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INSTITUTIONAL AND COMPETITIVE BANDWAGONS: USING MATHEMATICAL MODELING AS A TOOL TO EXPLORE INNOVATION DIFFUSION

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The sheer number of organizations adopting an innovation can cause a bandwagon pressure, prompting other organizations to adopt this innovation. Institutional bandwagon pressures occur because nonadopters fear appearing different from many adopters. Competitive bandwagon pressures occur because nonadopters fear below-average performance if many competitors profit from adopting. Our mathematical model of bandwagons examines how organizational collectivities' characteristics determine (a) whether a bandwagon will occur, (b) how many organizations jump on it, and (c) how many retain the innovation it diffuses. Simulating the model suggests, first, that any technological, organizational, or strategic innovation with ambiguous returns can diffuse in a bandwagon manner; second, that minor differences in organizational collectivities can have major effects on bandwagons' occurrence, extent, and persistence; and third, that bandwagons can prompt most organizations in a collectivity to adopt an innovation, even when most of them expect that this adoption will yield negative returns. We suggest how to test our bandwagon model.

Many reviewers of the innovation literature point to its proinnovation bias—the often unwritten assumption, in theory and research, that innovations benefit their adopters (Abrahamson, 1991; Kimberly, 1981; Rogers, 1965; Van de Ven, 1986; Zaltman, Duncan, & Holbeck, 1973). Kimberly (1981) argued that the quest to find ways to accelerate the diffusion of innovations presumed to benefit adopters resulted in an innovation-diffusion literature narrowly focused on explaining diffusion rates. Kimberly and Evanesko (1981) also pointed to the lack of theorizing and research on the rejection of innovations. Abrahamson (1991) went on to argue that management researchers should focus less attention on diffu-

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sion rates and more attention on processes that can either diffuse technically inefficient innovations or cause technically efficient innovations to be rejected.

This article focuses on bandwagons because they can have both effects. *Bandwagons* are diffusion processes whereby organizations adopt an innovation, not because of their individual assessments of the innovation's efficiency or returns, but because of a bandwagon pressure caused by the *sheer number* of organizations that have already adopted this innovation (Abrahamson & Rosenkopf, 1990; Tolbert & Zucker, 1983). Bandwagons can animate cycles in which increases in the number of adopters raise bandwagon pressures, and raised bandwagon pressures cause the number of adopters to grow.

Bandwagon cycles can cause many organizations to adopt innovations they assess as technically inefficient. Indeed, imagine that a few organizations adopt what they assess as a technically efficient innovation that will produce profits. These adoptions initiate a bandwagon pressure. As a result, organizations that decide not to adopt the innovation because they assessed that it would yield small losses will experience an added bandwagon pressure to adopt the innovation. If some of these organizations succumb to this bandwagon pressure, then the number of adopters and the pressure increase further, prompting organizations that assessed the innovation as even more technically inefficient and unprofitable to jump on the bandwagon. This bandwagon cycle may recur until even organizations that assessed the innovation as highly inefficient and expected very large losses from adopting it ultimately adopt the innovation because of bandwagon pressures. Of course, if in any cycle of a bandwagon, all nonadopters assess the innovation as so inefficient and unprofitable that they do not succumb to the bandwagon pressure, then the bandwagon stops. Moreover, if some organizations reject the innovation, they may trigger a bandwagon cycle of rejections, even if the innovation is technically efficient or profitable for some of these bandwagon rejecters.

This article examines bandwagons in order to address three questions about the adoption and rejection of innovations, with little attention to diffusion rates. First, if bandwagons can diffuse innovations assessed as technically inefficient by organizations in a collectivity,[1] what characteristics of organizations in collectivities determine whether bandwagons will occur? Second, even if there is a bandwagon diffusion of an innovation assessed as technically inefficient by organizations, it cannot be concluded that all organizations will adopt this innovation. What characteristics of organizations in collectivities affect how many organizations will join a bandwagon? Finally, as Zucker (1987: 26) pointed out,

[1] We define a *collectivity* as a group of competitors such that each competitor knows when another competitor has adopted an innovation.

"Few innovations are widely adopted, by organizations or elsewhere, with most looking more like the sociological characterization of 'fads' than social change." If fads can lead to the rejection of innovations assessed as technically efficient by certain organizations, what characteristics of organizations in collectivities affect how many organizations retain the innovation they adopted during a bandwagon?

This article has four parts. In the first part, we review theories that can inform the study of bandwagon processes. In the second part, we use these theories in order to distinguish certain characteristics of organizations in a collectivity that could exert a major effect on the occurrence, extent, and persistence of a bandwagon in this collectivity. In the third part, we develop a mathematical model of bandwagons that suggests testable propositions about bandwagons' occurrence, extent, and persistence. Because bandwagons are cyclical processes, in which increases in the number of adopters influence how many organizations subsequently adopt the innovation, a mathematical model enables us to trace whether and how many times either a bandwagon or a counter-bandwagon process will cycle in a particular collectivity. In the fourth part, we discuss how researchers can test this article's theory and model of bandwagons.

THEORIES OF BANDWAGONS

Diffusionists have long recognized that increases in the number of organizations that adopt an innovation influence the number of remaining organizations that will subsequently adopt this innovation (Mansfield, 1961). At least two types of theories explain this phenomenon: rational-efficiency theories and theories of fads (Abrahamson, 1991). Proponents of rational-efficiency theories assume that organizations rationally choose to adopt an innovation that is diffusing based on updated information about the innovation's technical efficiency or returns. Advocates of theories of fads, in contrast, assume that organizations choose to adopt an innovation based on what other organizations have adopted it, rather than its technical efficiency or returns.

Rational-Efficiency Theories

Certain rational-efficiency theorists make the complete-information assumption that nonadopters become instantaneously aware of information about innovations' technical efficiency or returns. They argue that as the number of adopters of an innovation increases, its costs decrease or its returns increase, causing more adoptions. Some theorists argue that returns may increase because of network externalities (Farrell & Saloner, 1985; Katz & Shapiro, 1985). Others argue that even if returns decrease with the number of adopters, the innovation may still diffuse if costs drop for later adoptions (Fudenberg & Tirole, 1983; Quirmbach, 1986; Reinganum, 1981). Still other theorists assume incomplete information. They argue that the more organizations adopt an innovation, the more knowledge revealing the innovation's true technical efficiency is generated and disseminated by adopters to nonadopters, and the greater the subsequent number of organizations that adopt when they find out that the innovation is technically efficient (Chatterjee & Eliashberg, 1989; David, 1969; Feder & O'Mara, 1982; Lattin & Roberts, 1989; Mansfield, 1961; Oren & Schwartz, 1988; Rogers, 1965).

Rational-efficiency theories have two limitations. First, even though information about who has adopted an innovation flows rapidly across competitors (Mansfield, 1985), there are many collectivities in which information about the innovation's technical efficiency or returns cannot influence nonadopters' decisions to adopt. To influence nonadopters' decisions, information must flow through channels from early adopters to nonadopters. For this to happen, there must exist (a) information, (b) channels, (c) a propensity of early adopters to disseminate this information, and (d) a propensity of nonadopters to be influenced by it.

If any of these four conditions is not met, then diffusion cannot be explained by rational-efficiency theories which assume that organizations adopt innovations based on updated information about their efficiency or returns. First, no *information* may exist about an innovation's technical efficiency or returns when, for instance, a long time is taken to install the innovation or a long time is taken for the innovation to penetrate its market and generate sales. Under these conditions, some nonadopters may not risk waiting to adopt the innovation until they find out about its technical efficiency or returns from early adopters because, by then, early adopters would have sizable first-mover advantages. Second, no *channels* may exist through which information can flow. There are few channels in new industries, for instance, because word-of-mouth networks disseminating information about technical efficiency have not yet been formed. Third, *early adopters* may not wish to disseminate information about an innovation to nonadopters. Indeed, in many competitive settings, adopters of an innovation do not want their competitors to find out about this innovation's technical efficiency. Fourth, information about an innovation's technical efficiency, even if it reaches *nonadopters,* may not influence their adoption decisions. This information may be so ambiguous that nonadopters cannot learn from it whether or not they should adopt the innovation. Technical information has no influence, for instance, when innovations' technical efficiencies remain ambiguous, even to those who have adopted them. It may also occur if innovations have a relatively small effect on organizations' performances. In this case, nonadopters cannot ascertain whether the innovation or some other factor caused adopters' performances to change.

