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Keywords

bandwagons, diffusion, fads, organizational collectives, reputation, unprofitable, innovations

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Business Administration, Management, and Operations

Modeling Reputational and Informational Influences

in Threshold Models of Bandwagon Innovation Diffusion

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Bandwagon innovation diffusion is characterized by a positive feedback loop where adoptions by some actors increase the pressure to adopt for other actors. In particular, when gains from an innovation are difficult to quantify, such as implementing quality circles or downsizing practices, diffusion is likely to occur through a bandwagon process. In this paper we extend Abrahamson and Rosenkopf's (1993) model of bandwagon diffusion to examine both reputational and informational influences on this process. We find that the distribution of reputations among the set of potential adopters affects the extent of bandwagon diffusion under conditions of moderate ambiguity, and we find that bandwagons occur even when potential adopters receive information about others' unprofitable experiences with the innovation.

1. Introduction

Reviews of the innovation diffusion literature have repeatedly denounced its pro-innovation bias -- the assumption that the diffusion of innovations benefits organizations (Rogers, 1983; 1995; Zaltman, Duncan and Holbeck, 1973; Kimberly, 1981; Van de Ven, 1986; Abrahamson, 1991). Much of this literature implicitly assumes that profitable innovations diffuse and that innovations that diffuse must be profitable[1].

Pro-innovation biases have two consequences. First, because these biases suggest that innovations benefit adopters, researchers often assume that innovations diffuse fully across potential adopters, and few researchers examine how ***extensively*** innovations diffuse (Rogers, 1983: 97). Most researchers focus, instead, on explaining diffusion rates. Second, because pro-innovation biases suggest that only profitable innovations diffuse, few researchers examine the diffusion of ***unprofitable*** innovations (Kimberly, 1981). As a result, we still know little about when unprofitable innovations diffuse in a fad-like fashion at the expense of adopting organizations.

Examples of the diffusion of unprofitable innovations abound. Quality circles diffused widely through U.S. firms in the 1980s, accompanied by a wave of popular press, yet their value was equivocal at best (Abrahamson and Fairchild, forthcoming). The practice of downsizing, originally heralded by consultants and markets alike, has more recently been associated with negative impact on productivity, morale and trust over the longer term (Cameron, 1998).

[1] Certain innovation-diffusion theories explain why, when multiple variants of an innovation contend for dominance, one variant prevails, even if it is less technically efficient. These theories and models explain, for example, why Matsushita's less-efficient VHS standard in VCRs won out over Sony's more-efficient Betamax standard (Arthur, 1983). Others explain why more-efficient variants of innovations fail to replace less-efficient variants. They explain, for instance, why the more efficient Dvorak standard in typewriter key boards did not replace the less efficient QWERTY standard (David, 1985). These theories do not explain, however, why innovations that remain unprofitable diffuse. More generally, this paper is concerned only with theories explaining the diffusion of one type of innovation, not of its variants.

Our aim in this paper is to extend our threshold model of bandwagon diffusion (Abrahamson and Rosenkopf, 1993) in two ways. First, we consider how the distribution of reputations among organizations in a collectivity affects whether and when an unprofitable innovation is likely to diffuse in a bandwagon fashion. Second, we explore whether these effects are robust even under conditions where we permit knowledge about the unprofitability of the innovation to become discernable and public after each adoption.

The combination of these two aims results in a model that combines features of what Abrahamson (1991) called "efficient-choice" and "fad" theories of bandwagon diffusion. In their extreme form, efficient-choice theories assume that organizations make rational adoption decisions based only on information about an innovation's technical efficiency and profitability. In contrast, extreme-form fad theories assume that information about efficiency and profitability is either not communicated to potential adopters, or is so ambiguous that it does not influence adoption decisions. Under these conditions, organizations do not premise their adoption decisions on technical or profitability information, but rather on information about the number and reputation of previous adopters (Meyer and Rowan, 1977; DiMaggio and Powell, 1983). Our model, by incorporating aspects of efficient-choice and fad theories, follows in the tradition of theorists who acknowledge both economic and social influences on the decision to adopt (Burt, 1973; 1980; Tolbert and Zucker, 1983; Scharfstein and Stein, 1990; Banerjee, 1992).

2. Theoretical Review

2.1 Threshold Models of Bandwagons

In bandwagon models, a collectivity is defined as a set of members where when one member of the collectivity adopts an innovation, other members obtain information about this adoption (Abrahamson and Rosenkopf, 1993). 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. Not all members of a collectivity necessarily give in to a bandwagon pressure. Threshold models assume that members of a collectivity have varying predispositions against adopting an innovation. A member will give in to a bandwagon pressure to adopt only if it exceeds this member's ***threshold*** -- the point at which the strength of the bandwagon pressure to adopt is greater than the member's predisposition against adopting (David, 1969). Therefore, a member with a high threshold adopts only in response to a strong bandwagon pressure, whereas it only takes a weak bandwagon pressure to cause a member with a low threshold to adopt, and it takes no bandwagon pressure for a member with a zero threshold to adopt.

We employ a threshold model in this paper because such models can easily describe complex processes that cause bandwagons to start and various proportions of a collectivity's members to adopt. Members with zero thresholds have no predisposition against adopting and they adopt first. Their adoptions cause the strength of the bandwagon pressure to increase. Members 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 not sufficient to prompt the non-adopter with the lowest threshold to adopt. A bandwagon's extent equals the proportion of adopters when the bandwagon cycle stops.

Note that threshold models can explain why a bandwagon would stop before all members of a collectivity had adopted. Indeed, if at any stage of a bandwagon, all non-adopters have a threshold that exceeds the bandwagon pressure, the bandwagon stops. Threshold models indicate that the ***distribution*** of thresholds in collectivities of individuals generally has a major impact on the extent of bandwagon diffusion in these collectivities (Granovetter, 1978; Schelling, 1978; Abrahamson and Rosenkopf, 1993). In addition, the network of relations among collectivity members also has a major impact on bandwagon extent (Valente, 1995; 1996; Krackhardt, 1997; Abrahamson and Rosenkopf, 1997).

2.2 Efficient-choice Theories of Bandwagons

Efficient-choice theories assume that organizations adopt innovations based on information about their technical efficiency or profitability. Assumptions about the availability of this information vary. One type of efficient-choice theory assumes complete information -- all organizations find out unambiguous information about innovations' profitability instantaneously. Some of these complete-information theories assume negative externalities, where returns to any adopter decline with the number of adopters, yet more adoptions occur because costs decline the latter the adoption date (Reinganum, 1981; Fudenberg and Tirole, 1983; Quirmbach, 1986). Other complete-information theories assume that profits increase with the number of adopters. This occurs because of positive externalities, such as the network case where the more organizations 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).

Complete-information theories have been modeled using threshold models. These models rest on the assumption that organizations vary along certain characteristics, usually size, that determine their adoption thresholds -- the magnitude of an innovation's profitability that will prompt an organization to adopt it (David, 1969; Davies, 1979). As organizational size, for example, varies from low to high, so too will adoption thresholds. As an innovation's costs or returns change because of forces either endogenous or exogenous to the diffusion process, more organizations are pushed over their adoption thresholds and they adopt.

A second type of efficient-choice theory assumes incomplete information (Mansfield, 1961), so that organizations are assumed to be uncertain about the profitability of innovations. As more organizations adopt an innovation, however, they generate more information about the innovations' true efficiency and profitability (Rogers, 1983: 244). Information about technically-efficient and profitable innovations tends to cause non-adopters to revise their initial assessed profits upward past some threshold at which point they adopt.

