which potential adopter i communicates, divided by the total number of potential adopters. This new proportion is equal for all potential adopters in the case of perfect information, but when information flow is constrained by less dense network structure, the proportion is reduced. Thus, in a set of 25 potential adopters, a potential adopter that communicates with 10 others can experience a maximum bandwagon pressure of 10/25, or 0.4, whereas in the perfect information case, it can experience a maximum bandwagon pressure of 24/25.

Research Design. Three sets of simulations were performed. In the first set, propositions were tested using a basic model of faddish diffusion, described below. A second set of simulations explored the robustness of these findings when the assumption that every firm was equally sensitive to information creating bandwagon pressures was relaxed. A third set of simulations explores how these findings differ using a model based on Learning rather than Fad theories.

First Set of Simulations. Network density is the ratio of the actual to the maximum number of links between actors in a network. Since we simulated core-periphery networks with fully-linked cores (Figure 2), network density was varied by varying the number of network ties beyond the core. We permitted the number of these ties to vary from 0 to 185 in intervals of 5. This yielded 38 cases to examine. Assessed profits were drawn randomly from a normal distribution with mean -1.0 and standard deviation 1.0. These settings create a situation where the majority of potential adopters assess negative returns, but a small percentage (0.16, on average) of potential adopters assess positive returns, thereby creating the possibility of bandwagons and extensive diffusions. Furthermore, as we noted above, A_i, denotes how much potential adopter i weights the information which causes the bandwagon pressure. In this first simulation, A_i was fixed to the same value for all firms, but this value was permitted to vary between 1 and 5 in intervals of 1. This range was selected because, with mean and standard deviation fixed at the levels just described, little diffusion occurred at the lower bound of 1, while extensive diffusion generally occurred at the higher bound of 5. These five levels of ambiguity increased the number of cases by a factor of 5, for a total of 190 cases. For each case, we ran 100 trials and calculated the average number of adopters in the focal and non-focal strata.

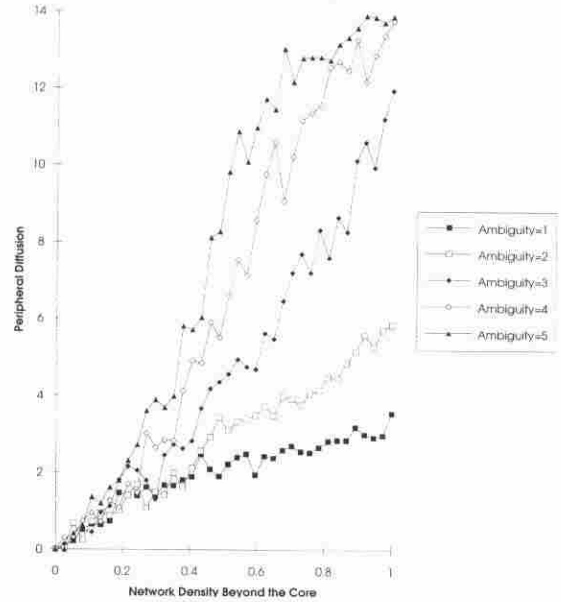
We also tested the robustness of our findings to changes in the mean and standard deviation from which assessed returns were drawn. Abrahamson and Rosenkopf (1993a) showed that, as the mean and standard deviation decrease, the level of ambiguity required to impel diffusion of equal extent must also increase. Likewise, when we varied means and standard deviations, results were not qualitatively different, although they occurred at higher levels of ambiguity. The results of these simulations are not presented here, but are available from the authors.

We argued above that social networks influence the extent of an innovation's diffusion by determining which potential adopters can become aware of information about this innovation and adopt it. It is clear, therefore, that the greater the number of links between core and peripheral strata, the greater the opportunities for non-focal stratum potential adopters to learn about the innovation, adopt it, and, therefore, the greater the extent of innovation diffusion into these non-focal strata. We advance Proposition 1, though it is rather obvious, so it can serve as a base line proposition against which more counterintuitive network effects will stand out.

PROPOSITION 1. *The greater network density, the greater the number of bandwagon adopters in the non-focal stratum.*

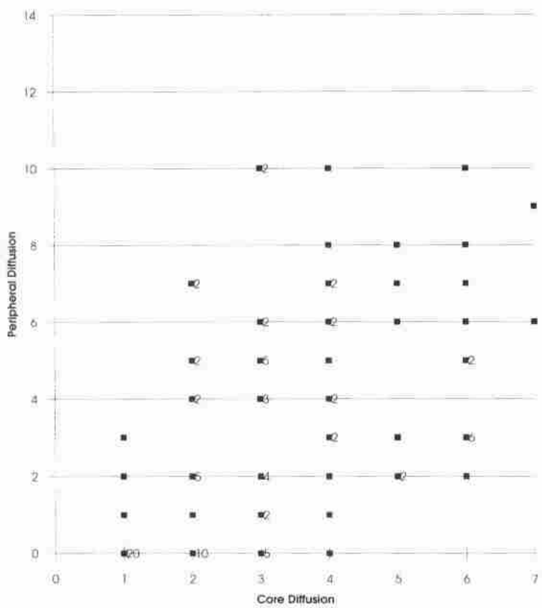
Figure 4 displays the results of our simulation for the trickle-down case. Due to space limitations, trickle-up