Rational-efficiency theories have a second limitation: they reinforce proinnovation biases (Abrahamson, 1991). Their assumption that organizations adopt innovations based on updated information about these innovations' technical efficiency suggests that organizations quickly detect inefficient innovations and either do not adopt them or reject them promptly (Rogers, 1983). These theories, therefore, do not readily explain the widespread diffusions of technically inefficient innovations or innovations that produce losses. Neither do these theories explain why organizations reject technically efficient or profitable innovations, because these theories assume that organizations reject innovations only when they find out that the innovations are technically inefficient or unprofitable.

Here, we focus instead on theories of bandwagons, because such theories provide parsimonious explanations for the patterns of innovation diffusion across organizations observed by researchers in multiple studies. Therefore, what these theories suggest about diffusion's occurrence, extent, and persistence should be examined before more complex theories involving information flows, organizational learning, and expectation revision are used.

Fad Theories

Rumelt (1974) tested Chandler's (1962) claim that organizations selected multidivisional structures (M-forms) because they efficiently solved diversification strategies' administrative problems. Diversification did correlate with M-form adoption from the 1940s to the 1960s, but not after. This finding suggests an analytic distinction between an early stage of diffusion, when organizations adopt innovations to solve organizational problems, and a later stage, when they adopt innovations for some other reason. Researchers have found this two-stage pattern across a variety of contexts and innovations (Armour & Teece, 1978; Baron, Dobbin, & Jennings, 1986; Fligstein, 1985; Meyer, Stevenson, & Webster, 1986; Pennings, 1992; Tolbert & Zucker, 1983).

Organizational theorists explain two-stage patterns with theories of bandwagons. They argue that the later stage of diffusion occurs even if organizations are unaware of updated information about the innovation's efficiency or returns. They claim that the *sheer number* of organizations adopting an innovation in the early stage, rather than updated information about the innovation's technical efficiency or returns, creates a pressure causing other organizations to adopt this innovation in the later stage. We use the term *bandwagon pressure* to denote a pressure to adopt or reject created by the sheer number of adopters or rejecters. We say that a *bandwagon* occurs when certain organizations adopt an innovation because of such pressures, rather than their individual assessments of the innovation's efficiency or returns. We say that a *counter-bandwagon* occurs when organizations reject an innovation because of bandwagon pressure, rather than their updated assessments of the innovation's efficiency or returns.

In organization theory, two types of theories explain bandwagon pressures. One type specifies institutional bandwagon pressures—pressures on organizations arising from the threat of lost legitimacy

(Meyer & Rowan, 1977), whereas the other type describes competitive bandwagon pressures—pressures on organizations arising from the threat of lost competitive advantage (Abrahamson & Rosenkopf, 1990). We examine each type in turn.

Institutional bandwagon pressures. Certain institutional theorists argue that in the early stage of diffusion, organizations make independent decisions to adopt innovations because they assess that these innovations can efficiently solve problems and yield positive returns (DiMaggio & Powell, 1983; Tolbert & Zucker, 1983). Institutional theorists argue that, with increases in the number of organizations making independent, problem-solving decisions to adopt an innovation, the innovation becomes increasingly "infused with value beyond the technical requirements of the task at hand" (Selznick, 1957: 17). In other words, the mere fact that many organizations have adopted an innovation, and not individual organizations' assessment of its efficiency or returns, becomes the cue that it is normal, or even legitimate, for organizations to use this innovation.[2] When this happens, organizations that do not use the innovation tend to appear abnormal and illegitimate to their stakeholders; these organizations tend to adopt the innovation because of the fear of lost stakeholder support (Meyer & Rowan, 1977). In sum, increases in the number of organizations that adopt an innovation to solve a problem in the early stage of a diffusion can, in a latter stage, cause other organizations to adopt the innovation because of a bandwagon pressure arising from the threat of lost legitimacy and lost stakeholder support.

Competitive bandwagon pressures. Abrahamson and Rosenkopf (1990) advanced a theory which suggests that bandwagons occur because of pressures on organizations arising from the threat of lost competitive advantage. They assumed that organizations adopt an innovation in the early stages of diffusion because of their assessments of the innovation's efficiency or returns. These authors assumed a utility schema in which organizations' perceived threat of a competitive disadvantage far outweighs the perceived value of an equally large competitive advantage (Kahneman & Tversky, 1979). An organization, therefore, will seek to avoid the worst-case scenario of being at a great competitive disadvantage by performing far below the average performance of organizations in the collectivity. With each increase in the number of adopters, nonadopters contemplate a worst-case scenario in which the innovation succeeds. In these scenarios, if the innovation is successful, then the average performance in the collectivity would increase, because the number of organizations that had adopted the innovation had increased. Because nonadopters would not reap the returns of such a success, their performance

[2] For a more general discussion of the process by which innovations become taken for granted, see Berger and Luckmann (1966), particularly on objectification, reification, and legitimation. For more specific discussions of this process, as it pertains to organizations, see Zucker (1977) and Jepperson (1991).

would fall increasingly below average in succeeding scenarios. Abrahamson and Rosenkopf (1990) argued, therefore, that organizations experience a competitive bandwagon pressure to adopt an innovation as they perceive, with an increasing number of adopters, a risk of falling farther and farther below average if the innovation succeeds. Adopting an innovation is very tempting to these organizations because adopters' performance will approach the average whether the innovation succeeds or fails.

In sum, both institutional and competitive theories and research on bandwagons suggest that during the early stages of diffusion, organizations only adopt an innovation if they assess returns from adopting that exceed a certain threshold. Organizations that do not adopt an innovation during this early stage may adopt it in a later stage because of a competitive or an institutional bandwagon pressure that grows with the number of adopters.

INFLUENCES ON BANDWAGONS' OCCURRENCE, EXTENT, AND PERSISTENCE

In this section, we use theories of bandwagons to examine how certain characteristics of organizations in a collectivity affect the occurrence, extent, and persistence of the bandwagon diffusion of an innovation in this collectivity. We begin by defining the term *collectivity*.

Collectivities

Theories of bandwagons, whether institutional or competitive, suggest that organizations should not be thought of as mere isolates that make independent adoption decisions based on their assessments of innovations' returns. Rather, they should be grouped into organizational collectivities—groups of competitors where each competitor knows when others in the group have adopted an innovation. Competition may be over legitimacy or performance.

Groups of organizations approximating this ideal type of collectivity may emerge in industries, that is, groups of organizations that produce close substitutes (Porter, 1980). Organizations approximating this ideal type also may emerge in strategic groups, that is, organizations that follow similar strategies (McGee & Thomas, 1986), or they may emerge in geographic localities (Knoke, 1982), as in the case of regional groups, such as computer-related firms located in Silicon Valley. The boundaries of collectivities also may occur around organizations that have the same size or status, such as large versus small banks or first- versus second-tier universities. Most important, network analysis may provide the tools necessary to distinguish the boundaries of these collectivities (Burt, 1980, 1987).

Proponents of bandwagon theories suggest that there are two characteristics of organizations in a collectivity that could have an important effect on the occurrence, extent, and persistence of bandwagons: (a) organizations' assessments of innovations' efficiency and returns and (b) the level of ambiguity surrounding these assessments.

Ambiguity

According to organizational theory, ambiguity is the main factor moderating the impact of the number of adopters on the strength of bandwagon pressures in a collectivity. Following March and Olsen (1976: 12), we define *ambiguity* as opaqueness or lack of clarity surrounding an organization's assessment of an innovation's technical efficiency. A variety of ambiguities can be distinguished depending on what is not clear. Three types of ambiguity concern us: (a) ambiguity of goals or when organizational goals are relatively unclear, (b) ambiguity of means-ends relations or the lack of clarity regarding both the range of possible outcomes of actions, like adopting an innovation, and the probability of each outcomes' occurrence, and (c) ambiguity of environments or the lack of clarity regarding both the range and probability of occurrence of future environmental states. Ambiguity can affect organizations' decisions to adopt an innovation in both early and late stages of diffusion. We examine each in turn.

