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FOLLOW THE SMALL? INFORMATION-REVEALING ADOPTION BANDWAGONS WHEN OBSERVERS EXPECT LARGER FIRMS TO BENEFIT MORE FROM ADOPTION

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We extend understanding of information-revealing bandwagons by considering a common condition under which adoption of a practice by small organizations, rather than large ones, has a disproportionate influence on future adoption propensities. We hypothesize that when the value of adoption increases with organizational size, smaller adopters have such disproportionate influence because they allow observers better to infer that adoption will be profitable for their own organization. We elaborate the theory by predicting that alternative information sources moderate the influence of smaller adopters. Empirically, we test our theory with longitudinal data on the adoption of the ISO 9000 quality management standard. Copyright © 2007 John Wiley & Sons, Ltd.

INTRODUCTION

Scholars have argued that adoption bandwagons are more likely to develop if organizations with certain attributes are already on board (Rosenkopf and Abrahamson, 1999). One explanation for this phenomenon is that adoption by certain organizations spurs future adoption because these organizations increase the social or economic value of adoption (DiMaggio and Powell, 1983; Scott, 2001; Tolbert and Zucker, 1983). Another theory is that adoption by certain organizations sets off bandwagons because these adopters better reveal information about the value of adoption (Bikhchandani, Hirshleifer, and Welch, 1992; Greve, 1996; Rao, Greve, and Davis, 2001). Although these two perspectives are not exclusive, we separate them in our discussion and label the former 'value-enhancing' and the latter 'information-revealing' theories of adoption bandwagons.[1]

Proponents of both adoption theories have stressed the role of large organizations in promoting bandwagons. Within theories of value-enhancing adoption, large organizations have a disproportionate effect on bandwagons because their actions increase the value of adoption (Haunschild and Miner, 1997; Haveman, 1993). Within theories of information-revealing adoption, large organizations have a disproportionate effect because they are more visible and thus more likely to be emulated (Baum, Li, and Usher, 2000). Large size also often brings with it greater resources, thereby giving an organization's actions an aura of good judgment (Rogers, 1995).

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[1] To simplify our exposition, we drop the repeated use of 'bandwagon.'

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The common agreement of the two theories on the importance of large organizations has made it difficult to untangle their effects on adoption bandwagons. In this paper, we contribute to efforts to differentiate the two perspectives by identifying a case in which an information-revealing theory of adoption makes the unusual prediction that adoption of a practice by smaller organizations, not larger ones, will more strongly influence future adoption propensities. Specifically, we argue that when observers expect the value of using a practice to increase with organizational size, adoption by smaller organizations will have a disproportionate influence because it reveals more information to observers about the size threshold at which adoption becomes valuable. This, in turn, can help observers determine whether adopting the practice would provide value for their own organization.

Our argument can be extended to attributes other than an organization's size. A more general statement of our argument would be that when observers expect the value of a practice to vary systematically with any attribute, these actors will be more strongly influenced by observing adoption at an entity that has less of this attribute (and consequently is expected to benefit less). For example, if the degree of automation in an organization increases the value of using just-in-time inventory (JIT) techniques, then the adoption of JIT techniques by a less automated organization should have a greater influence on the future adoption of JIT.

Despite the generalizability of our analysis to other organizational attributes, three rationales cause us to emphasize the effect of organizational size. First, as discussed earlier, previous research has theorized that the size of adopters plays an important role in shaping adoption processes (e.g., Baum *et al*., 2000; Haunschild and Miner, 1997; Haveman, 1993). Secondly, previous studies have demonstrated that the value of adopting practices and technologies often varies with organizational size (Cohen and Klepper, 1996; Dunne, 1994; Rogers, 1995). For example, adoption of manufacturing techniques, like computer-aided design or numerically controlled machine tools, generally provides a greater net benefit to larger organizations (Astebro, 2002). Finally, the size of an organization is a relatively observable and comparable attribute, and thus is more likely to be used in the adoption calculus of managers.

Previous research provides some precedence for theorizing that large size is not always the predominant determinant of influence. Some scholars have investigated the effect of similarly sized adopters and argued that these adopters may influence adoption propensities because they provide high-fidelity information to observers (Baum *et al*., 2000; Greve, 1998; Kraatz, 1998). The potential effect of smaller adopters, however, has largely been neglected. There has been some research on how cumulative adoption by fringe players shapes future adoption, but fringe players are not always associated with a specific size (Burt, 1980; Krackhardt, 1997; Rosenkopf and Abrahamson, 1999).

Our research contributes to the literature on adoption bandwagons in multiple ways. Firstly, we analyze an important case where theories of value-enhancing and information-revealing adoption make differing predictions about adoption patterns. Secondly, we develop a method for empirically exploring the relative influence of the two theories, and we find evidence that both play some role in adoption. Thirdly, we analyze how alternative information sources combine to determine adoption propensities. Specifically, we integrate theories of knowledge flows with those of adoption by exploring how localized adoption experience and corporate resources moderate the information effect of previous adopters. Finally, our study contributes to recent research efforts to explore the contingencies of adoption patterns and outcomes (Greve and Taylor, 2000; Kim and Miner, 2000; Miner *et al*., 1999).

THEORY AND HYPOTHESES

Theories of information-revealing adoption bandwagons

Scholars have identified several mechanisms by which adopters provide observers with information (Bikhchandani *et al*., 1992; Rao *et al*., 2001; Rosenkopf and Abrahamson, 1999). At the most basic level, adopters can make observers aware of the mere existence of alternatives. More central to the theme of this paper, however, adopters can also provide observers with information about the potential value of adoption. When actors and observers have rich communication links, observers may be able to gather information from previous adopters about the realized costs and benefits of using a particular practice or technology.

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More commonly, however, observers must gather information by witnessing only the fact that others have adopted a practice (Greve, 1998; Mansfield, 1961).

Witnessing adoption can inform observers about the value of the diffusing practice by allowing them to infer the calculus that led to the adoption decision. Specifically, if observers assume that managers in other organizations are making decisions based on benefits and costs, they can infer that adopters thought that the practice would provide a positive return. In making this inference, observers can update their own beliefs about the value of adopting the practice themselves (Bikhchandani *et al*., 1992). After each subsequent observed adoption, this updating process is repeated, and a bandwagon can result. Such information-revealing adoption has been documented in the contexts of trading behavior in stock markets (Choe, Kho, and Stulz, 1999; Wermers, 1999), coverage behavior of securities analysts (Rao *et al*., 2001), and radio stations' adoption of market positions (Greve, 1998).

Though information-revealing adoption bandwagons are thought to result from each actor's attempt to infer beneficial actions, these bandwagons do not always result in efficient outcomes or *ex post* rational behavior. Indeed, an extensive literature has considered how 'information cascades' can cause undesirable outcomes (Bikhchandani, Hirshleifer, and Welch, 1998; Rosenkopf and Abrahamson, 1999). For example, if only a few organizations have private signals (i.e., information) about a practice's value, observers may be unduly influenced by the action of a few early adopters. Believing that previous adopters are acting on better information, observers (both informed and uninformed) may choose to follow the example of these early actors. This process can lead to bandwagon adoption of a useless or even harmful practice (Bikhchandani *et al*., 1998).

Note that theories of information-revealing adoption are agnostic about whether the value of adoption results from a practice's technical or symbolic benefits. These theories posit only that adoption is driven by growing awareness or clearer expectation of this potential value. As a result, this perspective is compatible with research suggesting that symbolic value can be a critical element of adoption decisions (Westphal and Zajac, 2001).

Smaller adopters in information-revealing adoption bandwagons

Theories of information-revealing adoption suggest that observation of certain adopters allows stronger inference about the potential value of adoption (Bikhchandani *et al*., 1998; Rosenkopf and Abrahamson, 1999). Assuming adoption can be observed at all, stronger inference can be made when (1) observers expect that adopters are likely to have made profitable adoption decisions, and (2) adopters provide relevant information to observers. This logic often causes scholars to theorize that larger and more similar organizations have a greater influence on future adoption propensities. Larger organizations are thought to have more impact because observers expect them to have greater resources for identifying valuable practices and thus to make more profitable adoption decisions (Bikhchandani *et al*., 1998; Rogers, 1995). Similar organizations are expected to have more impact because observers expect them to provide more relevant information, particularly when the profitability of adoption varies with organizational characteristics (Baum *et al*., 2000; Greve, 1998).