Figure 4 **Extent of Peripheral Diffusion for Varying Ambiguity and Network Density**



results are not presented here. While the effects of density and ambiguity are similar in trickle-up scenarios, the extent of diffusion into the core is about half that of the trickle-down case. In Figure 4, the average number of adopters in the periphery is graphed against network density beyond the core. Five trends are displayed, one corresponding to each level of ambiguity from one to five. Notice that the extent of diffusion grows with the level of ambiguity, since ambiguity magnifies bandwagon pressure. In accordance with Proposition 1, as the network density beyond the core stratum increases, so too does the total number of bandwagon adopters in the periphery. While this linear trend is clear, it masks the variability that can occur from trial to trial. Consider trickle-down cases (core to periphery diffusion) where ambiguity is set to the intermediate level of 3. When there are 90 links beyond the core (density equal to 90/189, or approximately 0.5), for example, the mean number of adopters is 7.3. This breaks down, on average, to 4.4 adopters in the core and 2.9 adopters in the periphery. A closer look at the outcomes of each of the 100 trials shows, however, the variability in the extent of diffusion in both the core and periphery. Figure 5 shows the number of adopters in the non-focal, peripheral stratum caused by the number of adopters in the focal, core stratum. The number next to each box denotes multiple trials with the same outcome. A weak linear trend exists between core and peripheral diffusion. What is notable, how-

Figure 5 **Variability of Core and Peripheral Diffusion (100 Cases with Ambiguity = 3 & Network Density = 0.5)**



ever, is that each level of core diffusion caused widely varying levels of peripheral diffusion.

Why, controlling for core diffusion, does the extent of peripheral diffusion vary so much from trial to trial? To answer this question, we explored how, controlling for variables such as focal-stratum diffusion, variations in the *structure of network ties* linking core and peripheral strata affect diffusion between these strata.

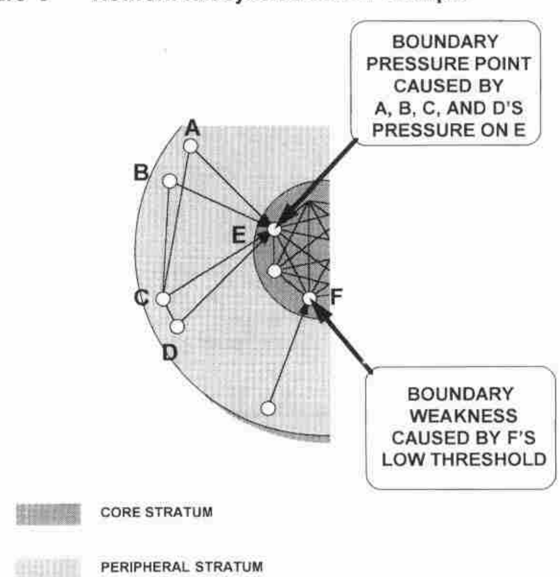
Network Idiosyncracies. We focused on chance interactions between our randomly generated network structures and threshold distributions that could have a major effect on the extent of innovation diffusion. We distinguished two such types of chance interactions which we call "network idiosyncracies." As the cases of AIDS, TQM, and scurvy prevention suggested, such network idiosyncracies occur at the internal boundaries of networks. At these boundaries, an idiosyncracy of the network that enables an innovation to diffuse across the boundary can have a major influence on the extent of innovation diffusion. This is because the diffusion is no longer confined to one side of the boundary, but rather can spread to the other side of the boundary, possibly prompting many more adoptions (Granovetter 1973). TQM, for example, broke the U.S./Japan geographical boundary and was introduced to a core network of Japanese executives. From there it broke another status boundary and trickled down to the peripheries of Japanese industry. To the contrary, when it was first discovered, the cure for scurvy could not break out of the periphery of the British naval circle. It only trickled up to its core two centuries later.

In our simulations, a boundary exists between the inner (core) and outer (peripheral) circles in Figure 2. A network idiosyncracy at this internal network boundary can cause the innovation to trickle either up or down the core-periphery status boundary. Figure 6 depicts the two types of network idiosyncracies, which we call "boundary pressure points" and "boundary weaknesses," that can coexist or occur independently.

A boundary pressure point occurs in Figure 6 when a potential adopter on one side of a boundary (actor E), has many linkages to potential adopters on the other side of the boundary (actors A, B, C and D). If most of these potential adopters adopt, they can create bandwagon pressure strong enough to prompt the potential adopter at the pressure point to adopt, even if it has a relatively high threshold. If, for example, a number of English captains had convinced the English navy's upper brass that lime juice was a cure for scurvy, they might have triggered this treatment's widespread diffusion two centuries earlier. Likewise, it may have been necessary for actors at the peripheries of Japanese industry to receive multiple messages from core actors about the benefits of TQM before they adopted it.