Ambiguity and early-stage adoptions of innovations. Ambiguity matters in the early stages of diffusion because the greater the ambiguity, the less decisions whether to adopt can be based on individual assessments of an innovation's returns (Meyer & Rowan, 1977). Ambiguity of goals has this effect because it renders unclear what returns an organization desires from an innovation. Ambiguity of means-ends relations has this effect because the efficiency of the innovation is unclear as is the range of returns it may produce and the probability of these outcomes. Ambiguity of environments has this effect because it renders unclear whether returns expected from an innovation will be appropriate in future environments.

In theories of bandwagons, authors have not specified how the level of ambiguity in a collectivity affects organizations' decisions to adopt an innovation in the early stages of diffusion. It is reasonable to assume, however, that when ambiguity is low, organizations will adopt innovations if they assess returns above some threshold. The threshold is probably close to zero under conditions of perfect competition and when organizations are risk neutral. The higher ambiguity, however, the higher this threshold will be, because organizations will not adopt an innovation in ambiguous situations unless the magnitude of the returns they assess compensates somewhat for the lack of clarity surrounding these returns.

Ambiguity and later-stage adoptions of innovations. Ambiguity matters in the later stage of diffusion because when decisions to adopt cannot be based fully on economic considerations such as the assessments of technical efficiency or returns, social considerations, such as bandwagon pressures, play a role in explaining bandwagons' occurrence, extent, and persistence (Thompson, 1967: 89). Most theories that explain bandwagons assume that the greater the ambiguity, the more social, as opposed to economic, considerations govern the adoption of innovations. Specifically, according to bandwagon theories, ambiguity moderates the impact of the number of adopters on the magnitude of bandwagon pressures. Thus, the greater ambiguity, the *greater* the bandwagon pressures on organizations to adopt an innovation that are generated by a given number of adopters (Abrahamson & Rosenkopf, 1990; DiMaggio & Powell, 1983; March & Olsen, 1976: 44; Meyer & Rowan, 1977).[3]

Experimental social psychologists provide some support for the assumption that ambiguity moderates the relation between the number of adopters and bandwagon pressures. Asch (1951) found that in one third of trials where a certain number of confederates assert that unequal-lengthed lines are equal, a naive subject will state publicly that the lines are indeed equal. Further research indicated that naive subjects yield more readily to pressures exerted by confederates when the stimulus is more ambiguous (Allen, 1965). In a lab study, Zucker (1977) found stronger conformity to such pressures in more institutionalized settings such as organizations.

Assessed Returns Distributions

The distribution of assessed returns across organizations in a collectivity tells us how many organizations will assess returns high enough to adopt an innovation in the early stage of diffusion and suggests the bandwagon pressure caused by these early-stage adopters. More important, the model we advance indicates that the distribution tells us how many times bandwagon or counter-bandwagon processes will cycle. Indeed, a bandwagon process will stop cycling whenever the increase in the bandwagon pressure, in one cycle of the process, is not sufficient to prompt an adoption of the innovation by the nonadopter that assesses the next lowest return. Knowing the distribution of assessed returns in a collectivity indicates at which point the cycle will stop.

MODELING BANDWAGON PROCESSES

Traditional rate-oriented models of innovation diffusion do little to explain the occurrence, extent, and persistence of bandwagons. These models are variants of the generic model,

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

[3] A few theories suggest, however, that when the number of adopters is quite high, so-called snob effects may tend to occur—certain organizations intent on looking *different* than other organizations may feel increasing pressure to *reject* an innovation, as more organizations adopt it. These "snobs" feel that too many other organizations have adopted the innovation and, therefore, that they appear too similar to most organizations (Abrahamson, 1986). We model this possibility only in a following section that deals with the rejection of innovations during a bandwagon.

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 & Peterson, 1985). Integrating Equation (1) produces the well-known logistic S curve for the cumulative number of adopters over time. Variations of this model do not help researchers to understand *when* bandwagon processes occur. It is apparent from Equation (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 do not help researchers to understand how many adoptions bandwagons cause. According to Equation (1), once diffusion has started, the adoption rate, R_t, is greater than zero, 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 the organizations in the collectivity have adopted the innovation. What, then, causes a situation of partial diffusion? Finally, these models do not help researchers to understand when organizations might reject an innovation they adopted during a bandwagon process. For this to happen, the rate of diffusion R_t would have to be negative. According to Equation (1), this could only happen in a clearly impossible situation, where the number of adopters exceeded the number of potential adopters.

In the following section we use assumptions embedded in theories of bandwagons to develop a mathematical model that can help develop propositions about the occurrence, the extent, and the persistence of bandwagons. The model's analytical solutions suggest how the distribution of assessed returns and ambiguity in a collectivity affect bandwagons in this collectivity.

A Model of Bandwagons

Theories and research which have bearing on bandwagons suggest that, in the early stage of diffusion, certain organizations assess returns too low to adopt the innovation. These organizations may adopt the innovation in a later stage, however, because of an added bandwagon pressure to adopt it caused by the sheer number of early-stage adopters. Therefore, we modeled organizations' adoption decisions by *summing* their individual assessment of the innovation's return and the bandwagon pressure.

Theories of bandwagons suggest that the strength of bandwagon pressure increases with the number of adopters. The level of ambiguity, however, moderates this main effect. Therefore, we modeled bandwagon pressure as the *product* of ambiguity and the number of adopters.

In sum, assessed returns, ambiguity, and the number of adopters influence organizations' decisions to adopt an innovation according to the equation,

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

where $B_{i,k}$ is organization i's "bandwagon assessment" of the innovation, in bandwagon cycle k. I_i and A_i denote, respectively, organization i's individual assessment of the innovation and ambiguity about this innovation. The bandwagon pressure during cycle k is denoted by the product of the level of ambiguity, A_i, and the proportion of adopters, n, after $k - 1$ cycles. The number of organizations in a collectivity that must adopt in order to prompt organization i's adoption is such that the bandwagon assessment, $B_{i,k}$, exceeds the adoption threshold. In the appendix we describe how the proportion of organizations that have adopted in cycle k of a bandwagon can be derived analytically from Equation (2).

This model is based on some strong assumptions. We list them here and discuss in the conclusion how these assumptions could be relaxed in order to generate a more general, yet more complex, model. First, in this model we assume that information about the innovation's technical efficiency does not flow from early to late adopters, or is so ambiguous that it does not lead them to reappraise their individual assessment of the innovation. So, I_i remains constant over k. Second, we assume that each organization's adoption gives an equal impetus to the bandwagon, and that only initial assessed returns and ambiguity affect an organization's susceptibility to bandwagons. Third, we assume that innovation diffusion neither eliminates organizations from the collectivity nor attracts new organizations to the collectivity.

Dynamic Implications of the Model

Figure 1 depicts the model's evolution over repeated bandwagon cycles. If the distribution of organizations' individual assessments is such that certain organizations assess returns from adopting above the adoption threshold, these organizations adopt the innovation. We do not mean to imply that all such organizations adopt the innovation simultaneously in this early stage, but rather that they adopt the innovation because of their individual assessment of the innovation's returns.