We extend this line of reasoning by considering how expectations of variable profitability could influence the relative impact of observed adoption by smaller organizations. We theorize that if observers expect larger organizations to benefit more from using a practice (but are uncertain whether their own organization would benefit as well), adoption by a smaller organization will exert a greater stimulus on future adoption. Since observers expect smaller adopters to benefit less, observed adoption by a larger organization need not indicate that a smaller organization can profit as well. In contrast, adoption by a smaller organization provides (*ceteris paribus*) more convincing evidence. Thus, when observers expect larger adopters to benefit more, a smaller organization's decision to adopt can allow particularly useful insight on the value of adoption.

In essence, we propose that observers reason: 'If the managers in *that* (smaller) organization think that they can profit from adoption, I can assume that my organization will profit as well.' To refine our intuition, we used Bayesian analysis to develop a formal model of how adopters of different sizes might influence future adoption propensities (see Appendix). This model assumes that adoption is visible to other organizations, that managers in

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all organizations expect the value of adoption to increase with size, and that some organizations have private information about the value of adoption. The model confirms our intuition that under these conditions smaller organizations will have a greater effect on future adoption propensities.

> *Hypothesis 1: When the value of adoption increases with organizational size, a focal organization's adoption propensity will increase more following adoption by a smaller organization than it will following adoption by a larger organization.*

It is important to stress that the direction of Hypothesis 1 is contingent on expectations of a positive relationship between the profitability of adoption and organizational size.[2] Such a positive relationship is not universal, but it has been frequently hypothesized and demonstrated empirically (Astebro, 2002; Cohen and Klepper, 1996; Sinclair, Klepper, and Cohen, 2000). Larger organizations are expected to profit more from adoption because they can (1) amortize fixed adoption costs or (2) achieve production efficiencies or market premiums over a larger number of units. Empirical studies confirm that smaller organizations frequently have difficulty profitably adopting practices in health insurance, human resource management, automation, and quality management (McGregor and Gomes, 1999; Scott *et al*., 1996). Using the survey *Manufacturing Technology 1988* from the U.S. Department of Commerce, Bureau of the Census, Current Industrial Reports, Dunne (1994) finds that the value of various technologies (ranging from flexible manufacturing systems to automatic storage and sensors) increases with organizational size. The common occurrence of a positive relationship between adoption value and size indicates the importance of research that explicitly considers how expectations of this relationship influence adoption processes.

The moderating effect of alternative sources of information

In the previous section, we extend theories of information-revealing adoption by suggesting that when the value of adopting a practice increases with organizational size, observation of smaller adopters can provide more information about the value of adopting. In an effort to further corroborate our argument, we next explore whether alternative sources of information moderate the influence of smaller adopters. If the influence of smaller adopters is indeed due to an information effect, it follows that alternative sources of information should reduce the influence of smaller adopters.

The preponderance of evidence suggests that information, as with most factors, exhibits diminishing returns, and that information from different sources usually act as partial substitutes (Arrow, 1974). Haunschild and Beckman (1998) argue that information from different sources tends to act as substitutes because the sources provide redundant information or cause information overload. In the context of foreign direct investment, Shaver, Mitchell, and Yeung (1997) also find that information sources act as substitutes so that organizations with prior investment experience gain relatively less from the information spillover created by other foreign entrants. Empirical studies in manufacturing and product development also have shown diminishing returns to information from different sources (Allen, 1995; Chase and Aquilano, 1992). Thus, in forming our hypotheses, we assume that information from different sources act predominantly as substitutes. Drawing on previous research, we identify two important alternative sources of information: local adopters and corporate information-gathering resources.

Research has demonstrated that information transfers more readily within the locale of an organization (Jaffe, Trajtenberg, and Henderson, 1993; Zucker, Darby, and Brewer, 1998). For example, Jaffe *et al*. (1993) used patent citations to demonstrate that innovators are likely to cite patents from geographically local sources. In the context of adoption processes, the notion of localized information spillovers implies that information about a practice should more easily disperse among organizations that are located in spatial proximity (Abrahamson and Rosenkopf, 1993; Knoke, 1982). Local adopters can provide detailed information about the circumstance and the rationale of adoption, thereby enabling observers to assess the value of adoption for their own organization. Through informal conversations among managers of local organizations, exchange of employees, or local networks of organizational relationships,

[2] Note, however, that the information effect from smaller adopters should be independent of whether or not every smaller adopter indeed made a profitable adoption choice. What matters is that observers believe that these adopters are not systematically mistaken.

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managers may also be able to gather information about *realized* costs and benefits among adopters (Darr, Argote, and Epple, 1995). Information about realized experiences may provide a powerful substitute to information inferred from observation of the mere fact of adoption.

Given the effectiveness of information diffusion within locales, we expect local adopters to diminish the influence of the information gained from observing smaller adopters, and we hypothesize:

> *Hypothesis 2: When the value of adoption increases with organizational size, adoption in the focal organization's locale reduces the effect of smaller adopters on the adoption propensity of the focal organization.*

Organizations vary in their ability to acquire information in order to identify and assess new opportunities. Some of these abilities reside within corporate development centers. One of the key roles of such centers is the identification and dissemination of information about valuable new practices (Lenox and King, 2004). Corporations also vary in their ability to engage outsiders or use information networks in finding and assessing new practices and technologies (Haunschild and Beckman, 1998). Cohen and Levinthal (1990) argue that this 'absorptive capacity' determines how well an organization can identify, assess, and acquire potentially valuable new practices.

Research suggests that organizational size provides a suitable proxy for information-gathering ability and activity. This is because size is closely related to investments in specialized knowledge activities. Haunschild and Beckman (1998) argue that corporate size is a suitable proxy for an organization's access to information because larger corporations tend to have greater slack (George, 2005) that can be used to employ boundary spanners and information acquisition personnel. In a similar vein, Dewar and Dutton (1986) find that larger organizations have more technical personnel who are better able to assess the suitability of new practices and technologies. The above discussion suggests that organizations that belong to larger corporations will have greater access to alternative information and thus be less influenced by the observation of smaller adopters. We expect:

> *Hypothesis 3: When the value of adoption increases with organizational size, the size of the corporation to which the focal organization belongs reduces the effect of smaller adopters on the adoption propensity of the focal organization.*

EMPIRICAL ANALYSIS

Research setting

Our study requires a setting in which adoption is observable and the value of adoption is positively related to organizational size. These constraints caused us to choose to explore certified adoption of the ISO 9000 quality management standard.[3] Certification with ISO 9000 allows organizations credibly to communicate to their customers attributes of their quality management system (Anderson, Daly, and Johnson, 1999). It allows us a way to ascertain that organizations have adopted a set of standardized practices for quality management. Since its creation in 1988, more than 500,000 organizations across the world have adopted ISO 9000 (ISO, 2003).

Empirical studies suggest that the cost of adopting ISO 9000 is relatively fixed and thus proportionally lower for larger organizations (e.g., Burg, 1997; SBRT, 1994). Research conducted by a team from several universities found that the average cost of certification for organizations in petrochemicals, for example, is about $9 per thousand dollars of sales for organizations with sales volumes smaller than $25 million, and $1 per thousand dollars of sales for companies with sales volumes of $25–100 million (Naveh *et al.*, 1999). Similar patterns hold for organizations in six other industries investigated.

Research also suggests that per unit benefits from certification are either independent of or positively related to organizational size. The dominant finding is that larger organizations benefit more because certification provides a price premium (or sales winning benefit) across a larger number of products (Zuckerman, 1997). Studies suggest that this premium is an important motivation for and benefit from certification (Anderson *et al.*, 1999; Cole, 1998). Because per unit costs of ISO 9000 are smaller for large organizations, and per unit

[3] In this paper, we use interchangeably the terms 'adoption of' and 'certification with' ISO 9000.

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benefits are equal or larger, the expected net benefit from adopting ISO 9000 should be positively related to organizational size.