In sum, we define a boundary pressure point as a concentration of social ties linking potential adopters of an innovation in one segment of a network to a

Figure 6 **Network Idiosyncracies: An Example**



potential adopter in another segment of that network. We argue that pressure points increase the likelihood that an innovation diffusing in one segment of a network would spread across a boundary to another segment of that network.

In the second set of simulations, we operationalized boundary pressure points by counting each non-focal potential adopter that communicates with at least half of the focal potential adopters. We also tried proportions other than one half, and the results did not differ substantially. We examined the following proposition.

PROPOSITION 2. *The greater the number of pressure points at the boundary of a non-focal stratum, the greater the number of bandwagon adopters in that stratum.*

Boundary weaknesses, like boundary pressure points, are not purely structural features. A boundary weakness occurs in Figure 7 when potential adopter F both has ties bridging two sides of a boundary *and* has a low adoption threshold. A single adoption can cause such a weakly linked potential adopter to adopt, spreading the innovation to many potential adopters across the boundary. The diffusion of TQM illustrates this phenomenon. The adoption of the TQM idea by Ichiro Ichikawa, and its resulting global diffusion, provides a powerful example of how a single boundary weakness can have a major effect on the extent of diffusion of an innovation.

In sum, we define a boundary weakness as a social tie linking a potential adopter of an innovation in one segment of a network to a potential adopter, in another segment of that network, who is highly predisposed to adopting this innovation. We argue that boundary weaknesses increase the likelihood that an innovation diffusing in one segment of a network will spread to another segment of that network.

Figure 7 summarizes our argument concerning the conditions when linkages and threshold cause network idiosyncracies. This figure indicates that boundary weaknesses and pressure points can occur simultaneously when multiple social ties link a potential adopter of an innovation in one segment of a network to a potential adopter, in another segment of that network, who is highly predisposed to adopting this innovation (has a low threshold).

In trickle-down diffusion, innovations diffuse from the core (focal stratum) to the peripheral (non-focal) stratum. In trickle up-diffusion, innovations diffuse from the peripheral (focal stratum) to the core (non-focal stratum). Therefore, in the second set of simulations, we operationalized boundary weaknesses by counting each non-focal potential adopter that satisfied two conditions: the potential adopter had to communicate with a focal potential adopter, and it had to have assessed profits high enough such that one adoption would create enough impetus for this potential adopter to adopt. We examined the following proposition.

PROPOSITION 3. *The greater the number of weaknesses at the boundary of a non-focal stratum, the greater the number of bandwagon adopters in that stratum.*

This article's central thesis is that the structure of social networks can matter greatly in explaining the diffusion of innovations when social network density is less than unity. Put differently, at less than unity, Propositions 2 and 3 become relevant, because network structure affects which potential adopter finds out what information about an innovation and, therefore, how many adopt it. By extension, these propositions may be *more* relevant in lower as opposed to higher density networks. Thus, we reasoned that,

PROPOSITION 4. *Boundary pressure points and weaknesses will have relatively greater effects on diffusion extent in lower- as opposed to higher-density networks.*

In the simulations we operationalized lower-density as less than 0.5 network density beyond the core and higher density as more than 0.5.

Following Nelson and Winter (1982), we verified whether we were justified in advancing Propositions 2 through 4 by performing regressions on data generated by the simulation. With 100 trials for each of the 190 cases (5 levels of ambiguity times 38 levels of density), we generated a sample of 19,000 different diffusion scenarios. Our dependent variable was the number of

Figure 7 Network Idiosyncracies

		THRESHOLD OF BOUNDARY SPANNER: LOW	THRESHOLD OF BOUNDARY SPANNER: HIGH
NUMBER OF CROSS-BOUNDARY LINKAGES	FEW	BOUNDARY WEAKNESS	NEITHER BOUNDARY WEAKNESS NOR PRESSURE POINT
	MANY	BOTH BOUNDARY WEAKNESS AND PRESSURE POINT	BOUNDARY PRESSURE POINT

adopters in non-focal strata. Both trickle-up and -down cases were examined.

We used hierarchical, Ordinary-Least-Squares regressions (OLS) to analyze our data (Cohen and Cohen 1983). In this approach, control variables are entered in a base model. Then independent variables of theoretical interest are added to the base model. The increase in R^2 from the addition of these variables to the model serves to assess their impact. Independent variables that are theorized to have a causative influence on other independent variables of theoretical interest are added before the causally-influenced variables. An F-test is used to determine whether the addition of each variable to the previous model results in a statistically significant increase in R^2 and whether, therefore, this variable's hypothesized effect is supported. In our analysis, sample size was large enough that all increases in R^2 were statistically significant. Therefore we do not report F tests.