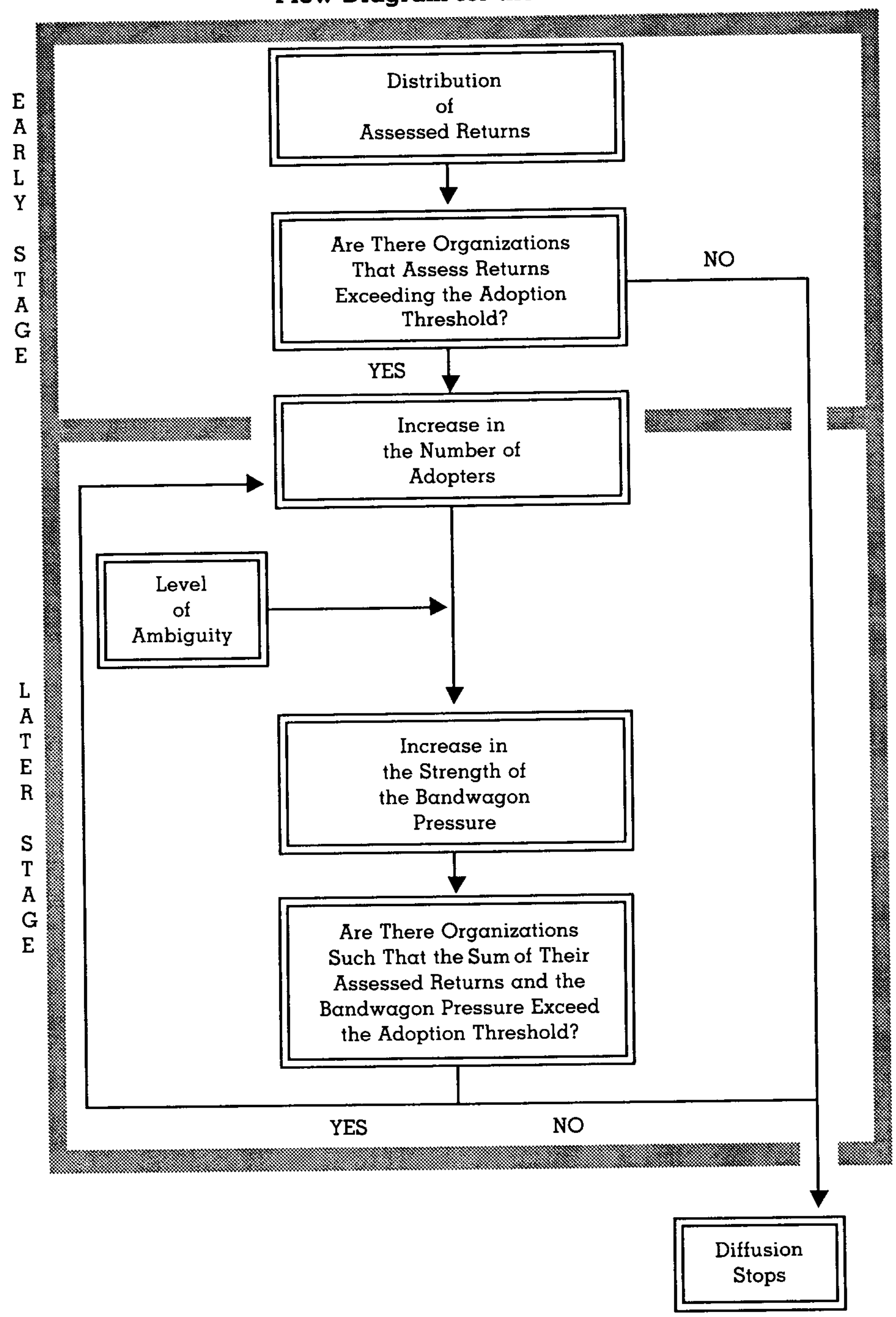
Organizations that did not adopt in the early stage now consider the sum of their assessed return and bandwagon pressure [Equation (2)]. If there does not exist a nonadopter whose bandwagon assessment of the innovation, $B_{i,k}$, exceeds the adoption threshold, then diffusion stops. If such a nonadopter does exist, then it adopts the innovation. We call this sort of organization a bandwagon adopter, because its adoption was prompted by the added bandwagon pressure, not by the organization's assessment of the innovation's returns.

The bandwagon process may not stop at this point. Bandwagon processes can animate a cycle in which growing bandwagon pressures prompt the number of adopters to increase, and increases in the number of adopters prompt bandwagon pressures to grow. How many times the process cycles, we argue, depends on ambiguity and the distribution of assessed returns.

Using Mathematical Modeling as a Theory-Development Tool

It is difficult to trace how the level of ambiguity and the distribution of assessed returns in a collectivity would affect the occurrence, the ex-

FIGURE 1
Flow Diagram for the Model



tent, and the persistence of the bandwagon process modeled in Equation (2). Consider that collectivities could differ in at least four ways if initial assessed returns and ambiguity are normally distributed across organizations. Both the mean and variance of organizations' assessed returns in a collectivity could be higher or lower. Likewise, the mean and variance of ambiguity could be higher or lower. How will changes in these four variables affect the extent of bandwagon adoptions?

In the next section, we show that the answers to these questions are nonobvious, but they can be derived using our model. We do this by using an approach employed by a number of scholars in order to understand the implications of complex dynamic models (Cohen & Cyert, 1965; Cohen, March, & Olsen, 1972; Cyert & March, 1963; Dutton & Starbuck, 1971; Lant & Mezias, 1992; Levinthal & March, 1981; Nelson & Winter, 1982). We derived results suggested by the mathematical model, observed the results, and induced how dynamic processes generated these results. Thus, the results of our model allow us to derive propositions about bandwagons' occurrence, extent, and persistence in different collectivities.

WHEN DO BANDWAGONS OCCUR, AND HOW EXTENSIVE WILL THEY BE?

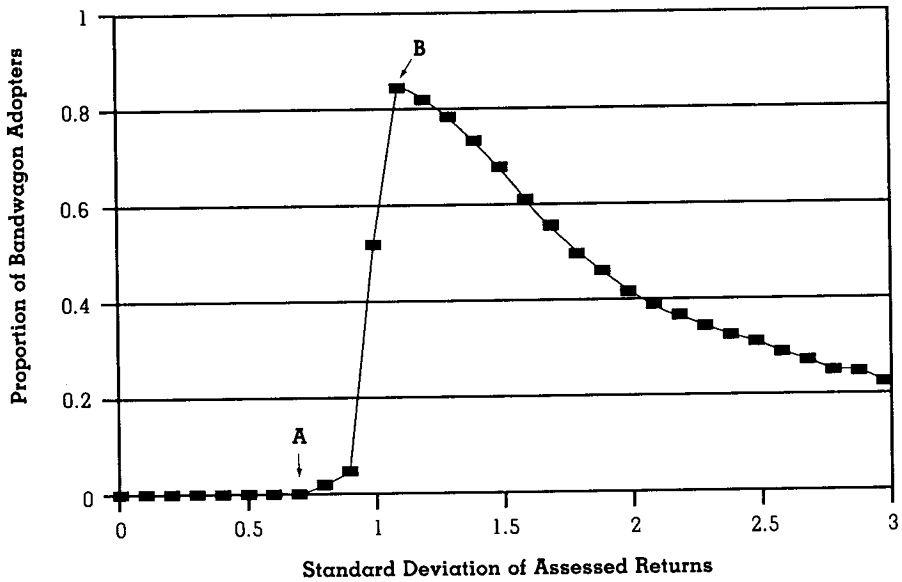
This article focuses on situations in which the bandwagon diffusion of an innovation occurs in a collectivity even though, on average, organizations in this collectivity assess negative returns from adopting this innovation. We chose, therefore, to analyze cases where the mean of assessed returns fell between 0 and -3. In this range, the extent of diffusion varied when the standard deviation of assessed returns fell between 0 and 3, and mean ambiguity fell between 0 and 7. Above these upper bounds, the extent of diffusion varied little. Clearly, the choice of these ranges is arbitrary and interdependent. However, in the last section of this article, we discuss how these ranges could be anchored using empirical research.

We assumed that organizations' assessments of the returns of an innovation are normally distributed in a collectivity. Therefore, we first asked the question: ceteris paribus, how does the standard deviation of this distribution affect what proportion of this collectivity adopts the innovation because of bandwagon pressures? We used a combination of graphic analysis and regression analysis to induce propositions that have a bearing on bandwagons' occurrences and extent.

For the graphical analysis, we fixed mean assessed returns at -1.5 and mean ambiguity at 3.5[4]; for this collectivity, we examined the relationship between standard deviation of assessed returns and the extent of bandwagon diffusion graphically, as shown in Figure 2. We used regres-

[4] These values were chosen because they represent the midpoints of the ranges for mean assessed returns and ambiguity.

FIGURE 2
Extent of Bandwagon Diffusion by Standard Deviation of Assessed Returns



Mean Assessed Returns = −1.5; Ambiguity = 3.5

sion analysis to test whether the results of the graphical analysis generalized across collectivities with mean assessed returns and mean ambiguities varying in the ranges specified above.

In both graphical and regression analyses, we assumed that an innovation appears equally ambiguous to each organization in a collectivity. This assumption that the standard deviation of ambiguity equals zero in collectivities is consistent with the argument that the technical characteristics of an innovation determine its ambiguity. It is possible, however, that organizational characteristics determine ambiguity and that it varies across organizations in a collectivity. Therefore, we will explore in another section of this article how the standard deviation of ambiguity affects the extent of bandwagon diffusion.

