FOLLOW THE SMALL?
INFORMATION-BASED ADOPTION BANDWAGONS WHEN PROFITABILITY EXPECTATIONS ARE RELATED TO SIZE

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ABSTRACT

We extend understanding of information-based bandwagons by considering a common condition under which adoption of a practice by small organizations has a disproportionate influence on future adoption propensities. We hypothesize that when the value of adoption is expected to increase with organizational size, smaller adopters have such influence because they allow observers to infer that adoption will be profitable for their own organization. We further elaborate the theory by predicting that alternative information sources will moderate the influence of smaller adopters. Empirically, we test our theory with longitudinal data on the adoption of the ISO 9000 quality management standard.

Keywords: Bandwagons, Mimetic Adoption, Institutional Theory, Inference, Information Cascades

Scholars have argued that bandwagons are more likely to develop if organizations with certain attributes are already on board (Rosenkopf & Abrahamson, 1999). One of these attributes, theory suggests, is the size of the organization. Large size often brings greater social prestige and thus increases the benefit of emulating a large organization's actions (Haunschild & Miner, 1997; Haveman, 1993). Large size also increases the visibility of an firm, thus making it more likely its actions will be observed (Baum, Li & Usher, 2000). Finally, large size often brings with it greater resources, thereby giving an organization's actions an air of good judgment (Rogers, 1995).

The common agreement on the importance of large adopters disguises differences in the underlying theories of bandwagons. One theory is that previous adopters change the social or economic value of adoption and thereby encourage others to adopt as well (DiMaggio & Powell, 1983; Scott, 2001; Tolbert & Zucker, 1983). This perspective matches the notion that large organizations are important because they increase the prestige of the focal practice that is being adopted. An alternative theory is that previous adopters reveal information about the value of adoption (Bikhchandani, Hirshleifer, Welch; 1992; Greve, 1996; Rao, Greve & Davis, 2001). This perspective matches the notion that large organizations have greater impact because they are expected to make better decisions or simply because their actions are easier to see. To distinguish these differing explanations, we label the former perspective "value-based theory" and the latter perspective "information-based theory" of adoption bandwagons. [1]

In this paper, we contribute to research on bandwagons by identifying a case in which information-based theory of adoption makes the surprising prediction that adoption

[1] To simplify our exposition, we drop the repeated use of "bandwagons".

of a practice by smaller organizations, not larger ones, will more strongly influence future adoption propensities. Specifically, we demonstrate that when observers expect the value of adopting a practice to increase with organizational size, an information-based theory of adoption predicts that the action of smaller adopters will have a greater influence on future adoption propensities than the action of larger adopters. We argue that smaller adopters have this influence because they provide more information to observers about the size threshold at which adoption becomes profitable. Put differently, we argue that when larger adopters benefit more from adopting a practice, smaller adopters better allow observers to infer that adoption is profitable for their own organization.

Our argument can easily be extended to attributes other than an organization's size. A more general statement of our theory is that when observers expect the profitability of a practice to vary systematically with any organizational attribute, these observers will be more strongly influenced by observing adoption at an organization that has less of this attribute (and consequently is expected to benefit less). For example, if less mechanized organizations receive a smaller net benefit from the adoption of just-in-time inventory techniques, then the adoption of these techniques by less mechanized organizations should have a greater influence on future adoption. Further a field, our theory suggests that less sophisticated dairy farms should have a disproportionate influence on the adoption of the growth hormone rGBH to enhance milk production. This is because more sophisticated dairy farms gain a greater increase in production from the use of rGBH (Foltz & Chang, 2002), and thus adoption by a less sophisticated farm should send a strong signal of the value of adopting rGBH to observers.

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

Previous research provides some precedence for theorizing that large size is not always the predominant determinant of influence. Most commonly, researchers have focused on 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. In contrast to our theory, bottom-up theories have focused on fringe players, rather than small organizations, to suggest that cumulative adoption by fringe players can shape future adoption by changing the legitimacy of a practice that was initially illegitimate (Burt, 1980; Krackhardt, 1997; Rosenkopf & Abrahamson, 1999).