Incomplete-information theories have also been modeled using threshold models. These models also rest on the assumption that organizations, or their decision-makers, have different adoption thresholds -- how profitable information must reveal an innovation to be before they adopt it. When the same information about a profitable innovation reaches organizations, lower-threshold organizations adopt it before higher-threshold organizations. In these models organizations either learn-by-doing (Stoneman, 1981) or learn-by-others-doing about the technical efficiency or profitability of innovations (Feder and O'Mara, 1982; Oren and Schwartz, 1988; Chatterjee and Eliashberg, 1989; Lattin and Roberts, 1989). These models generally assume that organizations, or their decision-makers, update their assessments of innovations' profitability in a Bayesian fashion.

Another approach to incomplete information is seen in the literature that incorporates social network effects. In this case, even if profitability information is perfectly accurate, it is not uniformly available to all members of the collectivity. Here, actors will adopt if they communicate with a set of actors that provide information that validates the innovation. This information may be transmitted through cohesion (Burt, 1973) or through the monitoring that occurs via structural equivalence (Burt, 1980). Complexity in patterns of interaction has been modeled by Carley (1991; 1995) and Kaufer and Carley (1993), where we observe dramatic discrepancies in the knowledge of various actors due to their tendencies to exchange information with more homogeneous others. Valente (1995; 1996) and Abrahamson and Rosenkopf (1997) have modeled adoption thresholds as a function of the subset of actors that communicate with a potential adopter, rather than the entire collectivity of potential adopters.

In either case (complete or incomplete information), it should be obvious that profitability information will only lead a non-adopter to adopt when there is indeed profit to be gained by adopting the innovation. Ultimately, such models may reinforce at least one component of the pro-innovation bias, as no adopter will be swayed to adopt an unprofitable innovation.

2.3 Fad Theories of Bandwagons

In the extreme, fad theories do not admit any information about profitability. In reality, there is a continuum of approaches that relax the assumptions of efficient-choice models. The major theme of all of these models is the idea of ambiguity. Greater environmental turbulence and complexity causes information about innovations to be ambiguous (Aldrich, 1979; Milliken, 1987; Pfeffer and Salancik, 1978). Carley (1995) suggests that ambiguity increases diffusion by increasing actors' receptivity to new ideas.

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).

2.3.1 Two-stage diffusion processes

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

Certain scholars argue that bandwagon processes cause two-stage patterns of bandwagon diffusion. Initial-stage adoptions of an innovation occur because certain organizations assess an innovation's profitability, decide that this innovation is technically efficient and profitable, and adopt it. Kimberly's (1981: 88-90) review of the innovation-adoption literature indicates that an organization's assessment of an innovation's profitability depends on various characteristics of this organization's structure, network position, decision makers, and environment.

In the initial stage, certain organizations may not adopt because they expect a loss from adopting. Social comparison theory suggests, however, that these non-adopters are still vulnerable to social pressures to adopt this innovation in the later stage, if this innovation's technical efficiency and profitability is ambiguous (Festinger, 1954; Thompson, 1967: 89). Social comparison theory suggests that when confronted with empirically ambiguous questions (that is, questions that cannot easily be answered by pointing to concrete facts, such as the profitability of an innovation), organizational decision makers tend to base their decisions on social cues (such as the number and reputation of other adopters). In social networks, structurally equivalent actors have shown greater susceptibility to influence of this type, perhaps because structural equivalence encourages comparison (Burt, 1980). Moreover, social comparison theory suggests that the greater ambiguity, the greater the pressure to adopt caused by information about the number and reputation of organizations that have adopted (DiMaggio and Powell, 1983). These pressures may be great enough to cause organizations that did not adopt in the initial stage, because they expected a loss from doing so, to nonetheless adopt in the later stage.

2.3.2 Increasing bandwagon pressures

A variety of fad theories explain why increases in the number and reputation of adopters cause social bandwagon pressures to grow. One sociological variant specifies institutional bandwagon pressures -- pressures on organizations arising from the threat of lost legitimacy. In these theories, the more organizations adopt an innovation, and the greater these organizations' reputations, the more it becomes taken-for-granted that it is normal, or even legitimate, for organizations to use this innovation (DiMaggio & Powell, 1983; Meyer & Rowan, 1977). 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 legitimacy and stakeholder support (Tolbert and Zucker, 1983; Abrahamson and Rosenkopf, 1993). A similar approach from economics assumes that organizations tend to adopt an innovation the more other organizations have adopted it because they will be evaluated more favorably if they do what other organizations are doing (Scharfstein & Stein, 1990).

A second variant of fad theories describes competitive bandwagon pressures -- pressures on organizations arising from the threat of lost competitive advantage. Bandwagon pressures occur because, as the proportion of adopters increases, non-adopters experience a growing risk that if the innovation is a success, their performance will fall well below the collectivity average; they adopt to avoid running this risk (Abrahamson and Rosenkopf, 1990; 1993). Still a third variant of fad theories assumes that organizations adopt an innovation the more organizations adopt it because the number of adopters is taken as evidence that these adopters must know something that the non-adopters do not know (Banerjee, 1992).

2.4 Reputational Influences on Diffusion Processes

It remains to examine how varying reputations of adopters may influence processes of bandwagon diffusion. The most common finding is what Abrahamson and Fombrun (1994) call “trickle-down” diffusion, where adoptions by high-reputation actors trigger imitations by lower-reputation actors. Here, reputation may be assessed via response data, central network position, or other proxy characteristics such as organizational size. Trickle-down processes have been found among individuals (e.g. Burt, 1973; Rogers, 1995) as well as among organizations (e.g. Galaskiewicz and Wasserman, 1989; Davis, 1991; Mizruchi, 1992).

In contrast, "trickle-up" processes occur when adoptions by low-reputation actors trigger imitations by higher-reputation actors. Trickle-up processes tend to diffuse contra-normative innovations (Becker, 1970; Krackhardt, 1997) as lower-reputation adopters are willing to take the risk of appearing deviant by adopting a contra-normative innovation in the hope that reputation will improve if the innovations succeeds (Burt, 1980; Kimberly 1981; Rogers, 1995). Under certain conditions, higher-reputation actors imitate, and the contra-normative innovation diffuses. In many cases of trickle-up diffusion among organizations, incumbents fail to adopt contra-normative innovations, and are supplanted by new entrants who adopt and exploit such innovations (Tushman and Anderson, 1986; Bower and Christensen, 1995). In other cases, peripheral actors may forge coalitions that generate enough power to challenge the established order (Rosenkopf and Tushman, 1998).

In each case, research recognizes that actors of different statuses will have different influences on the diffusion process. Latane (1996), in his dynamic social impact theory, suggests that actors vary in their "strength" of influence on others. Podolny and Phillips (1996) offer empirical illustration of the evolution of status in the investment banking industry through examination of tombstone advertisements, and suggest that the dynamics of status evolution may depend on the initial distribution of status among the population.

If adopter reputations determine the extent of bandwagon pressures, then the distribution of reputations among actors in a collectivity may affect the dynamics of bandwagon diffusion. Specifically, we can imagine collectivities with higher or lower variance in the distribution of reputations. A collectivity with low reputational variance has most members with similar reputational levels, while a collectivity with high reputational variance will have some obvious outliers that may be stars or dogs.

Thinking about a few industries over time helps clarify the concept of reputational variance. Kodak and Xerox traditionally dominated the photographic and photocopier industries in the United States; each was perceived as the highest quality player and rewarded with high market share. Their reputations outweighed all of their competitors. More recently, however, each of these firms has had to share the spotlight with numerous other firms that have polished their reputations for innovativeness, quality, and value, so reputational variance in the industry has decreased. In contrast, consider the funeral services market. Traditionally operated through small, private businesses, no player outshone the others. Yet recent waves of consolidation have led to the rise of a few chains that generate reputations through quality control and advertising. In this industry, reputational variance is increasing.

3. Refining the Bandwagon Model

In two papers, Abrahamson and Rosenkopf (1993; 1997) have presented a threshold model of bandwagon diffusion and explored some of its implications. We extend this model to examine how information about adopter reputations and adopter experiences affect bandwagon extent, thereby combining features of both fad and efficient-choice models.