Graphical Results

Figure 2 has two critical points labeled A and B. Critical point A occurs when the standard deviation of assessed returns is relatively small. Below this point, bandwagons do not occur. A small increase in the standard deviation, however, results in many more bandwagon adoptions. Past the critical point B, however, increases in the standard deviation of individual assessments result in *fewer* bandwagon adoptions.

We examine critical point A first, and we ask why would bandwagons occur only rarely when organizations assess similar returns, but extensively if the standard deviation of these assessed returns is slightly greater? When organizations expect similar returns from adopting an innovation, the distribution of assessed returns clusters around the mean. Because this mean is negative, few organizations assess returns above zero and adopt the innovation in the early stage. The small number of early adopters generates weak bandwagon pressures, causing few bandwagon adoptions in the later stage. With larger standard deviations, more organizations initially assess returns above zero and adopt the innovation, creating a stronger bandwagon pressure, and prompting more bandwagon adoptions.

This is only a partial explanation, however, because it misses what is notable about Figure 2, the dramatic increase in the percentage of adopters above critical point A. A metaphor helps cast some light on this mystery. Imagine a row of dominoes of equal length separated by gaps of varying sizes. If the average gap between dominoes tended to be small, then a force sufficient to tip one domino would make this domino tip the next, which would cause the next domino to fall, generating a chain reaction of numerous falling dominoes. Note that if the initial force had been only slightly weaker, the first domino may not have fallen, and no chain reaction would have occurred. In sum, a very small difference in the force exerted on the first domino may have a very large impact on how many dominoes fall.

An analogous situation arises around critical point A. Because the standard deviation of assessed returns is relatively small, there tends to be small differences between organizations' assessed returns. Therefore, if enough organizations adopt to start a bandwagon process, the small increase in the bandwagon pressure resulting from one adoption will tend to prompt an adoption of the innovation by the organization with the next lowest assessed returns. This latest adopter will raise the bandwagon pressure and tend to provoke the organization with the next lowest assessed return to adopt the innovation. This process will tend to repeat itself, generating a chain reaction of adoptions among organizations that assess lower returns and resulting in numerous bandwagon adoptions. Note that if the number of initial adopters had been only slightly smaller, as it is below critical point A, then the falling-domino process would not have occurred. In sum, a small difference in the variance of assessed returns can have a major effect on the percentage of organizations that adopt an innovation during a bandwagon. This argument suggests the following two propositions.

> *Proposition 1: The bandwagon diffusion of an innovation does not tend to occur in collectivities where organizations assess very similar returns from adopting this innovation.*

> *Proposition 2: When organizations in a collectivity assess similar returns from adopting an innovation, minor*

increases in the difference between the returns organizations assess can cause major increases in the extent of this innovation's bandwagon diffusion.

Turning our attention now to critical point B, the higher dispersion of assessed returns about the negative mean leads more organizations to have initial assessed returns above zero. Consequently, more organizations adopt in the early stage, prompting stronger bandwagon pressures. These stronger pressures do not, however, result in more bandwagon adoptions. What counterforce produces these results?

The domino metaphor provides additional insight. Picture again dominoes of equal length in a row separated by gaps of varying sizes. If the gaps tended to be large, a chain reaction of falling dominoes would end whenever the gap between two dominoes exceeded the length of a domino. Analogously, if the variance in assessed returns across organizations in a collectivity is large, as it is above critical point B, then large differences tend to exist between one organization's assessed returns and the assessed returns of the organization with the next highest assessed return. It is these large differences in assessed returns that tend to stop bandwagons, because the increase in the bandwagon pressure caused by the last adopter of the innovation is not large enough to trigger an adoption by the organization with the next lowest assessed return. Under these conditions, although a bandwagon process may begin, it will tend to end more rapidly. In sum, although increasing variance of individual assessed returns produces stronger bandwagon pressures, it also reduces their impact, resulting in this declining percentages of bandwagon adopters past the second critical value B. This argument suggests the following proposition.

Proposition 3: When organizations in a collectivity assess somewhat dissimilar returns from adopting an innovation, increases in the difference between the returns organizations assess can cause decreases in the extent of this innovation's bandwagon diffusion.

Regression Results

To explore the generalizability of Propositions 1 through 3, we generated 1,000 diffusion scenarios and derived analytically the proportion of the collectivity that joined the bandwagon. In each scenario, the mean and standard deviation of initial assessed returns in the collectivity were drawn randomly, as was the mean ambiguity about initial assessed returns. Ordinary least squares (OLS) regression was then used to explore the effects of these independent variables on the proportion of bandwagon adopters. Table 1 presents OLS regression results. A correlation table of variables is not presented because, since each variable was drawn randomly, correlations between independent variables were virtually nil.

TABLE 1
Determinants of the Proportion of Bandwagon Adopters: Ordinary Least Squares Regression Coefficients

	Model 1	Model 2
Intercept	.12**	−.04
Mean assessed returns	.15**	.15**
Standard deviation of assessed returns (SDAR)	.061**	.38**
$(SDAR)^2$		−.10**
Ambiguity	.086**	.087**
R^2	.49	.54
F	323**	294**
df	996	995

** $p < .01$

We employed two models to test for the generalizability of the curvilinear relation in Figure 2. As shown in Table 1, model 1 suggests a positive linear relationship between the standard deviation of assessed returns and the proportion of bandwagon adopters. The inclusion of the squared standard deviation of assessed returns variable in model 2 yields a negative coefficient for this squared term and a corresponding increase in R^2. Therefore, larger values of the standard deviation of assessed returns reduce the proportion of bandwagon adopters. These results suggest that Propositions 1 through 3 generalize beyond the range of collectivities that we examined in the graphical analysis.

The results of Table 1 also reveal a positive, linear relation between the mean of initial assessed returns and the proportion of bandwagon adopters. This occurs because, for a given standard deviation of assessed returns, the more negative the mean of initial assessed returns, the fewer organizations assess returns above zero and adopt the innovation in the early stage. The smaller the number of these early adopters, the weaker bandwagon pressures, and the fewer bandwagon adoptions in the later stage. Proposition 4 follows from this argument.

> *Proposition 4: The lower the average assessment of an innovation by organizations in a collectivity, the less extensive this innovation's bandwagon diffusion will tend to be in this collectivity.*

One implication of the result is interesting to note. When the mean of assessed returns is large and negative, the predicted extent of bandwagon adoption tends to be high only under conditions of high mean ambiguity and moderate variance in assessed returns. As the mean of assessed returns moves closer to zero, the predicted extent of bandwagon adoption increases across all levels of mean ambiguity, and variance in assessed returns. The results when the mean of assessed returns is closest to zero indicate that even at low levels of mean ambiguity, strong bandwagons can occur, prompting a large proportion of a collectivity to adopt the innovation in the later stage of diffusion.

These results are surprising. Indeed, they indicate that even if almost all firms in a collectivity are quite certain that they can assess small losses from adopting an innovation, they are still very likely to adopt an innovation because other organizations in their collectivity have done so. These results also indicate that this effect will persist even if ambiguity and assessed losses are moderate. The results suggest the following proposition.

> *Proposition 5: Bandwagons can prompt most organizations in a collectivity to adopt an innovation, even when most of these organizations were quite certain in their assessment that the innovation would produce negative returns.*

Table 1 also indicates a positive, linear relation between the mean level of ambiguity surrounding organizations' assessments of an innovation and the percentage of its bandwagon adopters. This relation occurs because the model is built on the assumption that the greater the ambiguity, the greater the bandwagon pressure generated by a given number of adoptions. Therefore, the following proposition is suggested.

> *Proposition 6: The greater the ambiguity surrounding organizations' assessment of an innovation in a collectivity, on average, the more extensive this innovation's bandwagon diffusion will tend to be in this collectivity.*

What if ambiguity in the assessment of an innovation varies across organizations in a collectivity? Such an assumption complicates our analysis. The appendix presents a partial derivation suggesting that the standard deviation of ambiguity has the same type of effect on the proportion of bandwagon adopters as the standard deviation of assessed returns. For a given level of the standard deviation of assessed returns, a curvilinear relationship between the standard deviation of ambiguity and the proportion of bandwagon adopters exists. This occurs because the inclusion of the standard deviation of ambiguity introduces additional variance in bandwagon assessments, enhancing falling-domino effects.