Empirical evidence reveals that managers in relevant industries share the expectation that the net benefit of adoption increases with an organization's size. In a survey on ISO 9000, managers reported that 'it is difficult for small companies to pay the costs associated with obtaining and maintaining registration'; ISO may be 'a good system but too involved for small companies'; 'maintaining a quality system compliant to ISO 9000 is still hard for a small company'; and finally, 'the cost to get ISO certified was very high considering we are a small company' (Naveh *et al*., 1999: 291–293). Other surveys revealed that managers felt that 'the benefit of the accreditation process is more easily seen in larger businesses', and that 'marketing and competitive advantages ... are outweighed for most small firms by the cost and administrative burden' (Sims, 1994: 14). Finally, a survey that directly measured expected benefits from ISO 9000 revealed that managers of large organizations expected greater financial gains from adoption than managers of medium- and small-sized companies (Sun and Cheng, 2002).

Sample

ISO 9000 is principally adopted by manufacturing facilities. Thus, our unit of analysis is adoption at U.S. facilities in industries with SIC codes between 2000 and 4000. We use several data sources to construct our sample, including the McGraw-Hill Directory of ISO 9000 certificates, the Dun and Bradstreet (D&B) database of all U.S. manufacturing facilities, the Toxic Release Inventory (TRI), data from the Bureau of Economic Analysis (BEA), and data from the U.S. Census Bureau. The sample is somewhat constrained by the characteristics of the TRI database. Facilities must report to the TRI if their manufacturing processes generate scrap above certain levels and if they have more than nine employees.

Our sample comprises 13,710 U.S. manufacturing facilities. Because we need information on previous adopters to perform our analysis, a facility enters our sample after the first adoption by any facility in that industry. Some facilities enter the sample in 1988, but 1993 is the average entry year. For all industries, our panel ends in 1999 (2000 for the dependent variable). Facilities exit the sample once they have adopted ISO 9000, or at the end of the panel. Because we wish to explore how observation of other adopters influences the focal facility's adoption decision, we need to have a certain number of facilities in each industry for such an observation process to be plausible. We therefore only consider industries that contain more than 20 facilities. We distinguish 178 industries on the four-digit SIC code level.

Measures

Dependent variable

We measure adoption with ISO 9000 as a binary variable that takes on a value of '1' if the organization certifies with ISO 9000 anytime between 1988 and 2000. Certification occurs at the facility level. In our sample, 3,112 facilities (23%) gain certification.

Independent variables

To test Hypothesis 1 and ensure the robustness of our findings, we employ three different operationalizations of our main construct. The need for multiple operationalizations is driven in part by the dynamic properties of our theory. We conjecture that adoption by smaller organizations provides information to managers in larger organizations about whether or not their organization should also adopt. Analyzing this effect over two periods is straightforward: we can simply analyze how the pattern of adopters in the first period influences adoption in the subsequent period. Analyzing adoption for more than two periods, however, requires us to make assumptions about how observers might be differentially influenced by adopters in the first period (who presumably adopted because of their private information) and adopters in the following periods (who might themselves have been influenced by earlier adopters). Our three approaches use different assumptions of this process and allow us to test the robustness of our analysis.

Our first approach assumes that managers are predominantly influenced by the initial adopters. We create a measure (*Smaller Adopter*) that captures the pattern of adoption in the first year of adoption in each industry. The measure is a binary variable that captures for each facility whether

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a smaller facility in the industry (four-digit SIC code) adopted ISO 9000 in the first year of adoption (see below for our measure of facility size). To compare the influence of smaller and larger initial adopters, we follow the equivalent procedure to create *Larger Adopter*. Operationalizing *Smaller Adopter* and *Larger Adopter* in this way has the advantage that the variables only capture adopters whose adoption decisions were driven by private information and decision making (as opposed to some imitation or updating rule). From the perspective of theories of information-revealing adoption, it should be these initial adopters from whom observers can best infer information about the profitability of adoption.

Our second approach uses a common heuristic for how organizations may be influenced by the information provided by previous adopters. The variable used in this approach, *Number Smaller Adopters*, captures for each facility and year the logged number of adopters in the facility's industry (four-digit SIC code) that are smaller than the focal facility. We employ a logged count of adopters because previous research has shown that inference processes often follow a log form[4] (Argote, Beckman, and Epple, 1990; Rao *et al*., 2001). The variable *Number Larger Adopters* captures for each facility and year the logged number of adopters in the facility's industry that are larger. Using the count of previous adopters has the advantage that it represents a common method for capturing the influence of previous adopters (Haunschild and Miner, 1997; Haveman, 1993; Kraatz, 1998; Rao *et al*., 2001), thereby making our analysis more comparable to existing research. This specification has, however, the disadvantage that it does not differentiate between the influences of previous adopters who acted based upon private information and those who were themselves influenced by observed adoption.

The third operationalization of our main independent variable (*Bayesian Inference*) uses Bayesian inference analysis to estimate precisely what inferences an uninformed but rational manager could make by observing previous adopters. Our Bayesian model assumes that all managers expect the value of adoption to increase with size, but only some managers have private information about the size necessary to make adoption profitable. Other managers have no information (diffuse priors) about this threshold value. Uninformed managers attempt to infer the threshold value by observing previous adopters and using Bayes' rule. This final operationalization of our main independent variable has the advantage of allowing a formal derivation of our construct (see Appendix) but it sacrifices intuitive clarity.[5]

We use two approaches to test whether adoption in an organization's locale moderates the effect of adoption by smaller organizations (Hypothesis 2). Both approaches assume that internal information about realized costs and benefits of adoption disperse to geographically local organizations and that this internal information is valuable to all observers, not just those of a particular size. The two approaches differ in the assumptions they make about the parametric form of the moderating effect of local adoption. *Adopter in MSA* is a binary variable that captures whether there is any adopter in the industry (four-digit SIC code) and local area (measured by Metropolitan Statistical Area or MSA). *Number Adopters in MSA* captures the logged number of adopters that are located in the focal facility's industry and MSA. Both variables are updated for each year.

MSAs are defined by the U.S. Census and represent large population nucleus (and adjacent communities) that have a high degree of economic and social integration (FIPS, 1995). Approximately 20 percent of U.S. counties are captured in MSAs. Because most facilities in our sample are located in metropolitan areas, we are able to identify a Census-defined MSA for 75 percent of our facilities. For facilities whose zip code cannot be linked to an identifiable MSA, we assume that they are located in areas not captured as an MSA. For each of these facilities, we create a unique MSA, reflecting that these facilities do not belong to a local collective that has economic and social ties. For our measures, we only capture those facilities in the MSA that are also in the focal facility's industry because the exact relationship between size and value of adoption may be industry specific. A meat-processing plant with more than 20 employees, for example, may find adoption of ISO 9000 profitable, while the size threshold may be much

[4] As discussed later in the paper, we conducted robustness tests using other parameter specifications.

[5] Because the Bayesian inference process implicitly considers the potential influence of larger adopters, testing Hypothesis 1 using *Bayesian Inference* does not require including a separate measure of larger adopters.

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higher for a chemical manufacturer. As a result, even within an MSA, observers should find industry internal adoption to be the most informative. We capture previous local adopters irrespective of their size because we argue that spatial proximity enhances information flow such that observers learn not only about the fact of adoption but also about realized costs and benefits. Such internal information should provide sufficient details for observers to find the information useful irrespective of the size of the information sender.[6] To test the robustness of our spatial specification, we used an alternative measure of local area as the 50-mile area surrounding each facility. We obtained results that confirmed the interpretation of those reported.

We use *Corporate Size* to test Hypothesis 3. We capture corporate size as the number of facilities belonging to a corporation in each year. To test the robustness of this variable, we also measured corporate size as the logged sum of total employees of all facilities belonging to a corporation in each year. These two variables are correlated at 84 percent and generate results that are substantially the same. We chose to use the number of facilities in our reported results because the variability of labor intensity across our different industries may confound use of total corporate employees as an accurate measure of relative corporate size. Furthermore, in the context of our study, the number of facilities might be the more appropriate measure of corporate size because we examine adoption of ISO 9000 at the facility level.

Control variables

Alternative mimetic and normative processes, coercive pressures, and desires for operational improvement could shape ISO 9000 adoption decisions (Cole, 1998; Guler, Guillen, and MacPherson, 2002; Uzumeri, 1997). We use control variables to capture the influence of these factors.