Table 1 follows this logic of hierarchical regression. Model 1 introduces three control variables: ambiguity, focal diffusion, and network density beyond the core. We then examined the effects of two variables of theoretical interest: the number of boundary weaknesses and pressure points in models 2a and 2b. Since there is no clear causal ordering between the two network idiosyncracy variables, they were entered together in models 2a and 2b and standardized regression coefficients were used to determine their relative impact.

Table 1 displays the results for both trickle-down (core/focal to periphery/non-focal diffusion) and trickle-up scenarios (periphery/focal to core/non-focal diffusion). Each model produces an increase in R^2 over the previous model when network idiosyncracy variables are included. The increase of model 2a over 1a and model 2b over 1b verifies our network-idiosyncracy Propositions 2 and 3, in the trickle-down and trickle-up scenarios respectively. Moreover, the standardized regression coefficients indicate that, in both trickle-up and -down scenarios, boundary weaknesses had a greater impact on the extent of diffusion than boundary pressure points.

Table 1 results also indicate that the effects of ambiguity and network density are weaker in the trickle-up as opposed to trickle-up diffusion, and that trickle-up diffusion is rare and much less extensive than trickle-down diffusion. These results are consistent with the work of observers who have noted that trickle-up processes are rare in industry (Tushman and Anderson 1986, Bower and Christensen 1995). This phenomenon occurs in our simulations for two reasons.

Table 1 Extent of Diffusion in Non-focal Strata (Standardized Betas)

	TRICKLE-DOWN	
Variables	Model 1A	Model 2A
Ambiguity	0.15	0.13
Core diffusion	0.58	0.53
Density	0.38	0.17
Peripheral Weaknesses		0.28
Peripheral Pressure Points		0.13
R^2	0.761	0.819
Change In		0.058
df	18996	18994

Mean peripheral diffusion = 4.83
std dev = 5.09
min = 0
max = 14

	TRICKLE-UP	
Variables	Model 1B	Model 2B
Ambiguity	0.07	0.07
Core diffusion	0.81	0.76
Density	0.07	−0.02
Peripheral Weaknesses		0.24
Peripheral Pressure Points		0.08
R^2	0.793	0.845
Change In		0.052
df	18996	18994

Mean Core Diffusion = 2.42
std dev = 2.69
min = 0
max = 14

First, because trickle-down diffusion tends to occur relatively easily. Non-adopters in the core are densely networked. Consequently, during trickle-down diffusions, most core members find out when one core member adopts, causing strong bandwagon pressures in the core, and prompting many core members to adopt. These core adopters prompt still more adoptions by peripheral network participants. Second, because trickle-up diffusion occurs only with great difficulty. Non-adopters in the network's periphery are not densely interconnected. In trickle-up diffusion, therefore, adoptions by peripherals remain unknown by other peripherals. As a result, weak bandwagon pressures and few additional adoptions tend to result. For these two reasons, diffusion extent tends to be greater in trickle-down as opposed to trickle-up diffusion. Moreover, even when ambiguity and density are high in the trickle-up scenario, they do not influence diffusion as much as than in the trickle-down scenario, and therefore, the coefficients for ambiguity and density are lower in the former as opposed to the latter.

Proposition 4 stated that boundary pressure points and weaknesses would have relatively greater effects on diffusion extent in lower- as opposed to higher-density networks. To verify this proposition, we bisected our simulation results into lower-density (below 0.5) and higher-density (above 0.5) subsets in order to compare the relative effects of our network idiosyncracy variables in each subset. The results are displayed in Table 2. The addition of the weakness and pressure point variables in the higher density scenario yielded only 0.05 R^2 increases. In the lower-density scenario, however, they resulted in R^2 increases of 0.17 (trickle-down) and 0.13 (trickle-up). These results are consistent with Proposition 4's claim that network idiosyncracies matter more in lower- as opposed to higher-density networks. Note also that the standardized betas for network idiosyncracies are always greater in the low- as opposed to high-density case. Although we do not report the results here, it should also be clear to the reader that the network idiosyncracies will interact with the level of ambiguity, having greater effects on the extent of diffusion in more ambiguous conditions.

Table 2 Extent of Diffusion Non-focal Strata (Standardized Betas)

	TRICKLE-DOWN			
	Low Density		High Density	
Ambiguity	0.12	0.07	0.20	0.22
Core Diffusion	0.43	0.39	0.73	0.65
Density	0.44	0.10	0.099	0.10
Peripheral Weaknesses		0.50		0.23
Peripheral Pressure Points		0.11		0.01
R^2	0.481	0.651	0.804	0.851
Change in R^2		0.170		0.047
df	9496	9494	9496	9494
Mean	2.0		7.6	
Std Dev	2.9		5.3	
Min	0		0	
Max	14		14	

	TRICKLE-UP			
	Low Density		High Density	
Ambiguity	0.06	0.04	0.13	0.14
Peripheral Diffusion	0.67	0.61	0.79	0.73
Density	0.08	−0.03	0.06	0.06
Core Weaknesses		0.39		0.23
Core Pressure Points		0.11		0.01
R^2				
Change in R^2	0.534	0.663	0.806	0.854
df		0.129		0.048
	9496	9494	9496	9494
Mean	1.0		3.7	
Std Dev	1.8		2.7	
Min	0		0	
Max	7		7	