WHEN WILL BANDWAGON ADOPTIONS PERSIST?

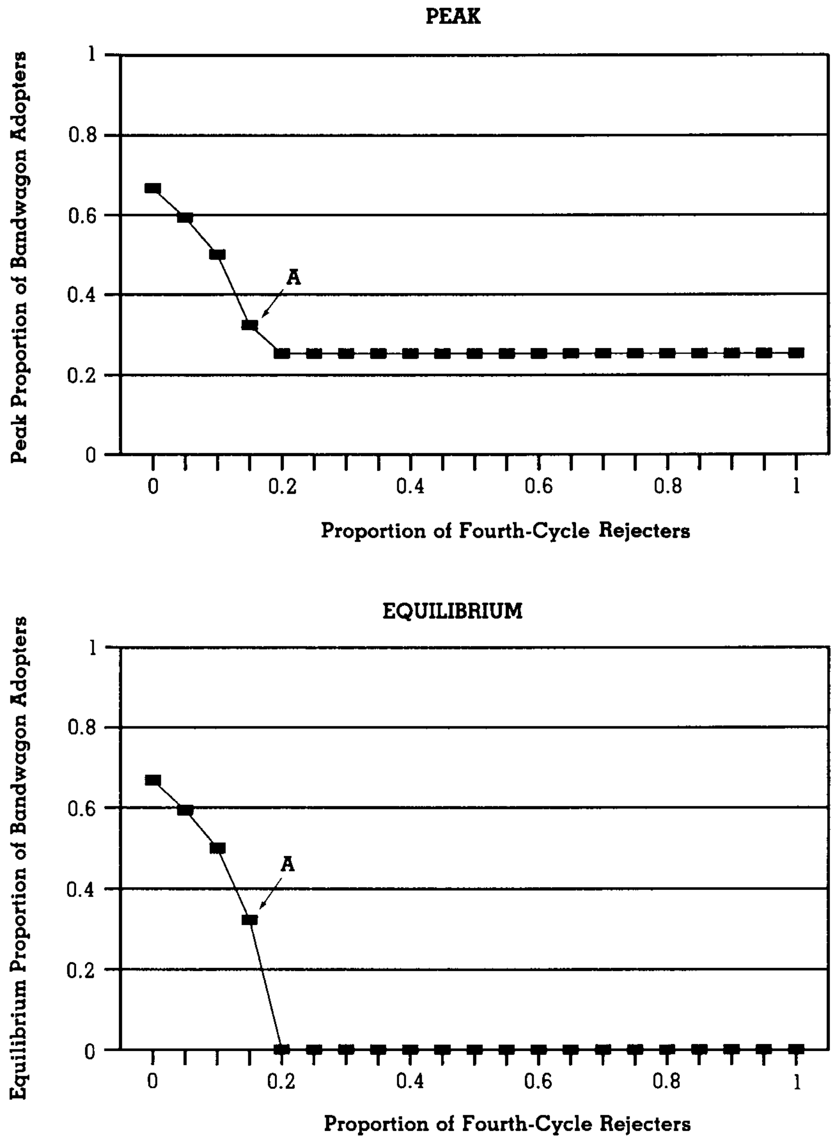
Besides examining the occurrence and extent of bandwagons, in this paper we also examine their persistence; that is, the proportion of organizations that adopt an innovation during a bandwagon and retain it. Abrahamson (1991) argued that, over time, organizations may reject innovations they adopted during a bandwagon for many different reasons. First, rejections might occur because the faddish appeal of the innovations dissipates. In such instances, the symbolic or emotional benefits that enticed organizations to adopt a "state-of-the-art" innovation dwindle rapidly. As a result, organizations reject this innovation. Second, powerful actors outside a collectivity in the grip of a bandwagon may intervene to discredit the innovation and halt the bandwagon (Cole, 1985; Rowan, 1982). Third, so-called snob effects may occur, where certain organizations are intent on looking different than other organizations and reject an innovation because too many other organizations have adopted it (Abrahamson, 1986). Fourth, density dependence arguments in population ecology suggest that organizations could reject an innovation because as the number of adopters of an innovation increase, so does competition surrounding this innovation (Hannan & Carroll, 1992).

It is beyond this article's scope to model each of these processes. These different processes have one common consequence, however. Each can prompt a certain proportion of the adopters to reject an innovation during one or more cycles of a bandwagon. In the remainder of this article, we consider the consequence of only one cycle of rejections. Such rejections could halt a bandwagon before it has run its course. Therefore, we must pose again the second question addressed in this paper: How many organizations will join a bandwagon? Moreover, when a bandwagon stops, organizations that reject the innovation can trigger a counter-bandwagon—a process such that the more organizations reject an innovation, the smaller the pressure on organizations using this innovation to continue using it, and the more rejections of this innovation. Negative feedback loops drive such counter-bandwagons; decreases in the number of adopters cause a drop in the bandwagon pressure. This drop in the bandwagon pressure, in turn, can prompt further decreases in the number of adopters. This counter-bandwagon process can cycle repeatedly, prompting more and more rejections. If we can ascertain when counter-bandwagons stop, then we can address our third question: How many organizations retain the innovation a bandwagon diffuses?

As we did previously, we used both graphical and regression analysis to examine these questions about the extent and persistence of bandwagons. First, for purposes of comparability to Figure 2, we set mean ambiguity at 3.5, mean assessed returns at -1.5, and the standard deviation of assessed returns at 1.5. We let the model cycle four times prior to having between 0 and 100 percent of adopters drop the innovation.[5] We derived analytically what we call the *bandwagon's peak*—the maximum proportion of the collectivity that become bandwagon adopters at any time during the process—and the *bandwagon's equilibrium*—the proportion of organizations in the collectivity that retain a bandwagon adoption after the process has ended. The top graph in Figure 3 graphs the peaks and the bottom one graphs the equilibria for various proportions of fourth-cycle rejecters. Second, we used regression analysis to test whether the results in Figure 3 generalized across collectivities that had different mean assessed returns, mean ambiguities, and standard deviation of

[5] Clearly, our choice of cycle four is arbitrary. Results are available from the authors which show that the cycle in which organizations reject an innovation does not qualitatively alter our propositions about counter-bandwagons.

FIGURE 3
Peak and Equilibrium of Bandwagon Diffusion by Varying Proportion of Fourth-Cycle Rejecters



assessed returns. We employed the same ranges as those used to produce the regression results in Table 1.

Graphical Results

One finding stands out in the top graph of Figure 3. As the proportion of fourth-cycle rejecters increases, the peak proportion of adopters decreases up to critical value A, beyond which it remains constant. This discontinuity occurs because in any bandwagon diffusion, the greater the proportion of rejecters in one cycle, the weaker the bandwagon pressure in the next cycle. A weaker bandwagon pressure does not necessarily cause the bandwagon to stop. It may prompt more adoptions in the next cycle and, possibly, still more bandwagon cycles of adoptions. A weaker bandwagon pressure does, however, prompt fewer adoptions in the next cycle and, consequently, fewer subsequent cycles. As a result, the bandwagon slows down faster, and it reaches a lower peak number of adopters. When the proportion of fourth-cycle rejecters exceeds a certain critical value A in the peak graph of Figure 3, the resultant bandwagon pressure is so weak that it prompts no adoptions in the next cycle; the bandwagon stops instantaneously at a certain peak proportion of adopters. The peak graph in Figure 3 is flat past critical value A, because *any* increase in the proportion of fourth-cycle rejecters greater than the critical value stops the bandwagon at this same peak proportion of bandwagon adopters. From this argument, the following proposition is advanced.

> *Proposition 7: Minor changes around some critical value in the proportion of adopters that reject an innovation in a bandwagon cycle can have major effects on the extent of bandwagon diffusion, whereas major changes above and below this critical value will have little or no effect.*

We use the term *bandwagon rollback* to denote the difference between the peak and equilibrium of a bandwagon. It is notable, when comparing the top and bottom graphs in Figure 3, when the proportion of rejecters is less than critical value A, that the peak equals the equilibrium proportion of adopters. This equality indicates that there is no bandwagon rollback. Above critical value A, however, the equilibrium proportion of bandwagon adopters drops to zero, and the bandwagon rolls back completely.