Two variables control for the influence of alternative mimetic processes: peer pressure and the degree of certification within each industry. We capture peer pressure by controlling for the potential influence of similarly sized adopters on mimetic adoption. Specifically, we construct *Peer Pressure* to estimate the extent to which adoption of ISO 9000 is more common among facilities of similar size to the focal facility. Using the total number of adopters in industry j and year t, we calculate a constant density function ($\phi(z_{jt}) = \alpha$) for adoption. We then estimate a function of observed density ($o(z_{jt})$) as a function of facility size in that industry and year (z_{jt}). When $o(z_{jt}) > \alpha$, it means that in industry j in year t facilities of approximately size z appear to have a greater than average tendency to adopt. We create a normalized measure of this tendency ($\gamma(z_{jt})$) by subtracting and dividing by the average adoption propensity α:

$$\gamma(z_{jt}) = \frac{o(z_{jt}) - \alpha}{\alpha} \tag{1}$$

Theories of peer influence speculate that facilities are more likely to be influenced by more similar others, but the functional form of this similarity has not been fully specified. For our analysis, we give it an inverse proportional form. Thus, for a facility i of size x in year t, the formula for peer group pressure can be written:

$$\text{Peer Group Pressure}_{it} = \int_0^\infty \frac{\gamma(z_{jt})}{(1 + |z_{jt} - x_{it}|)} \tag{2}$$

As desired, the behavior of more similar organizations will have a disproportionate effect on this measure. As z approaches x, the denominator approaches 1 and the effect of peers approaches $\gamma(z_{jt})$. As z moves away from x, the effect of other organizations on the focal organization decreases as an inverse function of the difference in their size.

Our second control variable for mimetic adoption captures the possibility that the sheer number of previous adopters shapes adoption propensities (Haunschild and Miner, 1997; Rosenkopf and Abrahamson, 1999). We measure *Industry Certification* as the annual percentage of certified facilities in each four-digit SIC code.

Industry associations may exert normative pressures for adoption. For example, the Aerospace Industries Association influenced the diffusion of ISO 9000 among U.S. airframe and jet engine companies (Velocci, 1999) and the Chemical Industries

[6] To test the robustness of this argument, we also tested the effects of (i) a smaller adopter and (ii) the number of smaller adopters in the focal facility's MSA and industry. Consistent with our hypotheses, we found that both a smaller adopter and a greater number of smaller adopters in the same MSA and industry significantly reduced the information effect of a smaller adopter(s) on the focal organization's adoption propensity. Detailed results of this analysis are available from the authors upon request.

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Associations in the U.K., Germany, and France were instrumental in the diffusion of ISO 9000 in the European chemical sectors (Chynoweth and Roberts, 1992). Yet not every industry association is equally active—in fact, budgets, staff, and committee activities vary greatly across associations (Barnett, 2006; Barnett, Mischke, and Ocasio, 2000). To capture the potential influence of industry association activity, we create *Association Pressure*. This variable measures the logged ratio of an industry association's expenses per association member.[7] Data for industry association expenses were taken from the Urban Institute, which makes available data collected on Form 990 by the Internal Revenue Service. Data for industry association membership were taken from the 2002 Encyclopedia of Associations Database provided by Thomson Gale, Gale Research Co., Detroit, Michigan, U.S.A.[8] Each industry association indicates a primary SIC code, and we use this SIC code to match facility and association data. Because association data are available for only 90 manufacturing SIC codes at the four-digit level, we fill in missing values by calculating the median value of *Association Pressure* at the three-digit SIC code level.

To account for the effect of coercive pressures, we calculate two supply chain variables. First, *Supply Chain Pressure* captures pressure to adopt from downstream supply chain partners in the United States. These pressures are particularly strong when supply chain partners are themselves certified (Uzumeri, 1997). *Supply Chain Pressure* thus measures for each year and SIC code the probability that a facility from that SIC code sells its outputs to an ISO certified buyer. To trace supplier relationships among industries, we transform the Input–Output codes from the BEA into four-digit SIC codes and convert the Input–Output tables into 'Sell-to and Buy-from' tables.

Coercive pressures for adoption may also originate from foreign buyers. Buyers that are located outside of the United States have greater difficulty accessing information about U.S. suppliers and thus find it harder to assess their quality (Caves, 1996). To overcome this problem of asymmetric information, foreign buyers may request suppliers to be ISO 9000 certified. In fact, many companies in the United States perceive ISO 9000 certification to be a prerequisite for exporting into Europe (Mendel, 2002; Uzumeri, 1997). To capture this coercive effect, we use export data from the Census Bureau of Foreign Trade and create *Supply to Foreign*. This variable measures the percentage of shipments that is exported for each four-digit SIC code and year. We tested for the effect of varying export destinations (e.g., Europe vs. Asia) but did not find differential effects for different export destinations.

We also control for the effect of facility-level variables. Controlling for a facility's size and operational performance is important since the value of adoption is expected to vary with organizational size and because some facilities may adopt ISO 9000 to improve their operations (Cole, 1998). We measure *Relative Facility Size* as the log of the number of employees employed in each facility in each year. Owing to the industry-level differences in labor intensity mentioned above, we normalize this variable by industry and year. We measure operational performance by using government-mandated data to estimate scrap rates for public and private facilities. To create *Operational Performance*, we calculate the difference between the observed level of scrap generated by the facility and the expected level for a facility of that size in that industry in that year (King and Lenox, 2000). Specifically, separately for each year and industry, we regress the log of scrap generation on *Facility Size* and the squared term of *Facility Size*. The residual of this regression (normalized by its standard error) provides an assessment of the facility's performance relative to its industry in that year. Facilities with positive residuals generated more scrap than expected given their size. We reverse the sign of this measure because relatively more scrap is evidence of lower operational performance.

Finally, we include industry and year dummies in our analysis. It is possible that larger diffusion patterns affect how adoption hazards change with time. To address the temporal elements of this concern in a nonparametric way, we include *Year Fixed Effects*. It is also possible that unobserved industry differences could confound our results. To account for this, we include *Industry Fixed Effects* (at the three-digit SIC code level). We present the descriptive statistics of our variables and a correlation table in Tables 1 and 2.

[7] An alternative specification with expenses per industry member yields confirmatory results.

[8] We would like to thank Michael Barnett from the University of South Florida for collecting and manipulating all association-related data, and for generously sharing these data with us.

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Table 1. Descriptive statistics

Variable	Mean	S.D.	Min.	Max.
1 Smaller Adopter	0.47	0.50	0.00	1.00
2 Number Smaller Adopters	1.32	1.21	0.00	5.26
3 Bayesian Inference	0.84	0.30	0.01	1.00
4 Larger Adopter	0.87	0.34	0.00	1.00
5 Number Larger Adopters	1.99	1.29	0.00	5.26
6 Number Adopters in MSA	0.30	0.63	0.00	5.01
7 Adopter in MSA	0.16	0.36	0.00	1.00
8 Corporate Size	1.71	1.56	0.00	5.76
9 Peer Pressure	−0.08	0.55	−2.51	2.84
10 Industry Certification	0.06	0.08	0.00	0.73
11 Association Pressure	9.75	1.40	7.31	13.45
12 Supply Chain Pressure	0.04	0.04	0.00	0.23
13 Supply to Foreign	0.04	0.04	0.00	0.55
14 Relative Facility Size[a]	−0.06	0.99	−5.51	5.37
15 Operational Performance[a]	0.02	1.01	−4.35	6.43

$N = 66,520$.
Year variables omitted from table.
[a] Variable values are normalized. Note that the means of these normalized variables do not perfectly equal zero. This is because we calculated the summary statistics considering only facilities until they adopt (once a facility adopts, it no longer is part of the risk set). For the normalization process, however, we used the entire sample.

Analysis

We use a logistic regression to perform the statistical tests of our theory. The model is specified as:

$$P_{it+1} = F(Z) = F(\mathbf{bX}_{it}) = e_{it}^{(Z)}/(1 + e_{it}^{(Z)})$$

where P is the probability that facility i will adopt ISO 9000 in the next period $(t + 1)$. The vector $\mathbf{X}_{it}$ represents the characteristics of the ith facility in period t. Once a facility adopts, it is no longer at risk for adoption and is removed from the sample. We also add a random-effect term to the analysis to partially correct for unobserved facility differences. We use a random- rather than a fixed-effect specification because the fixed-effect model would disregard all observations that do not adopt ISO 9000 within our panel. Furthermore, a fixed-effect specification would prohibit the interpretation of any variables with values that do not vary across groups. The drawback of the random-effect specification is that it assumes facility heterogeneity that is randomly distributed across facilities. To investigate the robustness of our estimations to violations of this assumption, we specified a reduced model that included facility fixed effects. For our main effect, we found confirming evidence for our findings.