Our research contributes to the literature on adoption bandwagons in multiple ways. Firstly, we analyze an important case where value-based and information-based theories make distinct 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 identifies an adoption process that can explain bottom-up adoption of a legitimate practice.

THEORY AND HYPOTHESES

Information-based theories of adoption bandwagons

Information-based theories of adoption suggest that previous adopters influence future adoption propensities by providing observers with information about the value of adoption (Bikhchandani et al, 1992; Rao, et al, 2001; Rosenkopf & Abrahamson, 1999). Sometimes, observers can acquire information about realized costs and benefits directly from organizations that have already adopted (Haunschild & Miner, 1997). Yet more commonly, observers must gather information by witnessing only the fact of adoption at other organizations (Greve, 1998; Mansfield, 1961). In doing so, observers that are uncertain whether adoption is profitable may use observation of previous adopters to update their beliefs about the profitability of the practice (Bikhchandani et al, 1992). After each subsequent adopter, the process is repeated, and a bandwagon can result. Such information-based adoption has been documented in the contexts of trading behavior in stock markets (Choe, Kho & Stulz, 1999; Wermers; 1999), coverage behavior of securities analysts (Rao et la, 2001), and radio stations' adoption of market positions (Greve, 1998).

Theories of information-based adoption tend to assume a reasonably high degree of rationality and agency. They assume that adoption is driven by an expectation that benefits exceed costs. Yet rationality and agency do not imply that firms always make the right choice. Indeed, collectively inefficient outcomes can result from an "information cascade" (Bikchandani et al., 1998; Rosenkopf & Abrahamson, 1999). For example, if only some organizations have private 'signals' (i.e., information) about a practice's profitability, organizations without information may be unduly influenced by the action of a few early adopters. Believing that previous adopters are acting on private information, they may choose to follow their lead and thereby exacerbate the bandwagon. This process can lead firms to adopt even though they do not benefit from doing so (Bikchandani et al., 1998).

Information-based adoption theories are agnostic about whether the value of adoption results from a practice's technical value or symbolic value. As a result, an information-based perspective is compatible with research that suggests that symbolic value can be a critical element of adoption decisions. Westphal & Zajac (2001, 1994), for example, find that companies adopt stock repurchasing programs and long-term incentive plans for their symbolic value rather than their technical value. An information-based theory of adoption would suggest that managers would infer whether it is in their own (or their organization's) interest to adopt these symbolic actions by observing whether other firms adopt them.

Smaller adopters in information-based adoption bandwagons

Theories of information-based adoption suggest that observation of certain adopters allows stronger inference about the potential value of adoption. Stronger inference can be made when observers (1) expect that the adopter is likely to have made a profitable adoption decision, and (2) the adopter is relevant to the observing organization. As we discussed earlier, this logic often causes scholars to theorize that larger and more similar organizations should have 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 (Bikchandani 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 adoption by smaller organizations. We theorize that if observers expect larger organizations to benefit more from adopting 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, a smaller organization's decision to adopt reveals unexpected confidence in the value of adoption. Such adoption may imply that these smaller organizations have private information that gives them this confidence. Adoption by a smaller organization also allows clearer inference about the value of adoption. If the value of adoption increases with organizational size, 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) convincing evidence.

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 better understand our intuition, we use Bayesian analysis to develop a more formal model of how adopters of different size might influence future adoption propensities (see Appendix 1). This formal model assumes that adoption is visible to other organizations, that managers in all organizations expect the value of adoption to increase with size, and that some organizations have private information about the value of adoption. This 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 (Asterbro, 2002; Cohen & Klepper, 1996; Sinclair, Klepper & Cohen, 2000). Larger organizations are expected to profit more from adoption because they can (1) amortize fixed adoption cost or (2) achieve production efficiency 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 resources, automation, and quality management (McGregor & Gomes, 1999; Scott, Jones, et al, 1996). Using the Survey of Manufacturing Technology, Dunne (1994) finds that the value of using 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

[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.

organizational size indicates the importance of research that explicitly considers how expectations of this relationship might influence adoption processes.