Second Set of Simulations. To assess the robustness of our findings concerning network idiosyncracies, we relaxed the assumption that all potential adopters place the same weight, A_i, on information, P_{k-1}, which creates a bandwagon pressure. We considered the possibility that this weighting factor, A_i, might be a function of an potential adopter's position in a core-periphery network. More specifically, research indicates that potential adopters in core strata, by virtue of their higher social status, are typically less sensitive to bandwagon pressures than lower-status potential adopters in peripheral strata (e.g., Hollander 1976). By extension, we reasoned that core potential adopters would be less sensitive to bandwagon pressures—lower A_i—than peripheral potential adopters.

We wanted to compare situations of homogeneous and heterogeneous A_is. Therefore, we used one simulation to create a homogeneous baseline. We compared these homogeneous baseline results to the results of heterogeneous simulations in which peripheral potential adopters' A_is were twice that of core potential adopters. For ease of exposition, we limited our presentation of results to a comparison between homogeneous scenarios where all A_is equal 3, the midpoint of the 1 to 5 range used previously, and heterogeneous scenarios, where A_is equals 2 for core potential adopters and 4 for peripheral potential adopters. Table 3 indicates that increases in R^2 caused by the addition of network idiosyncracy variables were comparable in homogeneous and heterogeneous scenarios. These results suggest that Propositions 2 and 3 generalize to contexts in which the susceptibility (A_i) of potential adopters to information causing bandwagon pressures

Table 3 Varying Ambiguity Between Core and Periphery (Standardized Betas)

	TRICKLE-DOWN			
	A = 2, 4		A = 3	
Focal Diffusion	0.43	0.40	0.57	0.50
Density	0.54	0.14	0.42	0.14
Nonfocal Weaknesses		0.30		0.30
Nonfocal Pressure Points		0.32		0.22
R^2				
Change in R^2	0.711	0.786	0.735	0.808
		0.075		0.073
df	3797	3795	3797	3795
Mean	5.9		4.8	
Std Dev	5.5		4.9	
Min	0		0	
Max	14		14	
	TRICKLE-UP			
A	A = 2, 4		A = 3	
Focal Diffusion	0.68	0.57	0.78	0.70
Density	0.14	−0.03	0.11	−0.05
Nonfocal Weaknesses		0.36		0.27
Nonfocal Pressure Points		0.20		0.18
R^2				
Change in R^2	0.627	0.745	0.739	0.806
		0.118		0.067
df	3797	3795	3797	3795
Mean	2.0		2.3	
Std Dev	2.1		2.5	
Min	0		0	
Max	7		7	

is heterogeneous. The results suggest, however, that the extent of diffusion varies across homogeneous and heterogeneous scenarios. Increasing peripheral ambiguity and decreasing core ambiguity in led to greater trickle-down diffusion (mean of 5.9 vs. mean of 4.8 in the homogeneous case) and lesser trickle-up diffusion (mean of 2.0 vs. mean of 2.3 in the homogeneous case). Increased peripheral ambiguity causes peripheral potential adopters to be more susceptible to trickle-down diffusion from the core, but causes core potential adopters to be less susceptible to trickle-up diffusion from the periphery.

Third Set of Simulations. We explored with a third set of simulations whether network effects in learning scenarios would be similar to those derived in fad scenarios. In modeling Fad scenarios, the information, $P_{i,k-1}$, that creates the bandwagon pressure reveals the number of adopters. It was operationalized by dividing the number of adopters with which potential adopter i communicates by the total number of potential adopters in the network. In modeling learning theories, the information that causes the bandwagon pressure, $P_{i,k-1}$, reveals the innovation's profitability for prior adopters. To represent this information, each firm, upon adoption, was randomly assigned either a "positive" or "negative" experience with the innovation.

To model learning theories, we had to make assumptions about the probability that potential adopters would have either a positive or a negative experience with the innovation. We assumed that potential adopters' assessments of whether their experience from adopting the innovation was going to be positive or negative would be correct, on average. It followed that the mean and variance of the distribution of assessed and achieved profitabilities from adopting the innovation would tend to be the same. Therefore, in the simulation, both assessed and achieved profitabilities (positive or negative) were drawn randomly and independently from a normal distribution with the same mean and variance (for a similar modeling approach, see Burgelman and Mittman 1994). Since we assumed that the distribution of assessed experiences had mean -1.0 and standard deviation 1.0, then on average, the likelihood of a positive experience was 0.16.

Rather than simply counting all potential adopters that had communicated adoptions, our learning model had each potential adopter sum the number of positive outcomes it learned about while subtracting the number of negative outcomes it learned about. This total was divided by the number of potential adopters in the network. In this way, information about one negative experience offsets information about one positive experience.