Results

Table 3 reports the results of our statistical analysis. Considering first the effect of our control variables, we find that adoption propensities increase with corporate size. With respect to normative and coercive pressures for adoption, we find that peer pressure, association pressure, supply chain pressure, and supplying to foreign buyers all increase adoption propensities. The degree of industry certification does not significantly affect adoption propensities in most models. However, this variable becomes strongly significant if we exclude the industry fixed effects, indicating that adoption trends may be industry specific. With respect to the influence of facility attributes, we find that greater relative facility size increases adoption propensities. This finding may represent confirmation that the net benefit of adoption increases with size. Below-average operational performance also increases adoption propensities, possibly indicating that facilities with inferior performance seek ISO 9000 in order to improve their performance.

Turning to the hypothesized impact of smaller adopters (Hypothesis 1), we find evidence that facilities have an increased tendency to adopt ISO 9000 if they are larger than an adopter in the initial year of adoption (Models 1 and 2), if there is a greater number of smaller facilities that have adopted (Models 3 and 4), and if Bayesian inference would predict that they are large enough to adopt profitably (Models 5 and 6). Using Model 1 to assess the economic impact of our independent variable, we find that initial adoption by smaller organizations increases the adoption propensity of an average facility from a 0.23 percent chance of adoption per year to a 0.45 percent chance. For the entire 10-year panel period, this implies that smaller initial adopters almost double future adoption propensities from 2.3 percent to 4.5 percent.

To fully test Hypothesis 1, we need to compare the effect of smaller adopters with that of larger adopters. Models 1–4 indicate that larger adopters exert a statistically significant influence, but one that is comparably weaker than that exerted by smaller adopters. For Models 1 and 2, a t-test reveals that the effect of smaller initial adopters is significantly stronger than that of larger initial adopters ($p < 0.05$). Similarly, for Models 3

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Table 2. Correlation table

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Smaller Adopter	1.00														
2 Number Smaller Adopters	0.34	1.00													
3 Bayesian Inference	0.40	0.58	1.00												
4 Larger Adopter	−0.41	−0.12	−0.21	1.00											
5 Number Larger Adopters	−0.24	0.45	0.21	0.41	1.00										
6 Number Adopters in MSA	−0.01	0.39	0.17	0.06	0.39	1.00									
7 Adopter in MSA	−0.01	0.31	0.15	0.05	0.32	0.74	1.00								
8 Corporate Size	0.16	0.12	0.10	−0.14	−0.14	−0.01	0.00	1.00							
9 Peer Pressure	0.30	0.30	0.06	−0.11	−0.33	−0.04	−0.03	0.15	1.00						
10 Industry Certification	0.04	0.57	0.25	0.10	0.59	0.36	0.25	0.04	−0.13	1.00					
11 Association Pressure	−0.05	0.07	0.02	0.10	0.12	0.03	0.06	0.08	−0.04	0.11	1.00				
12 Supply Chain Pressure	0.02	0.58	0.30	0.06	0.60	0.37	0.28	−0.06	−0.11	0.73	0.12	1.00			
13 Supply to Foreign	0.05	0.11	0.07	−0.11	0.08	0.08	0.06	0.12	−0.05	0.20	0.19	0.06	1.00		
14 Relative Facility Size	0.53	0.47	0.53	−0.44	−0.37	0.00	0.00	0.25	0.49	−0.04	−0.01	−0.04	−0.01	1.00	
15 Operational Performance	0.00	0.01	0.02	0.00	0.01	0.00	0.00	−0.06	−0.01	0.01	0.00	0.01	0.00	0.01	1.00

N = 66,520.
Year variables omitted from table.

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Table 3. Model results

	Model 1[a]	Model 2[a]	Model 3[b]	Model 4[b]	Model 5[c]	Model 6[c]
Independent Variable (IV)	0.477***	0.458***	0.563***	0.542***	1.204***	1.233***
	(0.087)	(0.086)	(0.055)	(0.054)	(0.184)	(0.185)
Larger Adopter/Number Larger Adopters	0.194*	0.191*	0.171***	0.174***		
	(0.082)	(0.083)	(0.041)	(0.041)		
IV × Number Adopters in MSA	−0.145*		−0.119***		−0.353	
	(0.063)		(0.028)		(0.206)	
IV × Adopter in MSA		−0.164		−0.157**		−0.804**
		(0.110)		(0.047)		(0.294)
IV × Corporate Size	−0.120***	−0.120***	−0.086***	−0.087***	−0.170*	−0.173*
	(0.030)	(0.030)	(0.012)	(0.012)	(0.069)	(0.069)
Number Adopters in MSA	0.171**		0.319***		0.413*	
	(0.051)		(0.083)		(0.203)	
Adopter in MSA		0.358***		0.510***		1.010***
		(0.085)		(0.124)		(0.287)
Corporate Size	0.177***	0.177***	0.281***	0.283***	0.261***	0.264***
	(0.025)	(0.025)	(0.030)	(0.029)	(0.065)	(0.065)
Peer Pressure	0.205***	0.201***	0.160**	0.154**	0.288***	0.286***
	(0.045)	(0.045)	(0.049)	(0.048)	(0.045)	(0.045)
Industry Certification	−0.181	−0.189	−1.299*	−1.427**	0.021	0.037
	(0.475)	(0.473)	(0.530)	(0.531)	(0.465)	(0.462)
Association Pressure	0.243***	0.234***	0.122	0.126	0.218**	0.209**
	(0.066)	(0.066)	(0.070)	(0.069)	(0.065)	(0.065)
Supply Chain Pressure	7.714***	7.526***	6.079***	5.993***	7.029***	6.880***
	(1.550)	(1.552)	(1.629)	(1.630)	(1.533)	(1.533)
Supply to Foreign	2.439***	2.386**	1.881**	1.849*	1.861**	1.771**
	(0.685)	(0.688)	(0.728)	(0.728)	(0.661)	(0.661)
Relative Facility Size	0.306***	0.307***	0.226***	0.233***	0.199***	0.200***
	(0.037)	(0.037)	(0.049)	(0.049)	(0.035)	(0.035)
Operational Performance	−0.118***	−0.118***	−0.126***	−0.126***	−0.118***	−0.118***
	(0.024)	(0.024)	(0.025)	(0.025)	(0.024)	(0.024)
Year and Ind. Fixed Effects	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Log Likelihood	−11322.36	−11316.71	−11219.08	−11220.3	−11314.71	−11306.27
Chi-square (d.f.)	1847.9 (75)	1859.2 (75)	2054.4 (75)	2051.9 (75)	1863.1 (74)	1880.1 (74)

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. All tests are two-tailed.
Number of observations = 66,520. Number of facilities = 13,710.
Constant omitted from table due to inclusion of industry and year dummies.
[a] The independent variable in Models 1 and 2 is the binary variable 'Smaller Adopter.' Models 1 and 2 use the binary variable 'Larger Adopter.'
[b] The independent variable in Models 3 and 4 is the count variable 'Number Smaller Adopters.' Models 3 and 4 use the count variable 'Number Larger Adopters.'
[c] The independent variable in Models 5 and 6 is the inference variable 'Bayesian Inference.'

and 4, we find that a greater number of smaller adopters has a significantly stronger effect than a greater number of larger adopters ($p < 0.001$). For Models 5 and 6, such a comparative analysis is unnecessary because our specification of *Bayesian Inference* represents a test of a predicted functional form for the relative effect of smaller and larger adopters. Thus, across all models, we find consistent support for the hypothesis that smaller adopters exert a comparably stronger influence on future adoption than larger adopters.

Given that our theory suggests that smaller adopters provide more useful information, what might drive the significant effect of larger adopters? It is possible that our measures of larger adopters capture some industry-level adoption propensities. The tendency of *Industry Certification* to gain significance as we remove *Larger Adopters* supports this explanation. It also is possible that a larger adopter spuriously picks up the information effect that was initiated by a smaller adopter. For example, consider a case in which a

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small adopter triggers adoption by a large facility in $t + 1$ and adoption by a medium-sized facility in $t + 2$. Here, the medium-sized facility seems influenced by both the small and the large adopter, but the measured effect of the large adopter would be a spurious result. That said, the influence of larger adopters may well also represent evidence of a value-enhancing bandwagon that, albeit with a comparably weaker effect, may work in tandem with the information-revealing bandwagon as larger adopters influence the perceived legitimacy of the practice.