The moderating effect of alternative sources of information

In the previous section, we extent theories of information-based 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 & Beckman (1998) argue that information from different sources tend to act as substitutes because they provide redundant information or cause information overload. In the context of foreign direct investment, Shaver, Mitchell & Yeung (1997) also find that information sources act as substitutes so that firms 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 & Aquilano, 1992). Thus, in forming our hypotheses, we assume that information from different sources acts 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 & Henderson, 1993; Zucker, Darby & 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 & 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 firms, exchange of employees, or local networks of organizational relationships, managers may also be able to gather information about *realized* costs and benefits among adopters (Darr, Argote, Epple, 1995). Information about realized experience may provide a powerful substitute to information inferred from observation of adoption.

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

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

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 & King, 2004). Corporations also vary in their ability to engage outsiders or use information networks in finding and assessing new practices and technologies (Haunschild & 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 investment in specialized knowledge activities. Haunschild & 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 & Dutton (1986) find that larger organizations have more technical personnel that are better able to assess the suitability of new practices and technologies. The above discussion suggests that facilities 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 effect of smaller adopters on the adoption propensity of the focal organization will be moderated by the size of the corporation to which the focal organization belongs.*

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 firms to credibly communicate to their customers attributes of their quality management system (Anderson, Daly & Johnson, 1999). It allows us a way to ascertain that firms 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, Marcus, 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 benefits are equal or larger, the expected net benefit from adopting ISO 9000 should be positively related to organizational size.

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

Empirical evidence reveals that managers in relevant industries share the expectation that the net benefit of adoption will increase 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). Finally, a survey that directly measured expected benefits from ISO 9000 revealed that managers of large firms expected greater financial gains from adoption than managers of medium and small sized companies (Sun & Cheng, 2002).

Sample

ISO 9000 is adopted by facilities (principally those in manufacturing sectors). Thus, our unit of analysis is facility-level adoption 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 & 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 14,642 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 facilities and industries, our sample ends in 1999 (2000 for the dependent variable). We distinguish 227 industries on the 4 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, 3584 facilities 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 a smaller facility in the industry (4 digit SIC code) adopted ISO 9000 in the first year of adoption (see below for our measure of facility size). To test whether the effect of smaller initial adopters is larger than that of 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 decision likely was driven by private information (as opposed to some imitation rule). From the perspective of information-based adoption theories, it should be these initial adopters from which 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 (4 digit SIC code) that are smaller. We employ a logged count of adopters because previous research has shown that inference processes often follow a log form (Rao et al, 2001; Argote, Beckman, & Epple, 1990). 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 & Miner, 1997; Haverman, 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 that acted based upon private information and those that 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 organizations have private information about the size necessary to make adoption profitable. Other managers have no information (diffuse priors) about this threshold value. Later adopters attempt to infer this threshold 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 1) but it sacrifices intuitive clarity[4].

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 due to locally more effective information dispersion, proximate adopters regardless of their size provide information to observers. The two approaches differ in the assumptions they make about the parametric form of the moderating effect of local

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

adoption. *Adopter in MSA* is a binary variable that captures whether there is any adopter in the industry (4 digit SIC) 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% 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% 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 none of these facilities belongs 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 higher for a chemical manufacturer. As a result, even within an MSA, observers should find industry internal adoption to be the most informative. To test the robustness of our specification, we also used an alternative measure of local area. We captured adopters within a 50 mile area and obtained results that were statistically consistent with 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% 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.

Control Variables

Alternative mimetic and normative processes, coercive pressures, and desires for operational improvement could shape ISO 9000 adoption decisions (Cole, 1998; Guler, Guillen & MacPherson, 2000; 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.