These phenomena occur because when the proportion of rejectors is smaller than the critical value, the bandwagon continues prompting more adoptions in succeeding cycles. Thus, the proportion of adopters continues to grow until it settles at a peak proportion of adopters, which is also the bandwagon's equilibrium, and there is no bandwagon rollback. When the proportion of fourth-cycle rejecters exceeds the critical value, however, the number of rejecters exceeds the number of adopters, and the bandwagon stops. The bandwagon, however, does not remain stuck at this maximum proportion of adopters. A counter-bandwagon takes hold, prompting a complete bandwagon rollback. Therefore, the following proposition is presented.

> *Proposition 8: Minor changes around some critical value in the proportion of adopters that reject an innovation in a bandwagon cycle can have major effects on the pro-*

portion of organizations retaining the innovation, whereas major changes above and below this critical value will have little or no effect.

Regression Results

To explore the generalizability of Propositions 7 and 8, we generated 5,000 diffusion scenarios, and we derived analytically the bandwagon rollback in each scenario. In each scenario, the mean and standard deviation of initial assessed returns in the collectivity were drawn randomly, as was the mean ambiguity about initial assessed returns and the proportion of bandwagon rejecters in cycle four. OLS regression was then used to explore the effects of these variables on the extent of bandwagon rollback. Table 2 presents OLS regression results.

In our regression model, we need to control for mean ambiguity and the standard deviation and mean of assessed returns. Indeed, under greater mean ambiguity, rejections cause a greater counter-bandwagon pressure and more extensive rollback. Likewise, both the mean and standard deviation affect the peak proportion of adopters and, therefore, influence what proportion of adopters can reject the innovation during a counter-bandwagon.

The results in Table 2 indicate that in controlling for mean ambiguity and the mean and standard deviation of assessed returns, there exists a positive linear relation between the proportion of bandwagon rejecters in cycle four and the extent of bandwagon rollback. This relation is only an approximation of the step pattern in Figure 3—zero rollback below critical value A and complete rollback above it. These results suggest that Propositions 7 and 8 generalize beyond the range of collectivities that we examined in the graphical analysis.

TABLE 2
Determinants of the Proportion of Bandwagon Rejecters: Ordinary Least Squares Regression Coefficients

	Model 1	Model 2
Intercept	.043**	−.030**
Mean assessed returns	.14**	.14**
Ambiguity	.048**	.048**
Proportion of adopters that drop initially	.18**	.18**
Standard deviation of assessed returns (SDAR)	.062**	.21**
$(SDAR)^2$		−.049**
R^2	.52	.54
F	1333**	1150**
df	4995	4994

** $p < .01$

TESTING THEORIES AND MODELS OF BANDWAGONS: A RESEARCH AGENDA

There are two approaches to testing theories and models of bandwagons. A longitudinal approach is used to explore the dynamic processes of an innovation's diffusion in a collectivity. A cross-sectional approach compares the occurrence, extent, or persistence of diffusion across different collectivities.

Dynamic Approach

The primary challenge in a dynamic test of the theory and model advanced in this article is to operationalize the parameter values in the model. Grounding the variable n_k only requires measuring the proportion of the collectivity that has adopted the innovation over time. Therefore, in this section we focus on operationalizing initial assessed returns, I_i, and ambiguity, A_i.

Operationalizing the initial assessed returns variable is relatively easy because much has been written and researched in the innovation-adoption literature on how to estimate an organization's assessed returns. This literature points to two organizational characteristics: those affecting the real and perceived returns of an innovation (Zaltman, Duncan, & Holbeck, 1973). With respect to the former, for instance, the more diversified an organization, the greater its coordination problems and real returns generated by an M-form structure (Armour & Teece, 1978; Chandler, 1962). With respect to the latter, Kimberly's (1981) review indicates that characteristics of organizational decision makers, of organizational structure, and of interorganizational linkages affect the perceived returns of adopting organizations. Organizational size, for instance, is usually found to affect perceived returns from organizations adopting an innovation.

Operationalizing the ambiguity variable is the hardest. What, for instance, does an ambiguity level of "5" mean? Let k^* denote the cycle in which an organization adopts, that is, when its bandwagon assessment of the innovation, B_{ik}, first exceeds its adoption threshold, T. Because, from Equation (2), $B_{ik} = I_i + (A_i * n_k)$, then setting $B_{ik^*} = T$ suggests that the ambiguity, A_i, of an innovation for organization i can be estimated with the following equation,

$$A_i = \frac{T - I_i}{n_{k^*-1}} \qquad (3)$$

Therefore, if we look at one diffusion through a collectivity, we can calculate each organization's A_i by examining its initial assessed returns, I_i, and the proportion of the collectivity, $n_k{}^*$, at which this firm adopts.[6]

[6] It should be noted that the units in which initial assessed returns, I_i, are measured will not influence the results. They will, however, influence the scale on which A_i are measured.

This information can then be used to forecast the diffusion of the next innovation in the collectivity, if we assume that A_i is relatively constant. This assumption is consistent with the argument that the organization largely determines how ambiguously the innovation is perceived.

Another approach is to assume that A_i is relatively constant across organizations in a collectivity. This assumption is consistent with the argument that the ambiguity of an innovation is largely determined by this innovation's characteristics. If this is the case, then the A_i values of early bandwagon adopters can be averaged to estimate a collectivity-level ambiguity, A^*, of the innovation. A^* can then be used to forecast the extent or persistence of innovation bandwagon diffusion. Alternatively, the value of A^* when the innovation diffuses in one collectivity can be used to forecast the occurrence, extent, and persistence of this innovation's diffusion in another collectivity.

Cross-Sectional Approach

All of the propositions in this study are also testable cross-sectionally. The first three propositions suggest that, ceteris paribus, in collectivities with negative mean assessed returns, the extent of bandwagon diffusion will be greater when the standard deviation of assessed returns is moderate (Proposition 2), than when it is either very low (Proposition 1) or very high (Proposition 3). Therefore, researchers could examine the diffusion of an innovation in three collectivities, similar in every important respect other than that the deviation of assessed returns was medium in the first collectivity, very high in the second, and very low in the third. The first three propositions suggest that the extent of bandwagon diffusion should be greater in the first collectivity than in the second and the third.

How could a researcher detect collectivities with high, moderate, and low standard deviation of assessed returns? The standard deviation of assessed returns in a collectivity can be expected to be closely linked to the standard deviation of certain characteristics of organizations belonging to the collectivity. As we pointed out, the literature on the adoption of innovations by organizations suggests characteristics affecting the real and perceived returns of an innovation (Zaltman, Duncan, & Holbeck, 1973). By extension, the greater the standard deviation of the distribution of these characteristics in a collectivity, the greater the standard deviation of assessed returns in this collectivity.

Proposition 6 suggests that, ceteris paribus, the greater the mean level of ambiguity in a collectivity, the greater the extent of bandwagon diffusion. This could be tested by examining the bandwagon diffusion of the same innovation in high, medium, and low ambiguity collectivities that are similar in other important respects. In developing measures of ambiguity in collectivities, it is important to note that the level of ambiguity surrounding assessments of an innovation in a collectivity may not be based only on this innovation's inherent technical properties (Meyer &

Rowan, 1977). The same innovation may be more ambiguous or less ambiguous in different collectivities or for different organizations, depending on the stage of knowledge bearing on means-ends relations. Beliefs about means-ends relations would be clearer in older collectivities, in collectivities that have used similar innovations before, or in collectivities that employ more professionals who are knowledgeable about the innovation. Moreover, the technical properties of an innovation only exert some influence on the ambiguity of means-ends relations. Ambiguity of goals tends to vary with the presence of regulators that set standards for organizations in a collectivity, or with the presence of powerful buyers who set standards governing outputs. Ambiguity of environments might vary with the level of environmental dynamism, with demand instability, or with the rate of sales growth in the collectivity (Hambrick & Finkelstein, 1987).

Similar research strategies could be devised to test the remaining propositions. One warning is necessary, however. Recall that the generic diffusion-rate model in Equation (1) fits many research contexts, but that modifications to this model increase its precision in other contexts (Rogers, 1983). Likewise, we have developed a simple, generic model of bandwagons. Where does this model have greatest precision, and how might its precision be increased in other contexts?