Turning to Hypothesis 2, we find some evidence that adoption within the organization's locale moderates the information effect of smaller adopters. Across two of the three specifications, we find significant evidence that adoption by a nearby organization in the same industry reduces the importance of smaller adopters on future adoption propensities (Models 4 and 6). Likewise, more adopters in the facility's MSA reduce the information effect of a smaller initial adopter (Model 1) as well as that of more numerous smaller adopters (Model 3). A single local adopter does not, however, significantly reduce the information effect from a smaller initial adopter (Model 2), and more local adopters do not reduce the information effect from the Bayesian inference process (Model 5). We surmise that this weakness in our findings may be partially caused by the tendency of industries to cluster. The resulting correlation among industry and location variables may have expanded our standard error estimates.

We find consistent support for Hypothesis 3. Across all of our specifications, we find that facilities that are part of larger corporations are less influenced by smaller adopters. This result is consistent with the notion that larger organizations have better access to information about new practices such that facilities belonging to large organizations are less dependent on information inferred from observed adoption.

The chi-squares for all models indicate good model fits. Note, though, that the models are not nested and that a cross-model comparison of this fit criterion therefore would be misleading.

Robustness and specification analysis

To test the robustness of our analysis and to further explore its meaning, we investigated numerous alternative specifications. First, we relaxed the log odds specification of our logistic analysis and instead used a nonparametric partial-likelihood Cox regression. We obtained results for the hypothesized relationships that were consistent in sign and significance to those shown.

Second, we investigated whether or not our measure of the effect of smaller adopters might be confounded with the effect of general adoption. The concern is that as we observe more adopters, the probability of observing smaller adopters could increase even if adoption occurred randomly. This is because the more adopters we randomly 'draw' in one industry, the greater the variance in their size, and thus the greater the probability of drawing a small adopter in this industry. Thus, with more adopters, we should expect the smallest adopter to be relatively smaller, causing our independent variables to increase in value. To address this concern, we calculated the expected smallest adopter given the observed number of adopters in each industry and year (i.e., the first-order statistic), and created a dummy variable that takes a value of '1' if the size of the focal organization is above the size of the expected smallest adopter. The effect of this variable is insignificant when included in our analysis, and does not change the sign or significance of the reported results.

Third, we used Monte Carlo simulation to test whether or not failure on the part of managers to observe all adopters might influence our analysis. We performed this test for our *Baysian Inference* variable and describe it in more detail in the Appendix. We find that our results are robust as long as observers do not overlook more than 50 percent of the actual adopters.

Fourth, we explored the sensitivity of our analyses in Models 3 and 4 to the log specification of the impact of previous smaller adopters. We substituted two variables, the number of smaller adopters and the squared number of smaller adopters, and obtained similar results.[9]

We conducted a final robustness test to ensure that our analysis is capturing the effect of smaller adopters on observers in other facilities and not their effect on our estimation. Put differently, we wanted to rule out the possibility that a pre-existing size threshold existed and that we (the authors of this article) were simply learning about this

[9] For both Model 3 and Model 4, the coefficient of the main effect equals 0.034 ($p < 0.001$) and the coefficient for the square term equals -0.0003 ($p < 0.001$).

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threshold by observing successive adoption. To test this, we created for each industry the final Bayesian estimate of the size threshold based on all adoption in that industry up to the final period. We then included this estimate as a constant variable for all years. Including this variable in Models 5 and 6 did not change the sign or significance of the coefficient for our main independent variable, but it did reduce the significance of our interaction terms. This loss of significance may be caused by the expansion of the standard errors caused by the multicollinearity between our independent variable and the measure of the final size threshold used in the robustness test.

DISCUSSION

We extend theories of information-revealing adoption to analyze a case in which smaller adopters have an unusual and disproportionate influence on future adoption propensities. We empirically explore the adoption of ISO 9000—a setting that meets our case conditions—and find evidence that smaller adopters have a greater effect on future adoption propensities than larger ones. Moreover, we further validate our theory that observation of smaller adopters allows insight into the value of adoption by showing that access to other information sources reduces the effect of smaller adopters. Specifically, we find moderate evidence that access to information from spatially proximate adopters moderates the effect of smaller adopters. We also find that corporate size reduces the influence of smaller adopters. We suggest that this is because larger corporations have more resources to gather and disseminate information about new practices within the organization. The combined evidence provided by our main and ancillary predictions provides support for our theory.

Why do our findings differ from the preponderance of previous research? One explanation is that we purposely chose a setting that meets our conditions and where we therefore expected such an outcome: specifically, a setting where adoption is a visible act (because it is publicly certified) and actors expect the value of adoption to increase with organizational size. The contexts in which previous studies were conducted may not have fulfilled these conditions. Haunschild and Miner (1997), for example, explore adoption bandwagons in the context of investment banker choices for acquisitions and find that larger companies strongly influenced the choices of others. Baum *et al*. (2000) find that larger firms' location choices for chain acquisitions can sometimes set off bandwagons. In both of these empirical contexts, it is not clear that the value of adoption increases with organizational size, and smaller adopters may therefore have had little influence.

Another explanation is that the existence of published registries of ISO 9000 adopters may have reduced the relative visibility of larger adopters. Specifically, to the degree that previous studies found larger adopters to be more influential because of their greater visibility, this visibility effect may have been less pronounced in our context because published registries provide information on certified organizations of all sizes.

A principal implication of our study is that settings exist where theories of value-enhancing and information-revealing adoption make contradictory predictions. By analyzing these different settings, scholars may be better able to understand the mechanisms and import of the two theories. Do our findings suggest that information-revealing bandwagon processes are always more important than value-enhancing ones? Not at all. We may have considered a case in which previous adoption provides little change in the value of the practice and thus legitimacy concerns are relatively less important. ISO 9000 was widely considered to be legitimate from its very inception. ISO 9000 was created by the International Organization for Standardization in Geneva, which infused the standard with legitimacy. As a result, the size or status of previous adopters may not increase substantially the legitimacy of the standard. Moreover, our empirical approach may have underestimated legitimacy effects by only exploring *intra*-industry adoption processes of ISO 9000.[10]

Findings from at least one previous study are in line with ours and suggest that our results are not an isolated case. In a study of bandwagon effects in curriculum changes, Kraatz (1998) finds that larger previous adopters negatively affected program adoption and suggests that 'the legitimacy or status concerns at the heart of much theorizing on interorganizational imitation are not critical to program diffusion in the present context' (Kraatz, 1998: 632). One explanation for this finding is that

[10] We thank an anonymous reviewer for pointing out these explanations.

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the substantial organizational changes associated with curriculum modifications caused colleges to consider primarily whether these modifications fit the colleges' existing operations, thereby making legitimacy considerations a secondary issue. As a result, similar adopters, rather than larger ones, may have been more influential. Interpreted from the perspective of our study, it also is possible that curriculum changes provided greater value to larger institutions, which would have decreased the influence of large adopters on subsequent adoption.

We believe that our findings (and those discussed above) suggest the need for more research on how conditions in adoption environments (e.g., managerial expectations, observability, initial legitimacy) affect the relative influence of different types of organizations. In conducting such research, scholars may benefit by identifying contexts that allow comparison of various theories. Our results suggest that multiple forces are often at play, and that scholarship should consider the contingencies that affect their relative strength and direction.

Our study opens some interesting avenues for future research. In this study, we have assumed that managers do not *systematically* misjudge the value of adoption. In future research, we hope to explore cases where the reliability of the information from previous adopters varies systematically as a function of different organizational and industry-level attributes.

Future research could also investigate patterns in abandonment subsequent to adoption. Rao *et al.* (2001) find that inference from a greater number of previous adopters causes systematic overestimation of adoption profitability and leads to subsequent abandonment. While our theory allows for such a process, we do not specifically address it in this study. A theoretical and empirical exploration of the conditions for systematically unprofitable adoption (and resulting abandonment of the adopted practice) would represent a substantial contribution to scholarship.

Need for further research also exists with respect to the moderating effect of additional information sources. We have argued that corporate size reduces the effect of observed adoption because larger corporations have the resources to provide their facilities with information about new practices. Using the number of facilities as a measure of corporate size, we found evidence for such a moderating effect in this study. However, we did not explore whether the degree to which corporations are diversified (i.e., have facilities in different industries) influences facility adoption behavior. It is conceivable that highly focused corporations use the information from observed within-industry adoption differently than broadly diversified corporations.