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

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:

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

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 & Miner, 1997; Rosenkopf & Abrahamson, 1999). We measure *Industry Certification* as the annual percentage of certified facilities in each 4-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). The Chemical Industries Associations in the U.K., Germany, and France were instrumental in the diffusion of ISO 9000 in the chemical sectors (Chynoweth & Roberts, 1992). Yet not every industry association is equally active – in fact, budgets, staff, and committee activities vary greatly across associations (Barnett, 2005). 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.[5] Data for industry association expenses was taken from the Urban Institute, which makes available data collected on Form 990 by the Internal Revenue Service. Data for industry association membership was taken from the Encyclopedia of Associations.[6] Each industry association indicates a primary SIC code, and we use this SIC code to match facility and association data. Because association data is available for only 90 manufacturing SIC codes (4 digits), we fill in some of the missing values by calculating the median value of *Association Pressure* on the three digit SIC code.

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 U.S.. 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 U.S. 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 foreign suppliers to be

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

[6] 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 this data with us.

ISO 9000 certified. In fact, many companies 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 versus 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. Due 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 how much scrap a facility generates as part of its production process and given its size (King & Lenox, 2000). Specifically, 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 non-parametric 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 a correlation table in Tables 1 and 2.

Insert Tables 1 and 2 about here

Analysis

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

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

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 i^{th} facility in period t. Once a facility adopts, it is no longer at risk for adoption and it is removed from the sample. We also add a random effect term (a_{it}) 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 firms. 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 both corporate size and facility size. 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 below average performing facilities seek ISO 9000 in order to improve their performance. With respect to normative and coercive pressures for adoption, we find that association pressure, supply chain pressures, and supplying to foreign buyers all increase adoption propensities. The degree of industry certification does not significantly affect adoption propensities. However, this variable becomes strongly significant if we exclude the industry fixed effects, indicating that adoption trends may be industry specific. Note that the coefficients in Table 3 are not standardized. Thus, large coefficients do not necessarily indicate larger real economic impact on adoption propensities. Assessing the economic effect of our independent variables, we for example find that the effect of a one standard deviation increase in *Supply Chain Pressure* is only 1% point greater than the effect of a one standard deviation increase in *Corporate Size*.

Insert Table 2 about here

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 0.3% chance of adoption in a year to a 0.55% chance. For the entire 10 year panel period, this implies that smaller initial adopters increase future adoption propensities from 3% to 5.5%. However, to fully test Hypothesis 1, we need to compare these effects with the influence of larger adopter(s). Models 1 through 4 indicate that larger adopters exert significant influence, but we find that this influence 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 and 4, we find that a greater number of smaller adopters has a significantly stronger effect than a greater number of larger adopters ($p<0.01$). For Models 5 and 6, such a comparative analysis is unnecessary because our specification of *Bayesian Inference* already incorporates the relative effect of 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 the significant effect of larger adopters merely reflects the overall propensity in an industry to adopt. 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. Consider a case in which a 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 smaller and the larger adopter, but the measured effect of the larger adopter is a spurious result from the perspective of our postulated information-based bandwagon. That said, the influence of larger adopters may well be attributable to a value-based bandwagon that, albeit with a comparably weaker effect, may work in tandem with the information-based bandwagon.

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. As a result, our industry fixed effects may be robbing some of the explanatory power from our tests of Hypotheses 2.

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 from other adopters.

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 non-parametric 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. This statistical process could harm our analysis by making it difficult to interpret coefficient estimates for our independent variables. To address this concern, we calculated the expected smallest adopter given the observed number of adopters in each industry and year (i.e. we calculate the ‘1^{st} 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 it does not change the sign or significance of the reported results.

Third, we used monte-carlo simulation to test whether or not failure on part of managers to observe all adopters might influence our analysis (see Appendix 1). For our Baysian Inference variable, we simulated a failure to observe 10%, 25%, and 50% of the adopters. For all three levels, our main independent variable retains its statistical significance. However, since we are adding noise to our analysis, some of the interaction terms lose significance for the most extreme case. In a similar robustness test, we considered that managers may misjudge the size of some of the previous adopters. Results remain stable as long as the uncertainty about the size of observed adopters was less than half a standard deviation of the industries size variance (i.e., managers distinguish between averaged sized organizations and those 0.5 standard deviations greater than average).

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.[7] This specification does, however, make interpretation of the coefficients for the interaction terms more difficult by increasing multicollinearity in the models.

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 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 did not change the sign or significance of the coefficient for our main independent variable in Models 5 and 6, 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.