The Abrahamson and Rosenkopf model is premised on the notion that an organization's assessment of the viability of an innovation rests not only on some initial, rational assessment, but is also inflated by other firm's adoptions. They have shown, in a variety of contexts, that unprofitable innovations can diffuse in a bandwagon fashion in ambiguous environments, and also that bandwagons are encouraged by certain structural properties of communication networks.

In the basic model, Abrahamson and Rosenkopf assume that an organization will adopt an innovation if its "bandwagon assessment" of the innovation's value is positive. The bandwagon assessment relies on the organization's individual assessment, the ambiguity experienced by the firm, and the number of organizations that have already adopted the innovation. To formalize:

Let $B_{i,k}$ = organization i's bandwagon assessment of the innovation's profitability in bandwagon cycle k

Let I_i = organization i's individual assessment of the innovation's profitability

Let A = level of ambiguity organizations experience[2]

Let n_{k-1} = number/proportion of adopters after bandwagon cycle k-1

Since threshold models operate by specifying how many non-focal actors must choose to adopt in order to persuade the focal adopter to do so, organizations whose initial assessments exceed zero will not require any other adoptions to make their own decisions to adopt, and hence their threshold is zero. In contrast, organizations whose initial assessments are less than zero will have nonzero thresholds. Specifically, these organizations will only adopt if the bandwagon pressure caused by adoptions exceeds $|I_i|$. So Abrahamson and Rosenkopf model later-stage adoption decisions by **summing**

[2] The initial formulation of the model allows the level of ambiguity to vary across organizations and therefore appears as A_i in the original text. The 1993 paper fixes A_i = A for all organizations, and we do the same here. Effects of

organization's individual assessments and the bandwagon pressure to create a "bandwagon assessment"; organizations adopt when the bandwagon assessment is greater than zero. Since bandwagon theories suggest that bandwagon pressure increases with the number of adopters, but that the level of ambiguity **moderates** this relation, the bandwagon pressure can be modeled as the **product** of ambiguity and the number of adopters.

As in Abrahamson and Rosenkopf (1993:496), this yields equation one:

$$B_{i,k} \; ? \; I_i \; ? \; (A * n_{k?1}) \qquad\qquad A \; ? \; 0$$

where organizations adopt whenever $B_{I,k} > 0$.

We extend this model in two ways for this paper. First, we incorporate reputational effects on bandwagon pressure. Since the original model counts the number of adopters, it weights all adoptions equally. As we wish to place more weight on adoptions by high-reputation organizations, we replace the number of adoptions with a reputation-weighted count. Specifically:

Let r_i = reputation of organization i

Let $D_{i,k}$ = 1 if organization i has adopted by bandwagon cycle k; 0 otherwise

This gives us equation two:[3]

$$B_{i,k} \; ? \; I_i \; ? \; (A * ? \; (r_i * D_{i,k?1})) \qquad\qquad A \; ? \; 0$$

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relaxing that assumption are explored in the appendix to the 1993 paper as well as in the 1997 paper.

[3] To standardize units, consider each term of the equation (bandwagon assessment on the left-hand side, initial assessed profits, and the reputational bandwagon pressure) to be measured in dollars. For the reputational bandwagon pressure term, r represents the dollar value increase in bandwagon assessment attributable to the adoption by a specific actor, and A is a constant. Thus the reputational bandwagon pressure terms offsets negative profits.

Second, we also consider how information about the outcomes organizations experience may influence the decisions of potential adopters. Hence we add another component to the model which captures the effect of the average profits achieved by all prior adopters. We assume that this profitability information is transmitted after some lag. Ambiguity also moderates this effect; however, in this case, the higher the ambiguity, the less weight placed on profitability information. Specifically:

Let p_i = actual profits achieved by organization i

Let L = number of cycles required to transmit profitability information (lag)

This gives us equation three,

$$B_{i,k} = I_i + (A * \sum (r_i * D_{i,k-1})) + ((1-A) * (\frac{\sum (p_i * D_{i,k-L-1})}{n_{k-L-1}})) \qquad 0 \leq A \leq 1$$

3.1 Simulation Assumptions

Three assumptions underlie our simulation. First, initial assessed profits and achieved profits are independently drawn from the same normal distribution. Kimberly's (1981) review of the innovation-adoption literature indicates that an organization's assessed and achieved profits depend on various characteristics of its structure, network position, decision-makers, and environment. Because organizations differ on these characteristics, we assumed that different organizations in a collectivity would tend to assess different profits from adopting the same innovation, and would achieve different profits as well. Moreover, since many weakly correlated forces affect organizations' assessed and achieved profits, we assumed that they would tend to be normally distributed across these organizations. Finally, since different forces determine assessed and achieved profits, we assumed that organizations' assessments of the profits they achieve would be correct only on average.

Therefore, the mean and variance of the distribution of initially assessed and achieved profits would tend to be the same (for a similar modeling approach, see Burgelman and Mittman, 1993).

Second, reputations are also normally distributed. To distinguish between trickle-up, -down and -around processes, we assumed strong relationships between reputations and initial assessed profits. Specifically, for trickle-down scenarios, we induced a correlation of +1.0 between organizations' reputations and initial assessed profits. So that, the higher an organization's reputation, the higher its initial assessed profits, and the higher its propensity to adopt initially. In contrast, for the trickle-up scenario, we induced a correlation of -1.0 between organizations' reputations and initial assessed profits. Here, the lower an organization's reputation, the higher its initial assessed profits, and the higher its propensity to adopt initially. In the trickle-around scenario, we did not induce any correlation between initial assessed profits and reputations[4].

Third, information about adoptions and outcomes is available to all organizations at the start of the next cycle[5]. A flow diagram of our model may be found in Figure 1.

3.2 Parameter Values

1) The number of organizations in the collectivity is set to 20. Note that for any given distribution of reputations, if the number of organizations were set extremely high (or low), bandwagon pressure would be so high (or low) as to motivate full (or no) diffusion

[4] It might appear that results could be obtained analytically, where the expected proportion of imitators each period is calculated via forward recursion, as in Abrahamson and Rosenkopf (1993). However, the dependency between reputation and initial assessed returns complicates the calculation of the expected value of ? (r_i * D_i), the total reputation of adopters. This complication occurs because while firm reputations are normally distributed, the reputation values of adopters are correlated with their assessed returns. Since adopters require assessed returns above a certain threshold, it follows that the reputations of these adopters are also clustered towards one end of the reputation distribution. Thus, the total reputation of adopters follows a conditional normal distribution, and the calculation of its expectation requires extremely sophisticated integration. We opted to use simulation to generate the proportion of imitators and to observe the dynamics of this process. The simulation code is very straightforward and is available from the authors for empirical test of the model.

[5] We have considered social network effects in our 1997 paper and do not restrict information flow here.

in nearly every case. We chose the level of 20 in conjunction with our reputational parameters in order to insure a range of bandwagon outcomes.

2) The mean of the distribution of initial assessed profits is set to –1.0. We picked a negative value for the mean of the profits distributions because we wanted to examine the bandwagon diffusion of unprofitable innovations. Indeed, the greater the mean of the distribution of initial assessed profits, the more organizations will tend to assess profits from adopting and adopt based solely on these initial assessed profits. Bandwagon pressures, therefore, will have a limited effect on what percentage of a collectivity adopts. The most interesting cases occur, however, when the mean is negative. Then, most organizations perceive losses from adopting an innovation, and it can diffuse widely only because of a bandwagon process dominated by reputational bandwagon pressure. Such bandwagons can occur if the variance of the distribution of initial assessed profits is large enough so that a few organizations will tend to assess initially that they will make a profit from adopting, triggering reputational pressure that causes many organizations to adopt an unprofitable innovation.