Insight on information-revealing bandwagons could furthermore be gained from direct measurement of managerial expectations about variations in the practice's profitability. For the purpose of this study, we chose a context in which previous studies had identified managerial expectations that matched the conditions of our theory, and we found that adoption behavior was consistent with stipulated expectations. However, when testing the applicability of our theory in other contexts, a direct measure of managerial expectations might allow a more differentiated view of the relationship between profitability expectations and adoption behaviors.

Finally, additional insights might be gained by testing our ideas across different adoption processes. Our study does consider the adoption process of ISO 9000 within multiple industries, and thus provides evidence that our ideas have explanatory power in different settings (so long as they meet the assumptions of our theory). However, our study only considers adoption of one practice, and thus care should be taken in extrapolating to adoption of different types of practices. In future research, we hope to explore our ideas in other empirical settings.

For practitioners, our study has important implications. In today's dynamic competitive landscapes, organizations must gather information from a variety of sources. Observation of others represents one important learning path to competitive advantage. Yet attention is a scarce resource, requiring managers to allocate carefully their consideration where it can be used best. While previous studies have emphasized the value of observing more salient or larger organizations, our study suggests that under some conditions managers should allocate more of their attention to the activities of smaller, less prominent organizations.

CONCLUSION

In this article, we contribute to theories of adoption bandwagons by investigating a case in which

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theories of information-revealing adoption predict that smaller organizations will have a stronger effect on future adoption than larger ones. Exploring this case proves valuable because it allows a means of distinguishing whether previous adopters spur bandwagons by revealing information about the value of adoption or by increasing the value of adoption. We argue and find evidence that when the profitability of a practice increases with organizational size—a relatively common case—smaller adopters, rather than larger ones, may have a greater influence on future adoption propensities because they allow observers better to infer that adoption will be profitable for their own organization. In support of this information story, we find that alternative information sources moderate the effect of smaller adopters.

We hope that our findings will encourage future research to advance further theories of adoption processes by exploring the effect of managerial beliefs on adoption patterns and by investigating the differences in the mechanisms underlying various bandwagons.

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REFERENCES

Abrahamson E, Rosenkopf L. 1993. Institutional and competitive bandwagons: using mathematical modeling as a tool to explore innovation diffusion. *Academy of Management Review* **18**(3): 487–518.

Allen TJ. 1995. *Managing the Flow of Technology*. MIT Press: Cambridge, MA.

Anderson S, Daly J, Johnson M. 1999. Why firms seek ISO 9000 certification: regulatory compliance or competitive advantage? *Production and Operations Management* **8**(1): 28–43.

Argote L, Beckman SL, Epple D. 1990. The persistence and transfer of learning in industrial settings. *Management Science* **36**(2): 140–155.

Arrow K. 1974. *The Limits of Organization*. W.W. Norton: New York.

Astebro T. 2002. Noncapital investment costs and the adoption of CAD and CNC in U.S. metalworking industries. *RAND Journal of Economics* **33**(4): 627–688.

Barnett M. 2006. Waves of collectivizing: a dynamic model of competition and cooperation over the life of an industry. *Corporate Reputation Review* **8**(4): 272–292.

Barnett WP, Mischke GA, Ocasio W. 2000. The evolution of collective strategies among organizations. *Organization Studies* **21**(2): 325–355.

Baum J, Li SX, Usher JM. 2000. Making the next move: how experiential and vicarious learning shape the locations of chains' acquisition. *Administrative Science Quarterly* **45**(4): 766–801.

Bikhchandani S, Hirshleifer D, Welch I. 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economics* **100**(5): 992–1026.

Bikhchandani S, Hirshleifer D, Welch I. 1998. Learning from the behavior of others: conformity, fads, and informational cascades. *Journal of Economic Perspectives* **12**(3): 151–170.

Burg R. 1997. Helping small firms get certified: consultants have teamed up with Sheridan to offer group training in ISO standards. *Toronto Star* 7 April: B3.

Burt RS. 1980. Innovation as a structural interest: rethinking the impact of network position on innovation adoption. *Social Networks* **4**: 337–355.

Caves RE. 1996. *Multinational Enterprise and Economic Analysis*. Cambridge University Press: Cambridge, U.K.

Chase R, Acquilano N. 1992. *Production and Operations Management*. Irwin: Boston, MA.

Choe H, Kho BC, Stulz RM. 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics* **54**(2): 227–264.

Chynoweth E, Roberts M. 1992. Quality in the European community: a market test for unification. *Chemical Week* **150**(17): 36–40.

Cohen WM, Klepper S. 1996. A reprise of size and R&D. *Economic Journal* **106**(437): 925–951.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* **35**(1): 128–152.

Cole RE. 1998. Learning from the Quality Movement: what did and what didn't happen? *California Management Review* **41**(1): 43–73.

Darr E, Argote L, Epple D. 1995. The acquisition, transfer, and depreciation of knowledge in service organizations: productivity in franchises. *Management Science* **41**(11): 1750–1763.

Dewar RD, Dutton JE. 1986. The adoption of radical and incremental innovation: an empirical analysis. *Management Science* **32**(11): 1422–1433.

DiMaggio P, Powell W. 1983. The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. *American Sociology Review* **48**(2): 147–160.

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Dunne T. 1994. Plant age and technology use in the U.S. manufacturing industries. *RAND Journal of Economics* **25**(3): 488–499.

FIPS (Federal Information Processing Standards Publication). 1995. *Metropolitan Areas*, FIPS Publication 8-6. National Institute of Standards and Technology: Gaithersburg, MD.

George G. 2005. Slack resources and performance of privately held firms. *Academy of Management Journal* **48**(4): 661–676.

Greve HR. 1996. Patterns of competition: the diffusion of a market position in radio broadcasting. *Administrative Science Quarterly* **41**(1): 29–60.

Greve HR. 1998. Managerial cognition and the mimetic adoption of market positions: what you see is what you do. *Strategic Management Journal* **19**(10): 967–988.

Greve HR, Taylor A. 2000. Innovations as catalysts for organizational change: shifts in organizational cognition and search. *Administrative Science Quarterly* **45**(1): 54–80.

Guler I, Guillen MF, MacPherson JM. 2002. Global competition, institutions, and the diffusion of organizational practices: the international spread of the ISO 9000 quality certificates. *Administrative Science Quarterly* **47**(2): 207–232.

Haunschild PR, Beckman C. 1998. When do interlocks matter? Alternate sources of information and interlock influence. *Administrative Science Quarterly* **43**(4): 54–80.

Haunschild PR, Miner AS. 1997. Modes of interorganizational imitation: the effects of outcome salience and uncertainty. *Administrative Science Quarterly* **42**(3): 472–500.

Haveman HA. 1993. Follow the leader: mimetic isomorphism and entry into new markets. *Administrative Science Quarterly* **38**(4): 593–627.

ISO. 2003. The ISO survey of ISO 9001 : 2000 and ISO 14001 certificates. Thirteenth cycle: up to and including 31 December 2003. http://www.iso.org/iso/en/iso9000-14000/certification/isosurvey.html [3 June 2007].

Jaffe A, Trajtenberg M, Henderson R. 1993. Geographic localization of knowledge spillovers as evidenced by patent citation. *Quarterly Journal of Economics* **108**(3): 577–598.

Kim JY, Miner AS. 2000. Crash test without dummies: a longitudinal study of interorganizational learning from failure experience in the U.S. commercial banking industry, 1984–1998. In *Best Paper Proceedings*, Academy of Management Annual Meeting, Toronto, Ontario, Canada.

King A, Lenox M. 2000. Industry self-regulation without sanctions: the chemical industries Responsible Care program. *Academy of Management Journal* **43**(4): 698–716.

Knoke D. 1982. The spread of municipal reform: temporal, spatial and social dynamics. *American Journal of Sociology* **87**: (September): 1314–1339.

Kraatz MS. 1998. Learning by association? Interorganizational networks and adaptation to environmental change. *Academy of Management Journal* **41**(6): 621–643.

Krackhardt D. 1997. Organizational viscosity and the diffusion of controversial innovations. *Journal of Mathematical Sociology* **22**(2): 177–200.

Lenox M, King A. 2004. Prospects for developing absorptive capacity through internal information provision. *Strategic Management Journal* **25**(4): 331–345.