[7] For both Model 3 and Model 4, the coefficient of the main effect equals 0.033 ($p<0.001$) and the coefficient for the square term equals -0.000 ($p<0.001$).

DISCUSSION

In this article, we extend information-based theories of adoption to analyze a case in which smaller adopters have a surprising 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, as compared to larger ones, are associated with greater future adoption propensities. 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 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 consistent support for our theory.

Why do our findings differ from the preponderance of previous research? One explanation is that we specifically chose a setting that meets our conditions and where we therefore expected such an outcome. Specifically, the value of adopting our practice, ISO 9000, increases with organizational size and adoption (certification) is a visible act. 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 firms strongly influenced the choices of others. Baum et al (2000) find that larger firms' location choices for chain acquisitions set off bandwagons. In both of these studies, it is not clear that the value of adoption systematically increases with organizational size, and smaller adopters may therefore have little influence.

Another explanation is that the existence of published registries of ISO 9000 adopters may reduce 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 become less pronounced in our context because published registries provide information on certified organizations of all sizes.

A principle implication of our study is that settings exist where value-based and information-based theories of 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-based bandwagon processes are always more important than value-based ones? Not at all. We may have considered a case in which previous adoption provides little change in the value of the practice such that legitimacy concerns may take a backseat to technical considerations. 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. [8]

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,

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

Kraatz (1998) finds that greater size of previous adopters negatively affected program adoption, suggesting 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 possibility is that because curriculum modifications require substantial organizational changes, technical concerns took the forefront and caused similar adopters, rather than larger ones, to be influential. Interpreted from the perspective of our study, it may also be possible that curriculum changes provided greater value at larger institutions which, subsequently, may have decreased the influence of larger adopters. We believe that these findings and the ones in our study suggest the need for more research on how the conditions present in adoption environments (e.g. managerial expectations, observability, initial legitimacy, etc.) influence the relative influence of different types of organizations.

Finally, it is important to keep in mind that neither our theory nor our findings preclude the simultaneous influence of other pressures. In fact, while our results provide evidence that the information effect of smaller adopters is greater than that of larger adopters, results also show that adoption is shaped by coercive pressures in the supply chain and from foreign buyers, and by normative pressures from industry associations.

Our study has several limitations. Most importantly, we assume that managers do not <u>systematically</u> 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. Furthermore, exploring abandonment subsequent to unprofitable adoption could shed additional light on adoption dynamics. 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 specify it in this study. Modeling and empirically exploring the conditions for systematically unprofitable adoption and potential abandonment would greatly add to this article's complexity.

Another limitation is that we do not directly measure managerial expectations about variations in the practice's profitability. Instead, we choose a context in which previous studies had identified managerial expectations that matched the conditions of our theory. We find that adoption behavior was consistent with stipulated expectations. However, when we test the applicability of our theory in other contexts, we plan to directly measure managerial expectations. This will allow a more differentiated view of the relationship between managerial profitability expectations and adoption behaviors.

Finally, we test our ideas in the context of only one adoption process. Our study does consider the adoption process of ISO 9000 across multiple industries, and thus suggests evidence that our ideas provide explanatory power in different settings that meet the assumptions of our theory (i.e., visible adoption and managerial expectations of a varying relationship between an organizational attribute and adoption profitability). However, our study only considers adoption of one practice, and thus care should be taken in extrapolating to adoption of different types of practices.

CONCLUSION

In summary, in this article we extend theories of adoption bandwagons by investigating a case in which information-based theories of adoption predict that smaller (as opposed to larger) organizations will have a disproportionately strong effect on future adoption. 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 not uncommon case – information-based theories of adoption predict that smaller adopters will have a greater association with future adoption propensities than larger organizations. In support of this information story, we find that alternative information sources moderate the effect of smaller adopters.