3) The standard deviation of the distribution of initial assessed profits (hereafter "assessed profits variance") ranges from 0.0 to 1.5 in increments of 0.075. Hence there are 20 values of assessed profits variance.

4) The mean of the distribution of reputations is set to 1.0. With this approach, when reputation variance is zero, the bandwagon effects reduce to a pure count of the number or proportion of adopters, as in Abrahamson and Rosenkopf (1993).

5) The standard deviation of the distribution of reputations (hereafter "reputation variance") ranges from 0.0 to 0.3 in increments of 0.025. Hence there are 12 values of reputation variance. Note that this range of values for reputation variance insures that

nearly all reputation draws will be positive; in the rare cases when the value is negative, we round the value up to zero.

6) Ambiguity ranges from zero to one in increments of 0.05. Hence there are 20 values of ambiguity.

7) The learning lag L ranges from 1 to 6 by increments of 1. However, in some simulations we set L to infinity, reducing equation three to equation two.

4. Results and Discussion

To interpret our results, we vary some parameter values while holding others constant. We run three different simulations to explore how different combinations of assessed profits variance, reputation variance, ambiguity, and learning lags each affect bandwagon diffusion extent.

In all three simulations, for every possible combination of parameter values, 500 iterations were performed and the proportion of bandwagon imitators averaged over all iterations. Each iteration was permitted to run until diffusion ceased; this could take no more than 20 cycles for the non-learning models and 26 cycles for the learning models.

4.1 Simulation 1: Varying Assessed Profits and Reputations

We begin by examining how assessed profits variance and reputation variance affect the percentage of bandwagon imitators in the collectivity. We do so without allowing learning (that is, we set L to infinity). We fix the level of ambiguity (A) at a moderate level of 0.2. This level was chosen, as will be seen in the subsequent simulation, because it is a value at which a lot of variability in outcomes may be observed. Since we utilize twenty values of assessed profits variance and twelve values of reputation variance, a total of 240 cases were simulated.

Figure 2 graphs the results for the trickle-up, -down, and –around scenarios. To aid the reader in viewing our outcomes graphically, we only present a subset of these cases which summarize the overall outcomes. Specifically, in Figure 2 we limit our presentation to three levels of reputation variance (RV): RV=0.0, RV=0.15, and RV=0.3. We do so because the interim values yield a plethora of lines that are difficult to distinguish.

Several patterns are observable from Figure 2. First, observe that ceteris paribus, the proportion of bandwagon adopters is greatest in the trickle-down scenario, followed by the trickle-around, and then the trickle-up scenario[6]. Further, increasing reputation variance increases diffusion extent in the trickle-down case, decreases diffusion in the trickle-up case, and has no clear effect on diffusion extent in the trickle-around case. These patterns occur because the greater the reputation of initial adopters, the greater the impetus they give to a bandwagon, and the more it diffuses the innovation.

More importantly, the results in Figure 2 suggest that a characteristic pattern reported in prior research (Granovetter, 1978; Abrahamson and Rosenkopf, 1993; 1997) obtains regardless of whether we examine trickle-down, -up, or –around scenarios. Specifically, we observe two inflection points in these curves. Bandwagons do not occur at assessed profits variances below approximately 0.4, but minor increases above this critical value result in many bandwagon adoptions. In contrast, at assessed profits variances above approximately 1.0, we observe that increases beyond this value results in fewer bandwagon adoptions.

Simulation 1 suggests two propositions that hold under moderate levels of ambiguity,

[6] Closer inspection reveals that when RV=0.0, essentially the same results obtain for all three scenarios. This is because when all reputations are equal, the bandwagon pressures are equivalent in each scenario.

P1: When the variance of initial assessed profits across organizations in a collectivity is small, minor increases in this variance can result in major increases in the percentage of organizations that adopt an innovation during a trickle-up, trickle-down or trickle-around bandwagon.

P2: When the variance of initial assessed profits across organizations in a collectivity is large, minor increases in this variance can result in decreases in the percentage of organizations that adopt an innovation during a trickle-up, trickle-down or trickle-around bandwagon.

What explains the first pattern (P1)? If the variance is small, then organizations assess roughly equal profits from adopting, and the distribution of initial assessed profits will tend to cluster around the mean, which is assumed to be negative. Because the mean of initial assessed profits is negative, there is only a small probability that organizations will not assess losses initially. Therefore, few organizations will tend to adopt. This small number of initial adopters will not generate a strong bandwagon pressure and, consequently, will not cause many bandwagon adoptions. If, however, the variance is larger, organizations' initial assessed profits will tend to differ to a greater extent, and there will be a greater dispersion of initial assessed profits about the mean. This will increase the number of organizations that assess profits initially and adopt. These initial adopters will generate stronger bandwagon pressure, causing more bandwagon adoptions.

What explains the second pattern, declining numbers of bandwagon adopters when the variance increases past the second critical value (P2)? The answer is complicated. Remember that 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 these bandwagon adopters prompts reputational pressure to grow. The process continues cycling only so long as the reputations of new bandwagon adopters raises the bandwagon pressure sufficiently in one cycle to cause at least one organization that assessed losses to adopt in the next cycle. When, however, this organization's initial assessed profits are much smaller than those of adopters in the previous cycle, the process will tend to stop cycling. This is so because the increase in the bandwagon pressure is too small to make this organization's bandwagon assessment positive. Consider now, that whenever the variance in initial assessed profits is large, organizations' assessments tend to differ more extensively, and it is more likely that an organization will assess profits that are much smaller than those of organizations that adopted in the previous cycle. It follows, therefore, that bandwagons will tend to stop cycling more often. In sum, increases in the variance of initial assessed profits produce stronger bandwagon pressures, but they also reduce their impact, resulting in this declining number of bandwagon adopters past the second critical value.[7]

4.2 Simulation 2: Varying Ambiguity and Reputation Variance

Our second simulation explores how the level of ambiguity, when allowed to vary, affects the influence of reputation variance on the extent of bandwagon diffusion. So we allow ambiguity to vary across the twenty increments from zero to one, while we fix assessed profits variance at its midpoint of 0.75. All other considerations remain the same as in Simulation 1.

Results are graphed in Figure 3. Again, to provide clarity, only a subset of the ambiguity results is shown on the graphs. Three distinct patterns are revealed. The first pattern is obvious – the greater the ambiguity, the more bandwagon adoptions will result. This is a direct consequence of equation 2 – greater ambiguity increases the reputational pressure and motivates more adoptions.

[7] Simulation results available from the authors indicate that in scenarios in which there are equal numbers of initial adopters, but different distributions of assessed profits, the proportion of bandwagon adopters varies substantially. This suggests that the extent of bandwagon diffusion depends not only on the impetus given to a bandwagon by initial adopters, but also on the variance of other organizations' assessed profits.

Second, and also to be expected, in the trickle-around scenario, reputation variance has little effect on the extent of diffusion, as denoted by the nearly-horizontal lines for all levels of ambiguity. Since there is no correlation between assessed profits and reputation in this scenario, the cumulative effect of adopters' reputations nets out.

The third pattern revealed in Figure 3 is the most interesting. When ambiguity is relatively low (no more than 0.05 in the trickle-down and trickle-up scenarios), the extent of adoption is low regardless of the level of reputation variance. This effect can be seen in the nearly horizontal lines at the bottom of the trickle-down and trickle-up graphs. As equation 2 suggests, at low ambiguity, initial assessed profits dominate the decision to adopt. When ambiguity is low, no distribution of reputations can create the conditions that enable extensive bandwagon diffusion.

P3: Under conditions of low ambiguity, the level of reputation variance in a collectivity has little effect on the extent of trickle-down or trickle-up diffusion.