Results of the regressions for the trickle-down and trickle-up cases are displayed in Table 4. Note that the learning effect reduces the extent of diffusion dramatically in learning scenarios (Table 4) as compared to fad scenarios (Table 1): mean diffusion in the trickle-down case is reduced to 1.5 as compared to 4.9, and mean diffusion in the trickle-up case is reduced to 0.79 from 2.4. Learning of an unprofitable experience with an innovation lessens the bandwagon pressure to adopt it, thereby retarding diffusion. Similarly, diffusion never spreads to all potential adopters in a group in this scenario: maximal diffusion in the periphery is 10 of 14, and maximal diffusion in the core is 6 of 7. Potential adopters with a higher adoption threshold are no longer enticed to adopt, since negative information offsets

Table 4 Incorporating Learning (Standardized Betas)

	TRICKLE-DOWN		TRICKLE-UP	
Ambiguity	−0.01	−0.11	0.57	0.50
Focal Diffusion	0.05	0.05	0.11	0.10
Density	0.43	0.07	0.33	0.14
Nonfocal Weaknesses		0.70		0.69
Nonfocal Pressure Points		0.09		0.07
R^2				
Change In	0.184	0.588	0.154	0.596
		0.404		0.442
df	18996	18994	18996	18994
Mean	1.5		0.79	
Std Dev	1.4		0.97	
Min	10		6	
Max	0		0	

news of adoptions. Note also that ambiguity now has a negative effect on diffusion, as this factor is magnifying a generally negative outcome set.

What was most striking about these results, however, is how the relative magnitudes of the network-idiosyncracy variable differ from the non-learning scenarios. Whereas in the fad scenario, the network-idiosyncracy variable explained roughly 5% of the variance in both trickle-up and -down diffusion extent, this variable explains over 40% of this variance in the learning scenario. This occurs because, since learning effects minimize bandwagon pressures, diffusion depends to a greater extent on whether information flows through social networks to the few potential adopters whose assessed returns predispose them to adopt.

Note also that in learning scenarios, the bulk of diffusion is predicted by the number of boundary weaknesses, and not by pressure points. This occurs because the mean of returns experienced by adopters is negative, so that most information that is learned is negative. It follows that at pressure points, non-adopters tend to find out mostly negative information, and they do not adopt. An innovation can diffuse across a boundary at a boundary weakness, however. This happens when an adopter on one side of the boundary has a positive experience with the innovation and it is connected to a low threshold non-adopter on the other side of the boundary that adopts in response to this information. More generally, our results indicate that Propositions 2 and 3 are reasonable in both fad and learning scenarios.

When Do Social Networks Influence Diffusion Extent?

In this section, we consider the generalizability of our thesis and of the propositions we derived. First, we examine when a focus on social networks can enrich theories of the diffusion of innovations with ambiguous profitability—administrative, technological, product innovations or ideas. We consider diffusion across a variety of potential adopters (both individuals and organizations), network structures (not only core-periphery networks, but island networks as well), and with different types of diffusion processes (both diffusion by cohesion and by structural equivalence). We also consider the effect of social networks on the extent of diffusion when the mean of initial assessed returns is not only negative, but positive as well. Second, we consider when a focus on social networks can enrich innovation diffusion theories, such as Increasing Returns theories, which assume that the profitability of innovations is unambiguous.

Ambiguous Profitability

Mixed-influence Theories. Mixed-influence theories attribute innovation diffusion both to influences internal to networks of potential adopters, as well as to influences exerted by actors located outside these networks, such as mass-media organizations or governmental agencies. In our simulations, we examined mixed influences in the diffusion of innovations across social networks with a core-periphery structure. Such mixed influences have been found in a broad variety of contexts (Rogers and Shoemaker 1971). They have been found not only with the diffusion of administrative innovations, but with the diffusion of technological innovations as well (e.g., Czepiel 1974). They have been found not only with the diffusion of technologies and techniques, but also with the diffusion of innovative ideas and information (Rogers 1995). Finally, they have been found not only with the diffusion of innovations across organizations, but also with the diffusion of innovations across individuals (Coleman et al. 1966). Though these studies pertain to the diffusion of many different types of innovations across both individuals and organizations they find similar network structures (core-periphery) and assume similar models of diffusion (Fad and Learning). It is our belief, therefore, that the propositions we developed in this article may generalize across a broad variety of contexts involving different types of innovations and adopters.

We focused on networks with a core-periphery structure because they have been found so frequently in studies of innovation diffusion (Walker 1969, Galaskiewicz and Wasserman 1989, Davis 1991, Mizruchi 1992, Burns and Wholey 1993, Haunschild 1993, Haveman 1993, Palmer et al. 1993). This focus, however, led us to de-emphasize diffusion through other types of network structures. In a classic article, Granovetter (1973) pointed to what Boorman and Levitt (1980) called "islands" in networks, areas of a network in which there are many links between actors on the island and few "weak ties"—links to actors on other islands (see also Burt 1992). He argues that in such "island models," weak ties affect innovation diffusion because they determine whether diffusion is confined to the island where the first adoption occurs, or spreads across weak ties to other islands. Using computer simulation, we found that our propositions in this article generalized to island models. Both the number of weak ties between islands, as well as network idiosyncracies occurring at island boundaries, had a major effect on the extent of diffusion in networks with island structure (Abrahamson and Rosenkopf 1993b, paper available from the first author upon request).