Our study falls squarely into recent research efforts to explore the contingencies of adoption patterns and outcomes (Greve & Taylor, 2000; Kim & Miner, 2000; Miner, Kim, Holzinger et al, 1999). We extend these studies by showing that predicted adoption patterns may be conditional on how managers expect the value of adopting a practice to vary with organizational characteristics. Our results indicate that theories of adoption processes could be advanced by exploring the effect of managerial beliefs on adoption patterns. We hope that future research will consider the effect of both shifting and misguided beliefs among potential adopters. We also hope that future research will seek to explore further the differences in the mechanisms underlying various bandwagons.

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Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
1 Smaller Adopter	0.47	0.50	0.00	1.00
2 Number Smaller Adopters	1.27	1.19	0.00	5.26
3 Bayesian Inference	0.83	0.30	0.01	1.00
4 Larger Adopter	0.86	0.34	0.00	1.00
5 Number Larger Adopters	1.92	1.29	0.00	5.26
6 Number Adopters in MSA	0.29	0.61	0.00	5.01
7 Adopter in MSA	0.15	0.36	0.00	1.00
8 Corporate Size	1.72	1.56	0.00	5.76
9 Peer Pressure	-0.09	0.54	-2.51	2.84
10 Industry Certification	0.06	0.08	0.00	0.73
11 Supply Chain Pressure	0.04	0.04	0.00	0.23
12 Operational Performance^	0.02	-1.01	-4.35	6.43
13 Relative Facility Size^	-0.06	-0.99	5.51	5.37
14 Supply to Foreign	0.04	0.04	0.00	0.55
15 Association Pressure	9.73	1.40	6.84	13.45

N = 70780
Year variables omitted from table.
^ Variable values are normalized. Note that the means of these normalized variables does 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 we however used the entire sample.

Table 2: Correlation Table

Variable	Mean	Std. Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Smaller Adopter	0.47	0.50	0.00	1.00	1.00														
2 Number Smaller Adopters	1.27	1.19	0.00	5.26	0.34	1.00													
3 Bayesian Inference	0.83	0.30	0.01	1.00	0.41	0.58	1.00												
4 Larger Adopter	0.86	0.34	0.00	1.00	-0.42	-0.12	-0.21	1.00											
5 Number Larger Adopters	1.92	1.29	0.00	5.26	-0.24	0.45	0.20	0.41	1.00										
6 Number Adopters in MSA	0.29	0.61	0.00	5.01	-0.01	0.39	0.17	0.06	0.39	1.00									
7 Adopter in MSA	0.15	0.36	0.00	1.00	-0.01	0.32	0.15	0.05	0.33	0.74	1.00								
8 Corporate Size	1.72	1.56	0.00	5.76	0.16	0.12	0.10	-0.14	-0.14	-0.01	0.00	1.00							
9 Peer Pressure	-0.09	0.54	-2.51	2.84	0.29	0.29	0.06	-0.11	-0.32	-0.04	-0.03	0.15	1.00						
10 Industry Certification	0.06	0.08	0.00	0.73	0.03	0.54	0.25	0.09	0.55	0.35	0.24	0.04	-0.14	1.00					
11 Supply Chain Pressure	0.04	0.04	0.00	0.23	0.02	0.56	0.30	0.06	0.58	0.36	0.28	-0.05	-0.11	0.72	1.00				
12 Operational Performance	0.02	-1.01	-4.35	6.43	0.00	0.01	0.02	0.00	0.01	0.00	0.00	-0.06	-0.01	0.01	0.01	1.00			
13 Relative Facility Size	-0.06	-0.99	5.51	5.37	0.53	0.47	0.53	-0.44	-0.36	0.00	0.00	0.25	0.48	-0.04	-0.04	0.01	1.00		
14 Supply to Foreign	0.04	0.04	0.00	0.55	0.05	0.09	0.07	-0.10	0.06	0.07	0.05	0.11	-0.05	0.19	0.06	0.00	-0.01	1.00	
15 Association Pressure	9.73	1.40	6.84	13.45	-0.05	0.07	0.01	0.10	0.12	0.04	0.06	0.08	-0.04	0.10	0.11	0.00	-0.01	0.18	1.00

N = 70780
Year variables omitted from table.