Mansfield E. 1961. Technical change and the rate of imitation. *Econometrica* **29**(4): 741–766.

McGregor J, Gomes C. 1999. Technology uptake in small and medium-sized enterprises: some evidence from New Zealand. *Journal of Small Business Management* **37**(3): 94–103.

Mendel P. 2002. International standardization and global governance: the spread of quality and environmental management standards. In *Organizations, Policy, and the Natural Environment*, Hoffman A, Ventresca M (eds). Stanford University Press: Stanford, CA; 407–434.

Miner AS, Kim J-Y, Holzinger I, Haunschild P. 1999. Fruits of failure: organizational level failure and population level learning. In *Advances in Strategic Management: Population Level Learning and Industry Change*, Miner A, Anderson P (eds). JAI Press: Stamford, CT; 187–220.

Naveh E, Marcus A, Allen G, Koo Moon H. 1999. *ISO 9000 Survey '99: An Analytical Tool to Assess the Costs, Benefits and Savings of ISO 9000 Registration*. McGraw-Hill: New York.

Rao H, Greve HR, Davis GF. 2001. Fool's gold: social proof in the initiation and abandonment of coverage by Wall Street analysts. *Administrative Science Quarterly* **46**(3): 502–526.

Rogers E. 1995. *The Diffusion of Innovations*. Free Press: New York.

Rosenkopf L, Abrahamson E. 1999. Modeling reputational and informational influences in threshold models of bandwagon innovation diffusion. *Computational and Mathematical Organization Theory* **5**(4): 361–384.

SBRT. 1994. *Small Businesses and BS5750*. Small Business Research Trust: Knutsford, U.K.

Scott P, Jones B, Bramley A, Bolton B. 1996. Enhancing technology and skills in small and medium sized manufacturing firms: problems and prospects. *International Small Business Journal* **14**(3): 85–99.

Scott WR. 2001. *Institutions and Organizations*. Sage: Thousand Oaks, CA.

Shaver JM, Mitchell W, Yeung B. 1997. The effect of own-firm and other-firm experience on foreign direct investment survival in the United States, 1987–92. *Strategic Management Journal* **18**(10): 811–824.

Sims C. 1994. Small business survey shows disenchantment with BS5750. *The Herald* (Glasgow, U.K.) 14 November: 14.

Sinclair G, Klepper S, Cohen W. 2000. What's experience got to do with it? Sources of cost reduction in a large specialty chemicals producer. *Management Science* **46**(1): 28–46.

Sun H, Cheng TK. 2002. Comparing reasons, practices and effects of ISO 9000 certification and TQM

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DOI: 10.1002/smj

implementation in Norwegian SMEs and large firms. *International Small Business Journal* **20**(4): 421–442.
Tolbert PS, Zucker LG. 1983. Institutional sources of change in the formal structure of organizations: the diffusion of civil service reform. *Administrative Science Quarterly* **28**(1): 22–39.
Uzumeri MV. 1997. ISO 9000 and other metastandards: principles for management practice? *Academy of Management Executive* **11**(1): 21–36.
Velocci AL. 1999. Primes pledge to cut excessive audits. *Aviation Week and Space Technology* **151**(11): 77.
Wermers R. 1999. Mutual fund herding and the impact on stock prices. *Journal of Finance* **54**(2): 581–622.
Westphal JD, Zajac EJ. 2001. Decoupling policy from practice: the case of stock repurchase programs. *Administrative Science Quarterly* **46**(2): 202–230.
Zucker L, Darby M, Brewer M. 1998. Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economics Review* **88**(1): 290–307.
Zuckerman A. 1997. Big Three automakers mean business on QS-9000 certification compliance. *Journal of Commerce* 12 November: 14C.

APPENDIX

This Appendix provides a formal model of a bandwagon process that matches the one hypothesized in this paper. It also clarifies how we constructed our measure of *Bayesian Inference* and how we conducted robustness testing on this approach.

The model

Managers of facilities in an industry believe that the value of adoption varies with some attribute θ. In our specific example, θ is facility size. Managers also assume that there is a value of θ above which benefits exceed costs ($B(\theta) > C(\theta)$) and below which they do not. We call this value of θ the 'separating level' S_θ and index it with industry j. We assume that of the N facilities in the industry, some have diffuse priors for S_{θ_j} and some have private information about benefits and costs and know whether their facility i in industry j can profitability adopt ($B_j(\theta_i) > C_j(\theta_i)$). This private information is distributed among facilities in the industry so that each facility has a chance p of having such information. We also assume that facilities observe adopters once a year (for example, when McGraw-Hill publishes its updated data on adopters). We assume that facilities adopt when the probability of $B_j(\theta_i) > C_j(\theta_i)$ exceeds a threshold level ϕ_{ijt}. We assume, however, that not all facilities adopt immediately, because random differences in organizational schedules or contingencies cause managers to delay adopting even though $P(B_j(\theta_i) > C_j(\theta_i)_t) > \phi_{ijt}$.

In the first period, facilities with private information know the value of $B_j(\theta_i)$ and $C_j(\theta_i)$, and thus $P(B_j(\theta_i) > C_j(\theta_i)) = 0$ or 1. Other facilities have no information about benefits and costs and learn about them by observing previous adopters. Thus, in the first year of adoption in the industry ($t = 1$), only facilities with private information adopt. Facilities without private information observe these adopters at the end of the year and use Bayes' rule to update their inference.

For each industry j in year $t = 2$ with $\omega = 1$ to M possible facility-separating levels, Bayes' rule would predict that

$$P(S_{wj}|\{\gamma_{j1}\}) = \frac{P(\{\gamma_{j1}\}|S_{\omega j})P(S_{\omega j})}{\sum_{\omega=1}^{M} P(\{\gamma_{j1}\}|S_{\omega j})P(S_{\omega j})} \qquad (1)$$

with

$S_{\omega j}$ = separating level is at size ω in industry j ($B(\theta)_j > C(\theta)_j$);
$\{\gamma_{jt}\}$ = set of observed adopters in industry j in year 1.

The probability that the focal facility is larger than the eventual smallest adopter (e.g., above the separating level) in industry j is

$$P(\theta_{\text{ij}} > S_{\omega j}) = \sum_{w<\theta_{\text{ij}}} P(S_{\omega j}|\{\gamma_j\}) \qquad (2)$$

where θ_i = size of the focal facility i and $P(\theta_{\text{ij}} > S_{\omega j})$ represents Bayes' estimation; i.e., it reflects the estimation of the focal facility $P(B_{ij} > C_{ij})$.

In years after the first ones, the inference process for non-adopters becomes slightly more complicated because any adopter may have private information (in which case its actions provide new information about the value of adoption) or it may be adopting based on its own inference from observing previous adopters (in which case its actions provide no new information). Since it is unlikely that managers know a priori the distribution of private information p, we assume that they must use observed behaviors to estimate

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whether observed adopters have private information. Because managers can estimate the information provided by previous adopters, they can also estimate the degree to which other managers could make such an inference. The probability that any observed adopter has private information is the probability that it is not adopting based on inferred information. For a facility of size θ in industry j observed adopting in year t, the probability that it has private information $= 1 - P(\theta_{\mathrm{ijt}-1} > S_{\omega j-1})$. In other words, it is the probability that it could not infer that $P(B_j(\theta_i) > C_j(\theta_i))$ given the information it had in the period before it adopted $(t - 1)$.

Calculation

Programs were created in the C programming language to estimate $P(B_j(\theta_i) > C_j(\theta_i)$ for each facility, industry, and year. To simplify calculation each industry was discretized into 40 size levels (ω) that spanned all observed sizes for the industry. The size of the observing facility was updated for each year, but the size of the adopting facilities was held constant at their size in the year of adoption.

Robustness testing

To ensure the robustness of our system, we constructed the measure using different assumptions. We assumed that (a) all adopters were observed, (b) 90 percent were observed, (c) 75 percent were observed, and (d) 50 percent were observed. We also assumed that (i) observers knew the size of all adopters, and (ii) observers estimated the size of adopters with a normally distributed error ε. This error was set at $0.25s$, $0.5s$, and s, where s is the measured standard deviation for the size of our sample of facilities in that industry in that year. Robustness tests confirm sign and significance consistency for observed adoption >50 percent and for size error estimation $\leq 0.5\ s$.

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