We also focused on diffusion by cohesion, where innovations spread across communication networks, rather than diffusion by structural equivalence, where innovations spread across actors who, by virtue of the fact that they are in similar positions in social networks, tend to compete with each other and to imitate each other (Abrahamson and Fombrun 1994, Burt 1987, Friedkin 1984, Lorraine and White 1971). Nonetheless, the argument's logic extends to diffusion by structural equivalence.

A group of structurally equivalent members is called a position. First, imagine positions α and β in a network. Imagine one actor, A, that is somewhat structurally equivalent to members of positions α and β. If A has a low adoption threshold, then it constitutes a boundary weakness between positions α and β that could allow an innovation to diffuse from members of α to members of β. Second, even if A has a high threshold against adopting an innovation, members, B, C, D, and E of position α could, nonetheless, cause a pressure point on A that would cause it to adopt and the innovation to flow from position α to β. In sum, boundary pressure points and weaknesses, by allowing innovations to diffuse from one structurally equivalent position to another, should have a major influence on the extent of innovation diffusion by structural equivalence.

Finally, in this article's simulation section, we focused on negative-mean scenarios: scenarios in which the majority of potential adopters assessed initially that they would obtain negative returns from adopting an innovation. Our argument and findings do, nonetheless, generalize to positive-mean scenarios, when most potential adopters assess positive returns from adopting. In such scenarios, it is the absence of boundary weaknesses or pressure points, rather than their presence, which greatly influences diffusion extent. It suffices, for example, that one actor bridging a social network boundary be negatively predisposed to adopting an innovation for the innovation not to diffuse widely on the other side of the boundary, even if most potential adopters on that side would have been strongly predisposed to adopting the innovation. Thus, in positive-mean scenarios, network idiosyncracies can greatly limit the extent of innovation diffusion.

External-influence Theories. Mixed-influence theories are not the only type of theories that explain the diffusion of innovations for which profitability is ambiguous. A second type of *external-influence* theories attributes the diffusion of innovations *primarily to* influences originating from outside the set of potential adopters. A review of the diffusion of administrative innovations across organizations revealed, for example, that external-influence theories have been found to explain the diffusion of administrative innovations when government agencies were actively involved in mandating the use of certain administrative techniques (Abrahamson 1991, Abrahamson 1996b). War Labor Boards forced the diffusion of personnel administration innovations both during World War I (Jacoby 1985) and World War II (Barron et al. 1986). These external influences left very distinctive cumulative-number-of-adopters curves that differ substantially from the S-curves left by mixed-influence processes. The external influencer forces adoption by many organizations quasi-simultaneously, and consequently, the cumulative adoption curve shoots up suddenly and rapidly, slowing only when most potential adopters have adopted (Mahajan and Peterson 1985, Valente and Rogers 1993).

External-influence diffusion patterns have been found in a number of studies involving various types of innovations and adopters (see Rogers and Shoemaker 1971; Rogers 1995; Mahajan and Peterson 1985, for reviews). It is unlikely that social networks could have had much influence on the extent of diffusion in such contexts. This is because if external influencers are influential, all potential adopters find out about the innovation and adopt it quasi-simultaneously. Under these circumstances networks can only play a minor role in shaping the spread of information about an innovation and thus the pattern and extent of its diffusion.

Non-ambiguous Profitability

Increasing Returns theories generally assume a context in which an innovation's costs decline or its returns increase with the number of its adopters. It is generally assumed that information about the innovation's lower cost is apparent from its price, whereas information about its greater returns is either apparent from the innovation itself or easily obtainable from an accurate and credible external source. Thus, information is assumed to be available and unambiguous, and it need not be communicated through a social network before it can prompt more adoptions. It would appear, therefore, that Increasing Returns theories cannot be enriched by a focus on social networks. Or, put differently, it would appear that a focus on social networks would enrich Increasing Returns theories only if they relaxed the assumption that information about an innovation is unambiguous and easily available.

We find only one exception to the general claim that social networks cannot enrich Increasing Returns theories as they are currently formulated. This exception occurs when increasing returns are generated by communication networks; the more potential adopters adopt a communication standard or device, such as an electronic-mail facility, the greater the returns to adopters because they can communicate with more adopters (Katz and Shapiro 1985, 1994; Farrell and Saloner 1985). Why would a focus on social networks help explain the diffusion of a communication device, even when information about this communication device was unambiguous and easily available? The answer is that the sheer number of adopters of the device may not be a good proxy of its utility for each adopter. This is because when a communication device has not fully diffused, it may be more useful to individuals with social ties to many adopters than to individuals with social ties to many non-adopters. For example, it makes little difference to me whether 100 million Americans use an e-mail facility if my social acquaintances are not connected to it. Alternatively, if they adopt this facility, I will benefit greatly from it, even if very few Americans have adopted it. Of course, if my social acquaintances adopt, this may prompt my acquaintances' acquaintances to adopt and the communication device may diffuse via such social ties. Thus the diffusion of certain communication devices and standards may be both channeled and limited by the structure of social networks. Social structures with more channels would lead to greater diffusion, as would network pressure points and weaknesses that allowed the communication innovation to diffuse across internal boundaries of the social network.