When ambiguity is relatively high (at least 0.40 in the trickle-down scenario; at least 0.60 in the trickle-up scenario), the extent of adoption is high regardless of the level of reputation variance. Thus while high ambiguity will cause organizations to place more weight on the reputations of adopters, and this bandwagon pressure will continue to impel adoptions throughout the collectivity, the ambiguity parameter is large enough so as to overwhelm any differences in the reputations of initial adopters. In other words, under high ambiguity, potential adopters are likely to be influenced by any adoptions, whether they be by extremely high- or extremely low-reputation firms. While each adopter individually places more weight on reputational characteristics in making the decision to adopt, the overall extent of diffusion throughout the collectivity is unchanged by the level of reputation variance.

P4: Under conditions of high ambiguity, the level of reputation variance in a collectivity has little effect on the extent of trickle-down or trickle-up diffusion.

Only under conditions of moderate ambiguity do we observe an effect of reputation variance on bandwagon extent. In Figure 3, for the trickle-down and trickle-up scenarios, we can observe non-horizontal lines in the middle of each graph. These lines are upward-sloping in the trickle-down scenario and downward-sloping in the trickle-up scenario. More specifically,

P5: Under conditions of moderate ambiguity, higher levels of reputation variance in collectivities will increase the extent of trickle-down diffusion and decrease the extent of trickle-up diffusion.

What explains these results? In trickle-down diffusions, initial adopters are high-reputation organizations. The higher their reputations, the stronger the reputational bandwagon pressure they cause, and the more bandwagon adoptions result. Initial adopters' reputations will tend to be higher when the variance in the distribution of reputations in the collectivity is greater, due to the strong correlation between initial assessed profits and reputations. It follows, therefore, that the higher this variance, the more bandwagon adoptions will occur during trickle-down diffusion.

In trickle-up diffusions, the reverse happens. Initial adopters are low-reputation organizations. The higher their reputations, the stronger the reputational bandwagon pressure they cause, and the more bandwagon adoptions result. Their reputations will tend to be higher when the variance in the distribution of reputations in the collectivity is lower, due to the strong negative correlation between initial assessed profits and reputations. It follows, therefore, that the lower this variance, the more bandwagon adoptions will occur during trickle-up diffusion.

4.3 Simulation 3: Introducing Learning

In Simulations 1 and 2 we explored the effects of assessed profits variance and reputation variance under varying levels of ambiguity. It remains to assess whether these effects are sustained when we incorporate learning by using equation 3 to motivate adoption decisions and by allowing the learning lag to vary between 1 and 6 cycles.

Since the addition of another variable complicates graphical interpretation of our data, we use an alternate approach to test the robustness of our earlier propositions. Following Nelson and Winter (1982), we generated random cases within the allowable ranges of our parameters, and tested the proposed effects via regression. Thus, for each case, we drew ambiguity randomly from a uniform distribution on [0,1]; assessed profits variance from a uniform distribution on [0.0, 1.5]; reputation variance from a uniform distribution on [0.0, 0.3], and the learning lag from the integer range between 1 and 6 inclusive. 5000 cases were simulated for each of the trickle-down and trickle-up scenarios[8].

Table 1 presents OLS regression results for both scenarios[9]. In the four nested models, support for the robustness of our propositions may be derived. First, we observe the curvilinear relationship between assessed profits variance and the extent of diffusion, as model 1 and model 2 display a significant positive relationship between these terms, while the inclusion of (assessed profits variance)^2 in model 2 obtains a significant negative coefficient and a corresponding significant increase in R^2. Note that these effects hold in both the trickle-up and trickle-down scenarios and thus, propositions 1 and 2 are robust when profitability information flows from early to later adopters. The regression results also highlight that the level of ambiguity retains its significant positive effect on the proportion of bandwagon adopters even when profitability information is available.

[8] The results for the trickle-around case are not qualitatively different and are available from the authors.
[9] We do not present a correlation table as correlations between randomly drawn independent variables are virtually nil.

Next, we explore the relationship between reputation variance and the extent of diffusion. Models 1 and 2 display significant coefficients for this effect: a negative relationship between reputation variance and bandwagon diffusion in the trickle-up case, but a positive relationship between reputation variance and bandwagon diffusion in the trickle-down case. These effects correspond to the effects observed in middle ranges of the graphs in Figure 3 (recall that we have controlled for ambiguity in these regressions).

We employed two additional models to test for the generalizability of the relation in figure 3. As shown in table 1, for both trickle-up and trickle-down bandwagons, model 3 suggests that a linear interaction term captured by the product of ambiguity and reputation variance is not statistically significant. However, if we model a curvilinear interaction by adding, in model 4, the product of ambiguity squared and reputation variance, the first interaction term is positive and significant, the second interaction term is negative and significant, as is the corresponding increase in R^2 of model 4 over model 3. Therefore, reputation variance for a collectivity tends to affect the proportion of bandwagon adopters only when ambiguity is moderate, not when it is either low or high. These results suggest that propositions 3 through 5 are robust when profitability information flows from early to later adopters.

We added a variable in this simulation: the length of the learning lag. The regression results indicate that, for both trickle-up and trickle-down bandwagons, this learning lag has a significant, positive effect on the proportion of bandwagon adopters. What explains this relationship? In this simulation, we randomly drew the profitability of an innovation for an adopter from a distribution with a negative mean. Therefore, after a learning lag, L, adopters tend to learn that the innovation produces losses. Non-adopters also learn this information, and it tends to dissuade them from jumping on the bandwagon. The longer the learning lag, however, the greater the number of cycles during which reputational bandwagon pressure impels bandwagon adoptions, and in turn, the greater the proportion of organizations in a collectivity that jump on the bandwagon before it is halted by information about the innovations' losses.

To explore the relationship between learning lags and ambiguity in more detail, we revert back to our original methodology. Here we set assessed profits variance to .75 and reputation variance to its midpoint, 0.15. Then we vary ambiguity and learning lags in the previously specified ranges, and graph our results in figure 4. This figure indicates that the relation between learning lag and the proportion of bandwagon adopters is also moderated by the level of ambiguity. More specifically, for a given level of ambiguity less than 0.10, we observe little variance in the proportion of imitators regardless of the length of the learning lag. At the same time, for a given level of ambiguity greater than 0.60, we observe the same phenomenon. Only for given levels of ambiguity between these two values do we observe substantial differences in bandwagon extent due to the length of the learning lag.

P6: Only under conditions of moderate ambiguity about an innovation's efficiency or profitability does a greater learning lag cause a more extensive trickle-up or trickle-down bandwagon of this innovation.

Why does the positive correlation between learning lag and proportion of adopters hold only under conditions of moderate ambiguity? Under low-ambiguity conditions, information about initial adopters' reputations creates weak bandwagon pressure and therefore few bandwagon adoptions due to this reputational pressure. Most organizations that did not adopt initially wait to learn whether the innovation profited adopters. Whether the learning lag makes them wait for more or fewer cycles, the outcome is the same. They learn that the innovation is unprofitable and they do not adopt it. Therefore, under low-ambiguity conditions, learning lags have little effect on the extent to which unprofitable innovations diffuse.

Under high-ambiguity conditions, information about initial adopters' reputations create powerful bandwagon pressures and many bandwagon adoptions of an innovation. These reputational bandwagon pressures overwhelm counter-bandwagon pressures caused by information revealing that an innovation is unprofitable. This occurs regardless of whether non-adopters learn of this information after few or many lags. Therefore, under high-ambiguity conditions, learning lags have little effect on the extent to which unprofitable innovations diffuse.

Under moderate-ambiguity conditions, information about initial adopters' reputations create bandwagon pressures strong enough to cause an innovation's bandwagon diffusion, but weak enough for this bandwagon to be halted by counter-bandwagon pressures caused by information revealing that this innovation is unprofitable. Under these conditions, learning lags can make a big difference in the extent to which unprofitable innovations diffuse. Long learning lags make it possible for reputational bandwagon pressures to prompt large proportions of collectivities to adopt unprofitable innovations. Short learning lags, to the contrary, cause bandwagons to grind to a halt after a few such bandwagon adoptions.