Table 3 - Model Results

	Model 1+	Model 2+	Model 3++	Model 4++	Model 5+++	Model 6+++
Independent Variable (IV)	0.437*** (0.083)	0.421*** (0.082)	0.501*** (0.052)	0.480*** (0.051)	1.126*** (0.170)	1.153*** (0.171)
Larger Adopter/Num. Larger Adopters	0.205** (0.077)	0.203** (0.078)	0.155*** (0.038)	0.156*** (0.038)		
IV x Number Adopters in MSA	-0.131* (0.063)		-0.101*** (0.027)		-0.278 (0.208)	
IV x Adopter in MSA		-0.141 (0.109)		-0.127** (0.046)		-0.737* (0.292)
IV x Corporate Size	-0.113*** (0.029)	-0.113*** (0.029)	-0.081*** (0.012)	-0.082*** (0.012)	-0.158* (0.065)	-0.160* (0.065)
Number Adopters in MSA	0.150** (0.050)		0.256** (0.081)		0.328 (0.205)	
Adopter in MSA		0.323*** (0.083)		0.414*** (0.122)		0.924** (0.284)
Corporate Size	0.166*** (0.024)	0.166*** (0.024)	0.257*** (0.028)	0.258*** (0.027)	0.242*** (0.061)	0.244*** (0.061)
Peer Pressure	0.200*** (0.044)	0.196*** (0.044)	0.167*** (0.048)	0.162*** (0.047)	0.282*** (0.044)	0.281*** (0.044)
Industry Certification	0.120 (0.435)	0.106 (0.433)	-0.735 (0.480)	-0.844 (0.480)	0.275 (0.426)	0.283 (0.425)
Supply Chain Pressure	7.291*** (1.388)	7.135*** (1.391)	5.595*** (1.467)	5.512*** (1.469)	6.787*** (1.374)	6.654*** (1.376)
Operational Performance	-0.105*** (0.023)	-0.106*** (0.023)	-0.114*** (0.024)	-0.114*** (0.024)	-0.106*** (0.022)	-0.106*** (0.022)
Relative Facility Size	0.317*** (0.036)	0.319*** (0.036)	0.250*** (0.046)	0.256*** (0.046)	0.205*** (0.034)	0.208*** (0.034)
Supply to Foreign	2.289*** (0.649)	2.241** (0.652)	1.773* (0.695)	1.747* (0.695)	1.725** (0.630)	1.645** (0.631)
Association Pressure	0.245*** (0.062)	0.238*** (0.062)	0.154* (0.065)	0.158* (0.065)	0.227*** (0.061)	0.220*** (0.061)
Year and Industry Fixed Effects	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Observations	70780	70780	70780	70780	70780	70780
Number of facilities	14642	14642	14642	14642	14642	14642

*** $p< 0.001$; ** $p<0.01$ (two tailed), * $p<0.05$. All tests are two-tailed.
Constant omitted from table due to inclusion of industry and year dummies.
[+] The independent variable in Models 1 and 2 is the binary variable “Smaller Adopter”. Models 1 and 2 use the binary variable “Larger Adopter”.
[++] 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”.
[+++] The independent variable in Models 5 and 6 is the inference variable “Bayesian Inference”

APPENDIX 1

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 exceeds costs ($B(\theta) > C(\theta)$) and below which it does 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 $S_{\theta j}$ and some have private information about benefits and costs and know whether for 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 *p* chance 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 facilities may not 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 it 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's Rule to update their inference.

For each industry *j* in year *t= 2* with ω =1 to M possible facility separating levels, Bayes's Rule would predict that:

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

with

$S_{\omega j}$ = *Separating level is at size* ω *in industry j* $(B(\theta)_j > C(\theta)_j)$,
$\{\gamma_{j1}\}$ = *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:

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

Where θ_i *= Size of the focal facility i and* $P(\theta_{ij} > S_{\omega j})$ *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 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 firms could make such an inference. The probability that any observed adopting firm 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 an adopter has private information $= 1 - P(\theta_{ij\,t-1} > S_{\omega j-1})$. 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 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% were observed, c) 75% were observed, and d) 50% 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 test confirm sign and significance consistency for observed adoption > 50% and for size error estimation <= 0.5s.