Conclusion

This article's central thesis was that theories explaining the timing and extent of innovations' diffusions could be enriched by a focus on social networks. We supported our thesis by reviewing theory and research indicating that social networks channel information about innovations to some potential adopters who might adopt these innovations and not others who could not adopt them. We reasoned therefore that networks could influence the extent of innovation diffusion. We then examined, using computer simulations of threshold models, how the extent of innovation diffusion might depend not only on threshold distributions, but also on variations in social network structures. In particular, we noted a variety of structural features that might influence diffusion extent. Not only the density of network ties, but also two types of network idiosyncracies—network pressure points and weaknesses at the internal boundaries of these networks.

In the final section, we argued that our social network effects thesis, as well as the propositions derived from it, may have broad generalizability. We argued that they might enrich theories of the diffusion of various types of innovations with ambiguous profitability (administrative, technological and product innovations or ideas) across a variety of potential adopters (organizations and individuals), across different types of network structures (core-periphery and island networks), and with different types of diffusion processes (both diffusion by cohesion and by structural equivalence). We also argued they might enrich Increasing Returns theories bearing on the extent of diffusion of communication innovation and the emergence of communication standards, even when the information about these standards was unambiguous and readily available.

We believe that our model is generalizable across a broad variety of contexts. This does not mean, however, that it need not be modified to fit these contexts. A number of examples illustrate this point. We assumed in our learning model that returns from adopting would remain constant as the number of adopters increased. This assumption would have to be relaxed in the context where there are first-mover advantages and the returns that potential adopters learn about decline with increases in the number of adopters. Likewise, we assumed that adopters' assessed returns might be influenced, in part, by their forecasts of how many potential adopters would adopt the innovation. We did not, however, consider the possibility that potential adopters might update these forecasts based on the number of adoptions they learned about through their networks. In contexts where this happens, our model would have to be modified accordingly.

We also examined only the diffusion of single innovations, rather than of competing variants of an innovation, and we focused on the adoption of innovations rather than their rejections. This focus leaves open several additional directions for future theorizing about social network effects on the extent of innovation diffusion. Future research could explore, via computer simulation, the simultaneous diffusion of competing variants of an innovation across networks with varying structures. Extrapolating from our results, it seems likely that small differences in the network location at which one variant was introduced could cause it to prevail over a competing, possibly technologically superior, variant. This could occur, for instance, if one variant was first adopted near a boundary weakness or pressure point, allowing it to spread across that boundary and to "lock out" the competing variant.

Likewise, multiple adopters of one variant might create a social pressure causing adopters of the other variants to reject it. Consequently, it would be interesting to explore innovation diffusion through social networks where bandwagon pressures to not only adopt innovations but also to reject them are operating. Such research might build upon previous research that has examined simultaneously the dynamics of bandwagon diffusion and rejections (Granovetter and Soong 1986, Abrahamson and Rosenkopf 1993a).

Our study may generate general interest across disciplines. We illustrated how sociologists' focus on social networks can enrich economists' theories of innovation diffusion (Granovetter 1985, 1992; Barron and Hannan 1994). These models, with their assumption that information is an easily available or purchasable commodity, may be less useful in contexts where social networks both channel such information and influence decision makers' interpretation of this information as well. It is our contention that in such contexts, economists' theorizing and research can be enriched by network analysis concepts and methods.

Our article also illustrates how focusing on economic variables, such as assessed profits from adopting, can complement sociological explanations stressing networks. We suggest, for instance, that purely structural features, such as the number of links between potential adopters in a network, affect the extent of bandwagon diffusions. However, whether or not these links have such an effect may also depend on whether or not they transfer information from an adopter to a potential adopter who expect profits from adopting.

In closing, this research highlights complementarities between two bodies of theorizing in the innovation diffusion literature that traditionally have had little to say to each other (Barron and Hannan 1994). Indeed, work that explores the distribution of assessed profits from adopting an innovation falls primarily in the domain of economists or of scholars in applied disciplines who use their theories (Schelling 1978, Katz and Shapiro 1985). Work that explores the embeddedness of actors in networks of social relations resides primarily in the domain of sociologists and applied scientists using their theories (Granovetter 1985, 1992; Burt 1987). This article highlights complementarities between these two domains in the hope of enriching both.

Acknowledgments

The authors would like to thank Warren Boeker, Frances Katrishen, Choelsoon Park, Paul Adler, and three anonymous reviewers for their comments.

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Accepted by Paul S. Adler; received October 1993. *This paper has been with the authors for two revisions.*