Recall that we made the simplifying assumption that achieved profits would not vary with the number of adopters. Obviously, a variety of functional forms could be used to represent externalities. An exploration of the consequences of using different functional forms is beyond the scope of this paper. In general, however, we can expect that positive externalities would increase average achieved profits and therefore the number of adopters, whereas negative externalities would have the opposite effect.

5. Conclusions

Our threshold model of bandwagon diffusion demonstrates how unprofitable innovations can diffuse through organizational collectivities, even when information about the innovation's unprofitability is available to organizations. While the model follows in the tradition of herd behavior findings (e.g. Scharfstein and Stein, 1990; Banerjee, 1992), two features distinguish it from these predecessors. First, our model is a multi-stage model, rather than a sequential model. Organizations revisit the decision to adopt during each cycle of the model, thereby delaying adoption until the bandwagon pressure builds to a level that overcomes the predisposition to not adopt the innovation. We have shown that under certain conditions, bandwagon pressure builds sufficiently to even override information about the unprofitability of the innovation.

Secondly, our model demonstrates how varying heterogeneity of organizational reputations influences bandwagon extent. The Scharfstein and Stein (1990) and Banerjee (1992) models treat decisions by each firm equally, as do the earlier Abrahamson and Rosenkopf (1993; 1997) models. Here, we model the case where adoptions by higher-reputation organizations create more pressure to adopt on non-adopters. We have shown how the variance of reputations in a collectivity influences bandwagon extent under moderate levels of ambiguity, and how this influence differs under trickle-up and trickle-down patterns of diffusion.

The relationships between ambiguity, reputation variance, and bandwagon extent are complex and merit further discussion. We find that very different processes impel bandwagon diffusions of innovations when ambiguity surrounding an innovation is high, moderate, or low. In low-ambiguity conditions, organizations that do not adopt an innovation in the initial stage of diffusion base their decision whether to adopt the innovation on information about its profitability for organizations that did adopt in the initial stage. Under these conditions, unprofitable innovations will tend not to diffuse past a few initial adoptions, because organizations that do not adopt initially will tend to receive information indicating that the innovation is unprofitable, and they will not adopt it.

Under high-ambiguity conditions, a very simple bandwagon process animates bandwagon diffusion. The greater the number of organizations that adopt an innovation, regardless of their reputations or of the profits they achieve from adopting, the greater the bandwagon pressure to adopt exerted on organizations that have not yet adopted in their collectivity. These "numerical" bandwagons can cause both profitable and unprofitable innovations to diffuse.

The most complex and interesting bandwagon processes occur under moderate-ambiguity conditions. Under these conditions, our theory and model suggest that information about both the reputation of adopters and the profits they achieve from adopting influence the course of bandwagon diffusions. More specifically, we show that the bandwagon diffusion of unprofitable innovations is greater when the learning lag before their unprofitability is revealed is longer. Moreover, trickle-down bandwagons are more extensive when reputational variance in a collectivity is greater, whereas trickle-up bandwagons are more extensive when reputational variance in the collectivity is smaller.

These implications of our threshold model suggest where researchers should focus their attention. With high ambiguity, researchers should focus only on the distribution of initial assessed profits to innovating. When ambiguity about initial assessed profits is low, researchers should focus primarily on the distribution of initial assessed profits to innovating, profits generated by innovations, and lags to learning about these profits. Finally, with moderate ambiguity, researchers should also focus on the distribution of initial assessed profits to innovating, the distribution of organizational reputations, profits generated by innovations, and lags to learning about these profits.

Several limitations of our model remain to be addressed in future research. Our model and its simulation may be most accurate in contexts where collectivity members' reputations, as well as the ambiguity surrounding the innovation's profitability, are relatively invariant. In other contexts, however, an organization's reputation may be only as high as its profits from the last innovation it adopted. In these contexts our model's accuracy may be enhanced by modifying it to reflect how initial adopters' profits or losses from adopting an innovation alter the distribution of reputations in the collectivity. In other contexts, the diffusion of an innovation may reduce ambiguity about its technical efficiency or profitability (Rogers, 1983: 244). In these collectivities, our model's accuracy may be enhanced by making ambiguity a function of the number of adopters.

Our model may also be most accurate in predicting the extent of bandwagon diffusion in collectivities of organizations that are both densely linked by communication channels and bounded by high entry barriers. High entry barriers guarantee that, as our theory and model assume, the number of collectivity members remains constant during bandwagons. The diffusion of certain innovations may, however, draw new members into low entry-barrier collectivities. Our model's accuracy may be enhanced for such low-entry-barrier collectivities by making collectivity size a function of the number of adopters. Dense linking in inter-organizational communication networks guarantees that, as we assume in our theory and model, all organizations obtain information about other organizations adoptions. Other collectivities, however, may be sparsely linked. Thus, the accuracy of the model may be enhanced by modeling the structure of the collectivity's communication network. While we have incorporated network structure into the basic model in a separate paper (Abrahamson and Rosenkopf , 1997), simultaneous consideration of network, reputational, and informational effects may yield additional insight.

Finally, our models may be more accurate in contexts where innovations are hard to reverse and organizations are slow to exnovate -- that is, to reject innovations that turn our to be unprofitable. Indeed, the theory and model in this article make no provision for exnovation. It does not because, as Abrahamson and Rosenkopf (1993) show, the dynamics of exnovation are much more complex than the dynamics of adoption. Perhaps for this reason, calls for theorizing and research in this area still remain unheeded (Kimberly, 1981). Bandwagon exnovation remains, therefore, a fruitful area for further theoretical development and modeling.

In conclusion, in today's environment of strict resource constraints, it is not only important that innovations diffuse quickly. It is also important that profitable innovations diffuse and that unprofitable innovations do not. This article has drawn on extant theorizing in the innovation diffusion literature in order to develop a general, yet relatively simple theory of innovation diffusion useful in explaining when and how extensively unprofitable innovations diffuse across organizations.

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Table 1

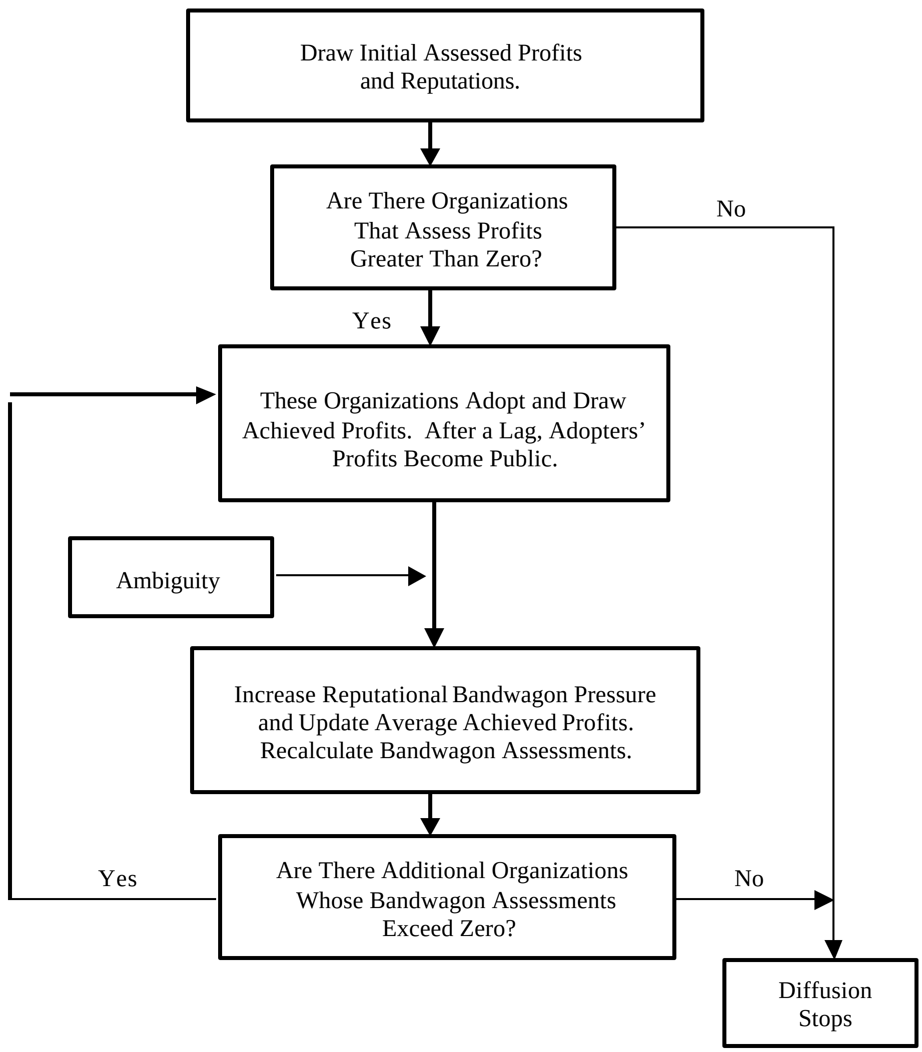
Determinants of Trickle-Up and Trickle-Down Bandwagon Adoption:

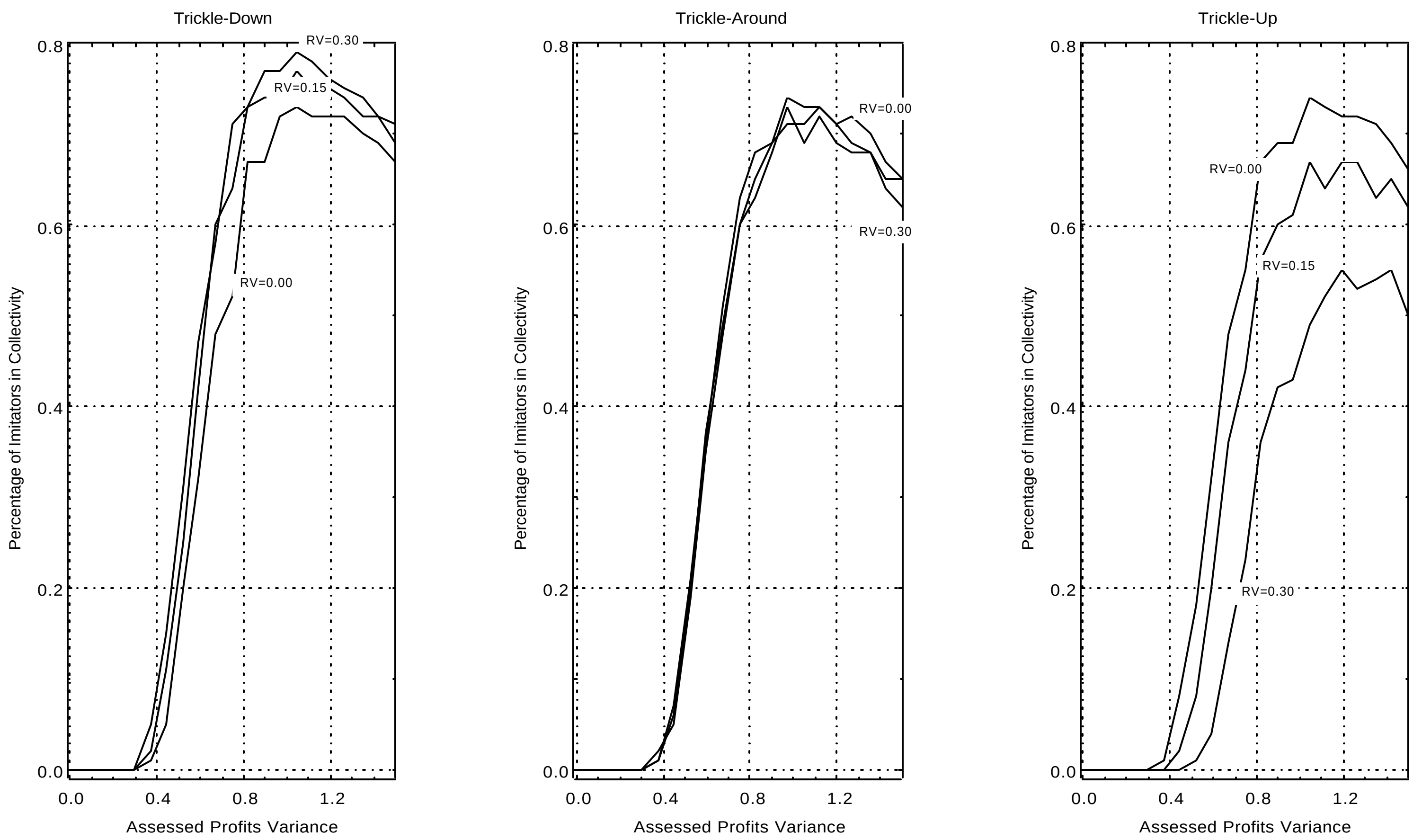
Ordinary Least Squares Regression Coefficients

Trickle-Up	Model 1	Model 2	Model 3	Model 4
Assessed Profits Variance (APV)	.57**	1.1**	1.1**	1.1**
$(APV)^2$		-.37**	-.37**	-.37**
Reputation Variance (RV)	-.19**	-.20**	-.28**	-1.1**
Learning Lag	.021**	.020**	.021**	.019**
Ambiguity (A)	.48**	.47**	.45**	.46**
A * RV			.15	4.9**
A^2 * RV				-4.8**
R^2	.70	.74	.74	.77
F	2934**	2776**	2314**	2361**
df	4995	4994	4993	4992