First, our generic model fits collectivities in which only initial assessed returns and ambiguity affect an organization's susceptibility to bandwagons. The generic model may perform less well in collectivities where other organizational characteristics, such as risk preferences, affect susceptibility to bandwagon pressures. In such contexts, organizations' individual assessments of the innovation may need to be calculated as a function of their risk preference or some other organizational characteristic.

Second, our generic model fits collectivities in which each organization's adoption exerts a similar impact on the growth of bandwagon pressures. The generic model may perform less well when organizations' market shares differ greatly, and adoptions by organizations with greater market shares thereby cause greater increases in competitive bandwagon pressures (Scherer & Ross, 1990). Likewise, the generic model may perform less well when organizations' reputations differ greatly, because adoptions by organizations with greater reputations may cause greater increases in institutional bandwagon pressures (DiMaggio & Powell, 1983). In these contexts, the generic model may need to be modified such that each adoption by an organization is weighted by either its reputation, its market share, or its size (Abrahamson & Rosenkopf, 1991).

Third, the generic bandwagon model best fits contexts where little unambiguous information about innovations' technical efficiency flows from early adopters to organizations that have not yet adopted the innovation. Indeed, the model assumes that the sheer number of adopters, rather than unambiguous information about an innovation's efficiency or returns, causes diffusion. In contexts where such information flows freely, it may be necessary to modify the generic model so that the number of adopters affects either nonadopters' assessed returns, the level of ambiguity surrounding these assessments, or both of these factors.

Finally, the generic bandwagon model fits groups of organizations that approach our ideal-type definition of collectivities—groups of competitors in which each competitor rapidly finds out when other competitors in the group have adopted an innovation. In certain contexts, the boundaries of collectivities may be fuzzy. Certain organizations may have better information about which organizations have adopted an innovation. In these contexts, the model may perform better if the bandwagon pressure on an organization is calculated by summing the number of organizations it knows have adopted an innovation (Abrahamson & Rosenkopf, 1993). Network analysis provides sophisticated tools to analyze organizations' communication networks (Burt, 1980, 1987). Bandwagons might also modify collectivities' boundaries, by either attracting new organizations to the collectivity or eliminating organizations that adopt inefficient innovations. These effects may need to be added to our generic model.

CONCLUSION

This article has a number of important implications. First, any innovation, whether organizational, technological, managerial, or strategic, can diffuse in a bandwagon manner, if there exists some ambiguity surrounding assessments of the innovation's return. Yet organization theory and research has been limited primarily to the two-stage diffusion of administrative innovations (DiMaggio & Powell, 1983; Meyer & Rowan, 1977; Tolbert & Zucker, 1983). Moreover, as Nystrom and Starbuck (1984) noted, it has typically focused on not-for-profit collectivities. Some organizational theorists justify this focus with two claims: (a) that less ambiguity exists in the assessment of nonadministrative innovations' technical efficiency and (b) that for-profit organizations have less ambiguous goals because they pay greater attention to the impact of innovations on the bottom line (Scott, 1991). Consequently, independent, rational choices premised on innovations' efficiency, rather than bandwagons, determine whether nonadministrative innovations diffuse, persist, or disappear in for-profit sectors.

Organizational theory's focus, however, may be unnecessarily restrictive. This article suggests that independent, rational choices may themselves trigger bandwagons. Moreover, competitive bandwagon pressures, as well as institutional bandwagon pressures, can impel these bandwagons. Finally, they can do so in contexts characterized by not just high, but also low to moderate levels of collectivity-wide ambiguity. Moderate levels of ambiguity may operate during the adoption of many nonadministrative innovations. In the technological realm alone, moderate ambiguity affects organizations' decisions about whether to engage in costly R&D or which of many competing technologies to adopt, particularly during periods of discontinuous technological change (Anderson & Tushman, 1990; Tushman & Anderson, 1986). Additionally, outside technological realms, moderate levels of ambiguity may characterize adoptions of innovations such as new financial instruments, strategies, or entrepreneurial ventures.

A second important implication of bandwagon theories is that minor differences in the characteristics of collectivities of organizations can have major effects on the occurrence, the extent, and the persistence of bandwagon diffusion within these collectivities. To the contrary, major differences in collectivities can have little effect on bandwagons. Small, seemingly inconsequential differences in collectivities can have major impacts on these collectivities' fates (Abrahamson & Rosenkopf, 1990). In certain "critical ranges," studies may find very different bandwagon patterns in very similar collectivities of organizations, or very similar bandwagon patterns in very different collectivities.

Third, theories that specify bandwagon pressures counter proinnovation biases because they can readily explain why technically inefficient innovations would diffuse or why technically efficient innovations would be rejected. Our model indicated, for instance, that bandwagons can prompt most organizations in a collectivity to adopt innovations, even when most of these organizations were quite certain, initially, that they would obtain negative returns from adopting the innovation. This mass adoption can occur according to bandwagon theories because organizations adopt innovations in response to pressures caused by the sheer number of adopters, and not because of their assessment of innovations' technical efficiency and returns.

By the same token, if bandwagons prompt diffusions and rejections of innovations, regardless of their efficiency and returns, then bandwagons may not only diffuse technically inefficient innovations or reject technically efficient ones, bandwagons also may diffuse technically *efficient* innovations or reject technically *inefficient* ones. So, it cannot be said that theories of bandwagons suffer from an antiinnovation bias. This argument, however, raises a final question: Are bandwagons economically harmful? The popular press typically claims that they are. Journalists justify this claim by citing adoptions of innovations that, in retrospect, appear to have caused serious harm to organizations. They point to bandwagon adoptions by U.S. banks of "jumbo loans" to developing countries and to the international debt crisis that resulted. Such episodes suggest that an understanding of how and when bandwagons occur may be of great practical utility.

Bandwagons, however, also present a paradox. Indeed, popular-press accounts rarely mention instances when adoptions generate pressures that force multiple organizations to overcome inertia shackling them to proven but outdated innovations in order to experiment with unknown but potentially useful ones. Such instances suggest that bandwagons may constitute important processes that animate the random variations from which improved organizational and technological forms evolve (Anderson & Tushman, 1990; Hannan & Freeman, 1977; Tushman & Anderson, 1986).

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APPENDIX

Assume that the individual assessments of organizations (I_i) are normally distributed with mean μ_I and standard deviation δ_I. We wish to calculate the proportion of bandwagon adopters for a given level of ambiguity (A) and a given adoption threshold (T).

Let n_k be the proportion of adopters (that is, organizations with bandwagon assessments (B_{ik}) exceeding the adoption threshold) by cycle k, where n_0 is zero. Because $B_{ik} = I_i + (A * n_{k-1})$, B_k is normally distributed with mean $\mu_i + (A * n_{k-1})$ and standard deviation δ_i. Then

$$E\{n_k\} = 1 - F\left(\frac{T - [\mu_I + (A \times n_{k-1})]}{\delta_I}\right),$$

where F represents the cumulative normal distribution function.

Using Equation (1), the expected proportion of adopters may be calculated in each cycle k by forward iteration. Diffusion ends at equilibrium, where $E\{n_k\} = E\{n_k - 1\}$. The expected proportion of bandwagon adopters is then given by the difference between the proportion of adopters at equilibrium and the proportion of adopters in the first cycle.

What if ambiguity is permitted to vary across organizations? Consider the case where ambiguity A_i is normally distributed with mean μ_A and standard deviation δ_A, and where the distributions of individual assessment and ambiguity do not covary. Then $B_{ik} = I_i + (A_i * n_{k-1})$, implying that B_k is normally distributed with mean $\mu_{Bk} = \mu_i + (\mu_A * n_{k-1})$ and standard deviation $\delta_{Bk} = (\delta^2_I + n^2_{k-1}\delta^2_A)^{.5}$. In this case,

$$E\{n_k\} = 1 - F\left(\frac{T - \mu_{Bk}}{\delta_{Bk}}\right).$$

Note that for a given level of mean ambiguity ($\mu_A = A$), the only difference between Equations (2) and (1) is that δ_{Bk} is always larger than δ_i. The effect of increasing δ_A is therefore curvilinear; when T is greater than μ_{Bk}, $E\{n_k\}$ increases, but when T is less than μ_{Bk}, $E\{n_k\}$ decreases.

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