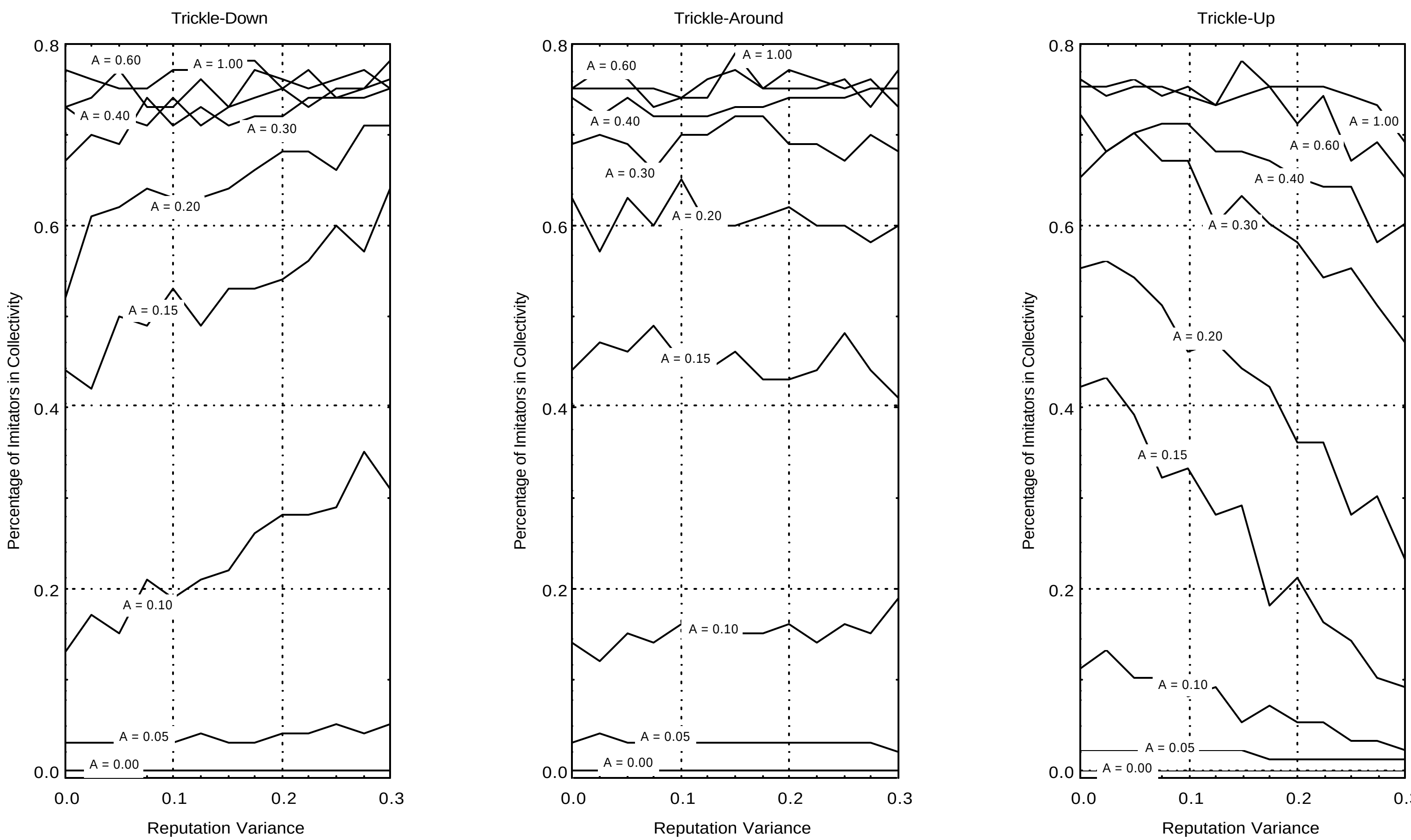
Trickle-Down	Model 1	Model 2	Model 3	Model 4
Assessed Profits Variance (APV)	.60**	1.4**	1.4**	1.4**
$(APV)^2$		-.50**	-.50**	-.50**
Reputation Variance (RV)	.063*	.079**	.16**	-.74**
Learning Lag	.014**	.014**	.014**	.014**
Ambiguity (A)	.40**	.40**	.43**	.43**
A * RV			-.17	5.2**
A^2 * RV				-5.4**
R^2	.69	.75	.75	.79
F	2767**	2990**	2493**	2719**
df	4995	4994	4993	4992

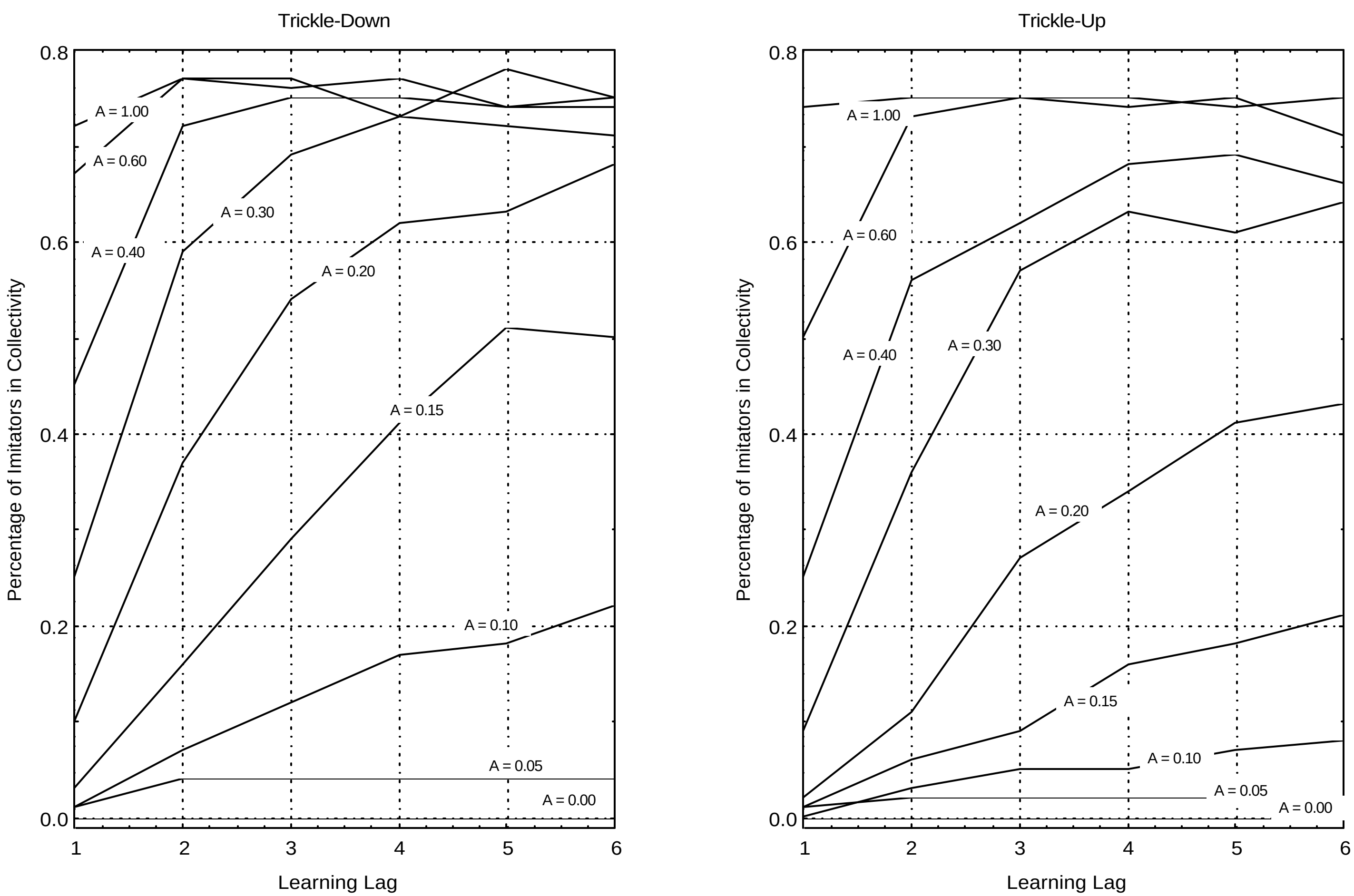
* $p < .05$; ** $p < .01$


Draw Initial Assessed Profits
and Reputations.
Are There Organizations
That Assess Profits
Greater Than Zero?
No
Yes
These Organizations Adopt and Draw
Achieved Profits. After a Lag, Adopters'
Profits Become Public.
Ambiguity
Increase Reputational Bandwagon Pressure
and Update Average Achieved Profits.
Recalculate Bandwagon Assessments.
Yes
Are There Additional Organizations
Whose Bandwagon Assessments
Exceed Zero?
No
Diffusion
Stops



Trickle-Down
Trickle-Around
Trickle-Up
RV=0.30
RV=0.15
RV=0.00
RV=0.00
RV=0.30
RV=0.00
RV=0.15
RV=0.30
Percentage of Imitators in Collectivity
Assessed Profits Variance
0.0
0.2
0.4
0.6
0.8
0.0
0.4
0.8
1.2


Trickle-Down
Trickle-Around
Trickle-Up
Percentage of Imitators in Collectivity
Reputation Variance
0.0
0.2
0.4
0.6
0.8
0.0
0.1
0.2
0.3
A = 0.00
A = 0.05
A = 0.10
A = 0.15
A = 0.20
A = 0.30
A = 0.40
A = 0.60
A = 1.00


Trickle-Down
Trickle-Up
Percentage of Imitators in Collectivity
Learning Lag
A = 1.00
A = 0.60
A = 0.40
A = 0.30
A = 0.20
A = 0.15
A = 0.10
A = 0.05
A = 0.00
0.0
0.2
0.4
0.6
0.8
1
2
3
4
5
6